dm-1-asst-3

November 25, 2023

[1]:
```
import pandas as pd
import seaborn as sns
import os
import keras
import matplotlib.pyplot as plt
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Conv2D, Dense, MaxPool2D, Flatten, Dropout,␣
↪BatchNormalization, DepthwiseConv2D, InputLayer, GlobalAveragePooling2D
from tensorflow.keras.regularizers import l2
from tensorflow.keras.models import Sequential
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

1.Association Rule Generation from Transaction Data

[3]:
```
dataset = pd.read_csv('/content/drive/MyDrive/Grocery_Items_25.csv')
dataset.head()
```

[3]:
```
                        0                   1             2  \
0                  pastry       baking powder           NaN
1                 sausage             sausage  frozen fish
2                     ham          whole milk           NaN
3       whipped/sour cream       baking powder           NaN
4  house keeping products  frozen vegetables           NaN

                        3    4    5    6    7    8   9   10
0                     NaN  NaN  NaN  NaN  NaN  NaN NaN NaN
1  house keeping products  NaN  NaN  NaN  NaN  NaN NaN NaN
2                     NaN  NaN  NaN  NaN  NaN  NaN NaN NaN
3                     NaN  NaN  NaN  NaN  NaN  NaN NaN NaN
4                     NaN  NaN  NaN  NaN  NaN  NaN NaN NaN
```

[4]:
```
dataset.shape
```

[4]:
```
(8000, 11)
```

[5]:
```
records = []
for i in range(8000):
  records.append([str(dataset.values[i,j]) for j in range(11) if str(dataset.
↪values[i,j]) != 'nan'])
```

[6]:
```
encoder = TransactionEncoder()
encoder_array = encoder.fit(records).transform(records)
dataframe = pd.DataFrame(encoder_array, columns=encoder.columns_)
```

[7]:
```
dataframe.head()
```

[7]:
```
   Instant food products  UHT-milk  abrasive cleaner  artif. sweetener   bags  \
0                  False     False             False             False  False
1                  False     False             False             False  False
2                  False     False             False             False  False
3                  False     False             False             False  False
4                  False     False             False             False  False

   baking powder  bathroom cleaner   beef  berries  beverages  …  turkey  \
0           True             False  False    False      False  …   False
1          False             False  False    False      False  …   False
2          False             False  False    False      False  …   False
3           True             False  False    False      False  …   False
4          False             False  False    False      False  …   False

   vinegar  waffles  whipped/sour cream  whisky  white bread  white wine  \
0    False    False               False   False        False       False
1    False    False               False   False        False       False
2    False    False               False   False        False       False
3    False    False                True   False        False       False
4    False    False               False   False        False       False

   whole milk  yogurt  zwieback
0       False   False     False
1       False   False     False
2        True   False     False
3       False   False     False
4       False   False     False

[5 rows x 165 columns]
```

C

[8]:
```python
frequent_itemsets = apriori(dataframe, min_support=0.01, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="confidence",
  min_threshold=0.1)
rules
```

[8]:
```
          antecedents          consequents  antecedent support  \
0              (soda)  (other vegetables)            0.103125
1  (other vegetables)         (whole milk)            0.122000
2        (rolls/buns)         (whole milk)            0.109625
3              (soda)         (whole milk)            0.103125
4            (yogurt)         (whole milk)            0.088125

   consequent support   support  confidence      lift  leverage  conviction  \
0            0.122000  0.010625    0.103030  0.844511 -0.001956    0.978851
1            0.154625  0.014250    0.116803  0.755397 -0.004614    0.957176
2            0.154625  0.012750    0.116306  0.752178 -0.004201    0.956637
3            0.154625  0.011875    0.115152  0.744715 -0.004071    0.955390
4            0.154625  0.011375    0.129078  0.834781 -0.002251    0.970667

