Data Mining: Programming Assignment 3

Libraries Imported

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import cv2
import random
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, fpmax, fpgrowth
from mlxtend.frequent_patterns import association_rules
import seaborn as sns
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split
from pathlib import Path
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
```

Association Rule Generation from Transaction Data

Dataset Used: Grocery_Items_23.csv

In [7]:
```
Grocery_Items_Files = '/Users/alokkumarjha/Downloads/Grocery_Items_23.csv'
data = pd.read_csv(Grocery_Items_Files)
print(Grocery_Items_Files)
```

```
/Users/alokkumarjha/Downloads/Grocery_Items_23.csv
```

In [9]:
```
grocery_items = pd.read_csv(Grocery_Items_Files)
grocery_items.head()
```

Out[9]:

	0	1	2	3	4	5	6	7	8	9	10
0	dishes	shopping bags	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	pastry	curd	bottled beer	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	sausage	whipped/sour cream	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	sugar	fruit/vegetable juice	margarine	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	frankfurter	cream cheese	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [11]:
```
grocery_items_ = grocery_items.apply(lambda row: row.dropna().to_list(), axis = 1)
grocery_items_list = grocery_items_.to_list()
```

In [13]:
```
te = TransactionEncoder()
te_ary = te.fit(grocery_items_list).transform(grocery_items_list)
df = pd.DataFrame(te_ary, columns = te.columns_)
```

Reference: https://rasbt.github.io/mlxtend/user_guide/frequent_patterns/association_rules/#association_rules-association-rules-generation-from-frequent-itemsets

In [15]:
```
frequent_itemsets = apriori(df, min_support = 0.01, use_colnames = True)
frequent_itemsets
```

Out[15]:

	support	itemsets
0	0.020250	(UHT-milk)
1	0.033750	(beef)
2	0.021625	(berries)
3	0.015375	(beverages)
4	0.044000	(bottled beer)
...	...	...
63	0.010500	(other vegetables, soda)
64	0.015500	(whole milk, other vegetables)
65	0.014750	(rolls/buns, whole milk)
66	0.013500	(whole milk, soda)
67	0.011875	(yogurt, whole milk)

68 rows × 2 columns

In [16]:

```
association_rules(frequent_itemsets, metric = "confidence", min_threshold = 0.1)
```

Out[16]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(soda)	(other vegetables)	0.09825	0.