   zhangs_metric
0      -0.170323
1      -0.269433
2      -0.270093
3      -0.276522
4      -0.178338
```

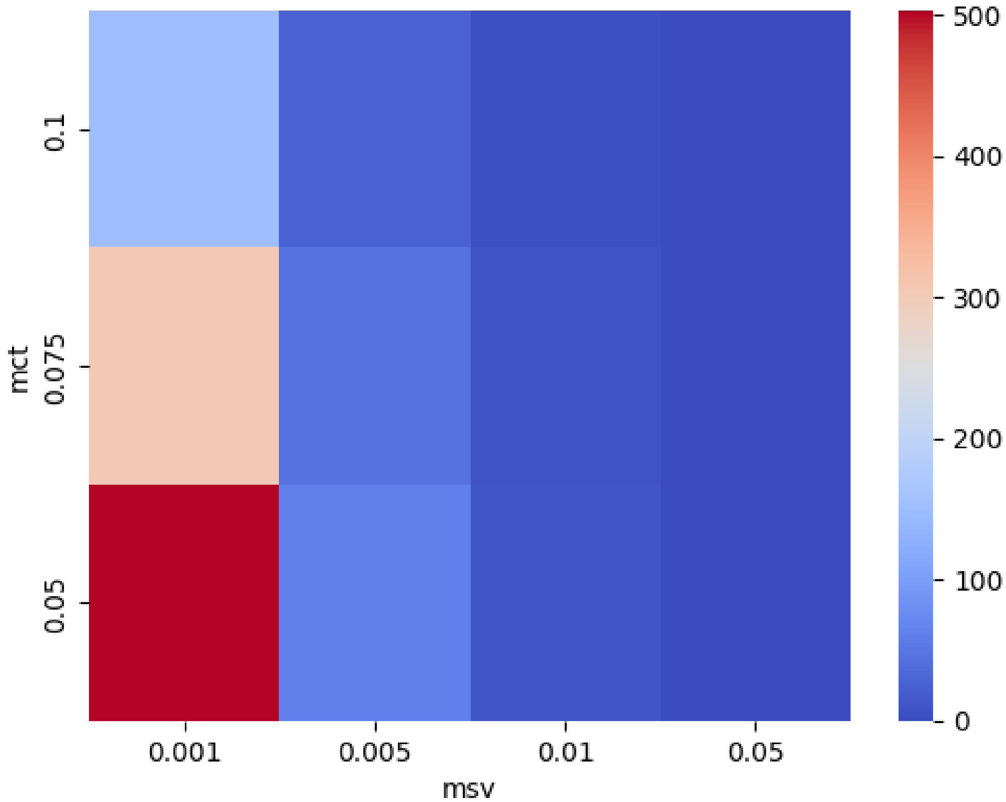
D

[9]:
```python
heatmap_data = []
for i in [0.001,0.005,0.01,0.05]:
    for j in [0.05,0.075,0.1]:
        frequent_itemsets = apriori(dataframe, min_support=i, use_colnames=True)
        rules = association_rules(frequent_itemsets, metric="confidence",
  min_threshold=j)
        heatmap_data.append({'msv': i, 'mct': j, 'no.of rules': len(rules)})
```

[10]:
```python
heatdata = pd.DataFrame(heatmap_data)
heatdata = heatdata.pivot(index='mct', columns='msv', values='no.of rules')
```

[11]:
```python
sns.heatmap(heatdata.sort_index(ascending=False),cmap='coolwarm')
```

[11]:
```
<Axes: xlabel='msv', ylabel='mct'>
```



E

```
[12]: frequent_itemsets_hc = apriori(dataframe, min_support=0.005, use_colnames=True)
rules_hc = association_rules(frequent_itemsets_hc, metric="confidence",␣
 ↪min_threshold=0.0)
rules_hc.loc[rules_hc['confidence'].idxmax()]
```

```
[12]: antecedents           (domestic eggs)
consequents              (whole milk)
antecedent support              0.035
consequent support           0.154625
support                      0.005625
confidence                   0.160714
lift                         1.039381
leverage                     0.000213
conviction                   1.007255
zhangs_metric                0.039263
Name: 15, dtype: object
```

2. Image Classification using CNN

```
[13]: directory = "/content/drive/MyDrive/Dogs_Dataset/images_cropped"
```

[14]:
```
Image = []
label = []
categories = sorted(os.listdir(directory))
for i in categories:
  for j in os.listdir(os.path.join(directory,i)):
    Image.append(os.path.join(directory,i,j))
    label.append(i)
```

[15]:
```
train_data,test_data,train_label,test_label = train_test_split(Image,
                                                              label,
                                                              train_size=0.8,
                                                              random_state=10)
```

[16]:
```
train = pd.DataFrame({'file_paths': train_data, 'labels': train_label})
test = pd.DataFrame({'file_paths': test_data, 'labels': test_label})
```

[17]:
```
datagen = keras.preprocessing.image.ImageDataGenerator(rescale=1./255)
train_gen = datagen.flow_from_dataframe(
    train,
    x_col='file_paths',
    y_col='labels',
    target_size=(256, 256),
    batch_size=32,
    class_mode='categorical',
)
test_gen = datagen.flow_from_dataframe(
    test,
    x_col='file_paths',
    y_col='labels',
    target_size=(256, 256),
    batch_size=32,
    class_mode='categorical',
)
```

```
Found 543 validated image filenames belonging to 4 classes.
Found 136 validated image filenames belonging to 4 classes.
```

[18]:
```
model = Sequential()

model.add(Conv2D(8, (3, 3), activation='relu', input_shape=(256,256,3)))
model.add(MaxPool2D((2, 2)))
model.add(Flatten())
model.add(Dense(16, activation='relu'))
model.add(Dense(4, activation='softmax'))
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```python
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 8)       224

 max_pooling2d (MaxPooling2D  (None, 127, 127, 8)      0
 )

 flatten (Flatten)           (None, 129032)            0

 dense (Dense)               (None, 16)                2064528

 dense_1 (Dense)             (None, 4)                 68

=================================================================
Total params: 2,064,820
Trainable params: 2,064,820
Non-trainable params: 0
_________________________________________________________________
```

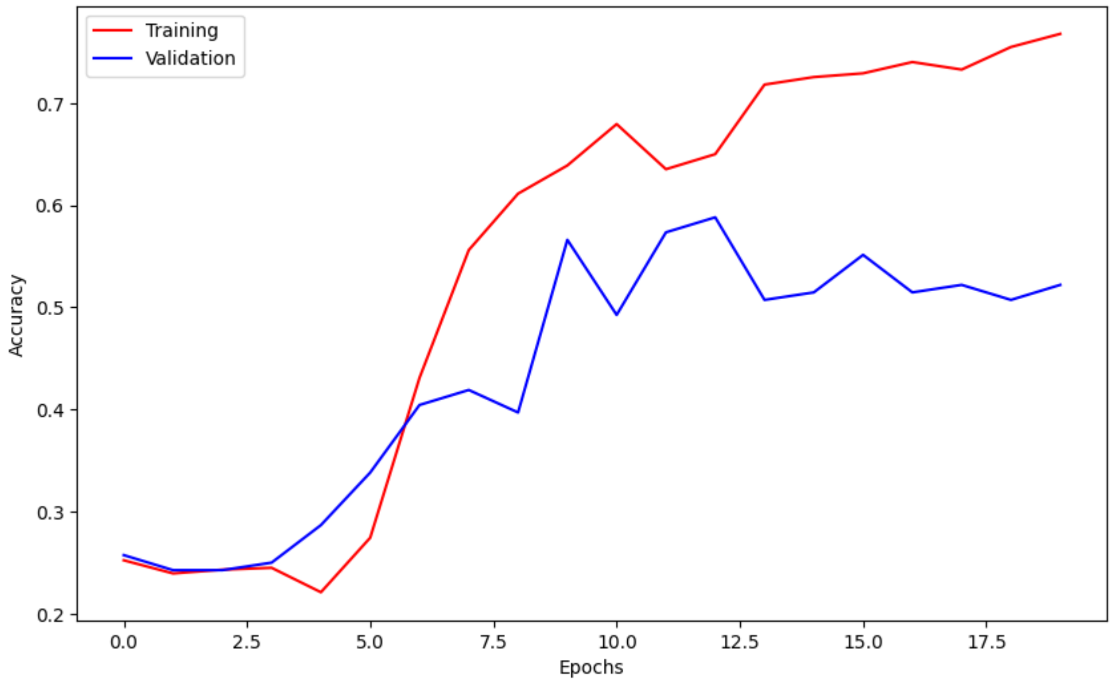
[19]:
```python
training = model.fit(train_gen,
                      validation_data = test_gen,
                     epochs = 20
                     )
```

```
Epoch 1/20
17/17 [==============================] - 108s 6s/step - loss: 3.4264 - accuracy:
0.2523 - val_loss: 1.3911 - val_accuracy: 0.2574
Epoch 2/20
17/17 [==============================] - 22s 1s/step - loss: 1.3826 - accuracy:
0.2394 - val_loss: 1.3997 - val_accuracy: 0.2426
Epoch 3/20
17/17 [==============================] - 21s 1s/step - loss: 1.3806 - accuracy:
0.2431 - val_loss: 1.3977 - val_accuracy: 0.2426
Epoch 4/20
17/17 [==============================] - 21s 1s/step - loss: 1.3781 - accuracy:
0.2449 - val_loss: 1.3985 - val_accuracy: 0.2500
Epoch 5/20
17/17 [==============================] - 22s 1s/step - loss: 1.3749 - accuracy:
0.2210 - val_loss: 1.3921 - val_accuracy: 0.2868
Epoch 6/20
17/17 [==============================] - 21s 1s/step - loss: 1.3565 - accuracy:
0.2744 - val_loss: 1.3635 - val_accuracy: 0.3382
Epoch 7/20
```

```
17/17 [==============================] - 20s 1s/step - loss: 1.2699 - accuracy:
0.4309 - val_loss: 1.2837 - val_accuracy: 0.4044
Epoch 8/20
17/17 [==============================] - 21s 1s/step - loss: 1.1688 - accuracy:
0.5562 - val_loss: 1.2000 - val_accuracy: 0.4191
Epoch 9/20
17/17 [==============================] - 20s 1s/step - loss: 1.0566 - accuracy:
0.6114 - val_loss: 1.2491 - val_accuracy: 0.3971
Epoch 10/20
17/17 [==============================] - 21s 1s/step - loss: 0.9540 - accuracy:
0.6390 - val_loss: 1.2111 - val_accuracy: 0.5662
Epoch 11/20
17/17 [==============================] - 21s 1s/step - loss: 0.8853 - accuracy:
0.6796 - val_loss: 1.1892 - val_accuracy: 0.4926
Epoch 12/20
17/17 [==============================] - 21s 1s/step - loss: 0.8399 - accuracy:
0.6354 - val_loss: 1.1656 - val_accuracy: 0.5735
Epoch 13/20
17/17 [==============================] - 21s 1s/step - loss: 0.8073 - accuracy:
0.6501 - val_loss: 1.1357 - val_accuracy: 0.5882
Epoch 14/20
17/17 [==============================] - 21s 1s/step - loss: 0.7715 - accuracy:
0.7182 - val_loss: 1.1178 - val_accuracy: 0.5074
Epoch 15/20
17/17 [==============================] - 21s 1s/step - loss: 0.7529 - accuracy:
0.7256 - val_loss: 1.1355 - val_accuracy: 0.5147
Epoch 16/20
17/17 [==============================] - 22s 1s/step - loss: 0.7438 - accuracy:
0.7293 - val_loss: 1.0690 - val_accuracy: 0.5515
Epoch 17/20
17/17 [==============================] - 23s 1s/step - loss: 0.7329 - accuracy:
0.7403 - val_loss: 1.1131 - val_accuracy: 0.5147
Epoch 18/20
17/17 [==============================] - 21s 1s/step - loss: 0.7039 - accuracy:
0.7330 - val_loss: 1.0837 - val_accuracy: 0.5221
Epoch 19/20
17/17 [==============================] - 21s 1s/step - loss: 0.6916 - accuracy:
0.7551 - val_loss: 1.1212 - val_accuracy: 0.5074
Epoch 20/20
17/17 [==============================] - 21s 1s/step - loss: 0.6631 - accuracy:
0.7680 - val_loss: 1.0856 - val_accuracy: 0.5221
```

[20]:
```
def plot_accuracy(train_data):
  acc = train_data.history['accuracy']
  val_acc = train_data.history['val_accuracy']

  epochs = range(len(acc))
```

```
    fig = plt.figure(figsize=(10,6))
    plt.plot(epochs,acc,c="red",label="Training")
    plt.plot(epochs,val_acc,c="blue",label="Validation")
    plt.xticks(fontsize=10)
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.show()
plot_accuracy(training)
```



Rowan Banner ID - 916462027

Hence, C) Train the CNN using 2 other number of nodes in the hidden layer 8 and 32 with all other parameters unchanged

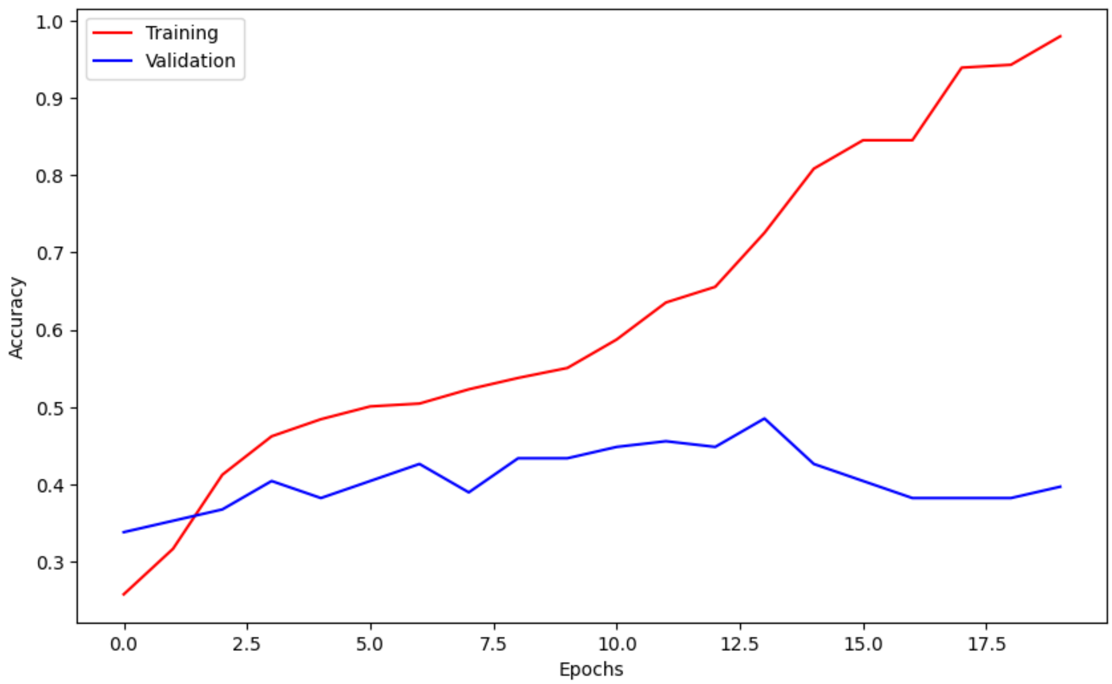
[22]:
```
model_2 = Sequential()

model_2.add(Conv2D(8, (3, 3), activation='relu', input_shape=(256,256,3)))
model_2.add(MaxPool2D((2, 2)))
model_2.add(Flatten())
model_2.add(Dense(8, activation='relu'))
model_2.add(Dense(4, activation='softmax'))
model_2.compile(optimizer='adam',
              loss='categorical_crossentropy',
```

```
               metrics=['accuracy'])

model_2.summary()

training_2 = model_2.fit(train_gen,
                      validation_data = test_gen,
                     epochs = 20
                     )
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 254, 254, 8)       224

 max_pooling2d_2 (MaxPooling  (None, 127, 127, 8)      0
 2D)

 flatten_2 (Flatten)         (None, 129032)            0

 dense_4 (Dense)             (None, 8)                 1032264

 dense_5 (Dense)             (None, 4)                 36

=================================================================
Total params: 1,032,524
Trainable params: 1,032,524
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
17/17 [==============================] - 22s 1s/step - loss: 3.9095 - accuracy:
0.2578 - val_loss: 1.4346 - val_accuracy: 0.3382
Epoch 2/20
17/17 [==============================] - 20s 1s/step - loss: 1.3623 - accuracy:
0.3168 - val_loss: 1.3316 - val_accuracy: 0.3529
Epoch 3/20
17/17 [==============================] - 28s 2s/step - loss: 1.1848 - accuracy:
0.4125 - val_loss: 1.3236 - val_accuracy: 0.3676
Epoch 4/20
17/17 [==============================] - 22s 1s/step - loss: 1.0577 - accuracy:
0.4622 - val_loss: 1.3026 - val_accuracy: 0.4044
Epoch 5/20
17/17 [==============================] - 19s 1s/step - loss: 0.9561 - accuracy:
0.4843 - val_loss: 1.3023 - val_accuracy: 0.3824
Epoch 6/20
17/17 [==============================] - 21s 1s/step - loss: 0.8640 - accuracy:
0.5009 - val_loss: 1.3390 - val_accuracy: 0.4044
```

```
Epoch 7/20
17/17 [==============================] - 22s 1s/step - loss: 0.7994 - accuracy:
0.5046 - val_loss: 1.3293 - val_accuracy: 0.4265
Epoch 8/20
17/17 [==============================] - 21s 1s/step - loss: 0.7424 - accuracy:
0.5230 - val_loss: 1.3229 - val_accuracy: 0.3897
Epoch 9/20
17/17 [==============================] - 21s 1s/step - loss: 0.7031 - accuracy:
0.5378 - val_loss: 1.3519 - val_accuracy: 0.4338
Epoch 10/20
17/17 [==============================] - 23s 1s/step - loss: 0.6647 - accuracy:
0.5506 - val_loss: 1.3860 - val_accuracy: 0.4338
Epoch 11/20
17/17 [==============================] - 23s 1s/step - loss: 0.6386 - accuracy:
0.5875 - val_loss: 1.3700 - val_accuracy: 0.4485
Epoch 12/20
17/17 [==============================] - 21s 1s/step - loss: 0.6167 - accuracy:
0.6354 - val_loss: 1.4254 - val_accuracy: 0.4559
Epoch 13/20
17/17 [==============================] - 22s 1s/step - loss: 0.5899 - accuracy:
0.6556 - val_loss: 1.4445 - val_accuracy: 0.4485
Epoch 14/20
17/17 [==============================] - 22s 1s/step - loss: 0.5615 - accuracy:
0.7256 - val_loss: 1.4723 - val_accuracy: 0.4853
Epoch 15/20
17/17 [==============================] - 19s 1s/step - loss: 0.5290 - accuracy:
0.8085 - val_loss: 1.6248 - val_accuracy: 0.4265
Epoch 16/20
17/17 [==============================] - 20s 1s/step - loss: 0.5032 - accuracy:
0.8453 - val_loss: 1.6332 - val_accuracy: 0.4044
Epoch 17/20
17/17 [==============================] - 20s 1s/step - loss: 0.4767 - accuracy:
0.8453 - val_loss: 1.6817 - val_accuracy: 0.3824
Epoch 18/20
17/17 [==============================] - 20s 1s/step - loss: 0.4291 - accuracy:
0.9392 - val_loss: 1.7655 - val_accuracy: 0.3824
Epoch 19/20
17/17 [==============================] - 21s 1s/step - loss: 0.3984 - accuracy:
0.9429 - val_loss: 1.8532 - val_accuracy: 0.3824
Epoch 20/20
17/17 [==============================] - 22s 1s/step - loss: 0.3525 - accuracy:
0.9797 - val_loss: 1.9700 - val_accuracy: 0.3971
```

[23]:
```
plot_accuracy(training_2)
```



[24]:
```python
model_3 = Sequential()

model_3.add(Conv2D(8, (3, 3), activation='relu', input_shape=(256,256,3)))
model_3.add(MaxPool2D((2, 2)))
model_3.add(Flatten())
model_3.add(Dense(32, activation='relu'))
model_3.add(Dense(4, activation='softmax'))
model_3.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

model_3.summary()

training_3 = model_3.fit(train_gen,
                    validation_data = test_gen,
                   epochs = 20
                   )
```

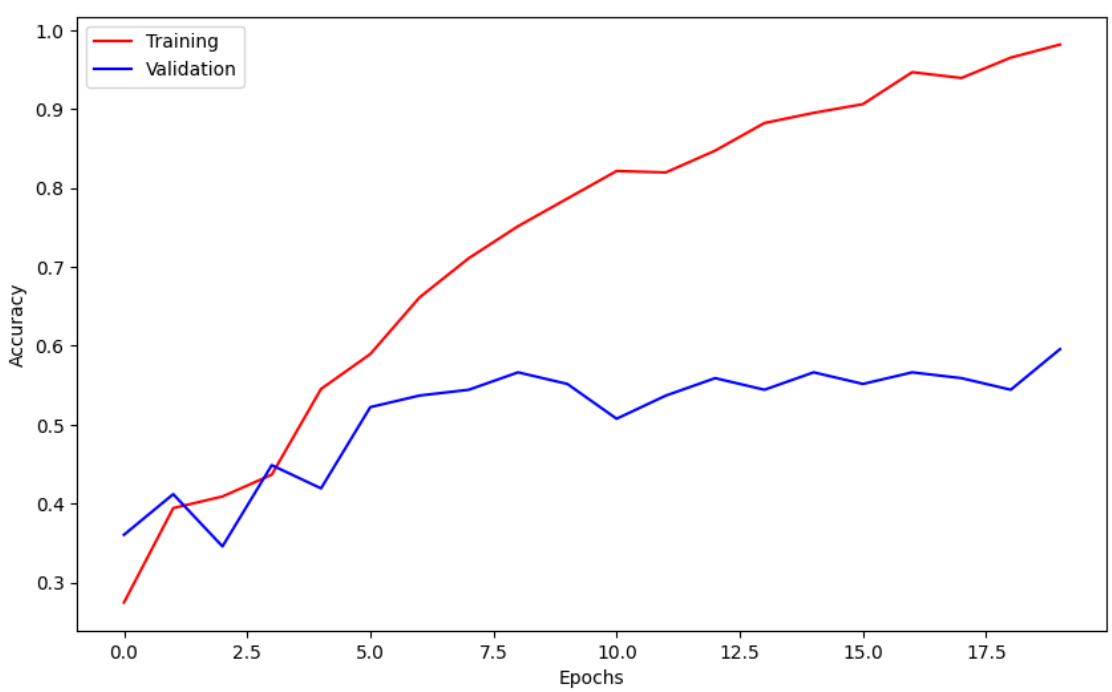
```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 254, 254, 8)       224


 max_pooling2d_3 (MaxPooling  (None, 127, 127, 8)      0
```

```
 2D)

 flatten_3 (Flatten)         (None, 129032)            0

 dense_6 (Dense)             (None, 32)                4129056

 dense_7 (Dense)             (None, 4)                 132

=================================================================
Total params: 4,129,412
Trainable params: 4,129,412
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
17/17 [==============================] - 22s 1s/step - loss: 5.9153 - accuracy:
0.2744 - val_loss: 1.8797 - val_accuracy: 0.3603
Epoch 2/20
17/17 [==============================] - 22s 1s/step - loss: 1.3461 - accuracy:
0.3941 - val_loss: 1.2720 - val_accuracy: 0.4118
Epoch 3/20
17/17 [==============================] - 22s 1s/step - loss: 1.1935 - accuracy:
0.4088 - val_loss: 1.2593 - val_accuracy: 0.3456
Epoch 4/20
17/17 [==============================] - 22s 1s/step - loss: 1.1040 - accuracy:
0.4365 - val_loss: 1.2239 - val_accuracy: 0.4485
Epoch 5/20
17/17 [==============================] - 22s 1s/step - loss: 0.9817 - accuracy:
0.5451 - val_loss: 1.1979 - val_accuracy: 0.4191
Epoch 6/20
17/17 [==============================] - 22s 1s/step - loss: 0.8965 - accuracy:
0.5893 - val_loss: 1.1076 - val_accuracy: 0.5221
Epoch 7/20
17/17 [==============================] - 22s 1s/step - loss: 0.8289 - accuracy:
0.6611 - val_loss: 1.1030 - val_accuracy: 0.5368
Epoch 8/20
17/17 [==============================] - 21s 1s/step - loss: 0.7611 - accuracy:
0.7109 - val_loss: 1.1469 - val_accuracy: 0.5441
Epoch 9/20
17/17 [==============================] - 22s 1s/step - loss: 0.6898 - accuracy:
0.7514 - val_loss: 1.0856 - val_accuracy: 0.5662
Epoch 10/20
17/17 [==============================] - 22s 1s/step - loss: 0.6354 - accuracy:
0.7864 - val_loss: 1.1186 - val_accuracy: 0.5515
Epoch 11/20
17/17 [==============================] - 23s 1s/step - loss: 0.5899 - accuracy:
0.8214 - val_loss: 1.2041 - val_accuracy: 0.5074
Epoch 12/20
17/17 [==============================] - 20s 1s/step - loss: 0.5474 - accuracy:
```

```
0.8195 - val_loss: 1.1547 - val_accuracy: 0.5368
Epoch 13/20
17/17 [==============================] - 22s 1s/step - loss: 0.4869 - accuracy:
0.8471 - val_loss: 1.1122 - val_accuracy: 0.5588
Epoch 14/20
17/17 [==============================] - 22s 1s/step - loss: 0.4412 - accuracy:
0.8821 - val_loss: 1.0308 - val_accuracy: 0.5441
Epoch 15/20
17/17 [==============================] - 22s 1s/step - loss: 0.4018 - accuracy:
0.8950 - val_loss: 1.0777 - val_accuracy: 0.5662
Epoch 16/20
17/17 [==============================] - 22s 1s/step - loss: 0.3533 - accuracy:
0.9061 - val_loss: 1.0271 - val_accuracy: 0.5515
Epoch 17/20
17/17 [==============================] - 22s 1s/step - loss: 0.3072 - accuracy:
0.9466 - val_loss: 1.0280 - val_accuracy: 0.5662
Epoch 18/20
17/17 [==============================] - 21s 1s/step - loss: 0.2683 - accuracy:
0.9392 - val_loss: 1.1177 - val_accuracy: 0.5588
Epoch 19/20
17/17 [==============================] - 28s 2s/step - loss: 0.2318 - accuracy:
0.9650 - val_loss: 1.2484 - val_accuracy: 0.5441
Epoch 20/20
17/17 [==============================] - 27s 2s/step - loss: 0.2002 - accuracy:
0.9816 - val_loss: 1.1632 - val_accuracy: 0.5956
```

[25]:

```
plot_accuracy(training_3)
```



From the training accuracy plots of the three models we can observe that from epoch 10 the model is starting to over-fit. The training accuacy keeps on increasing, where as the validation accuracy is starting to decrease.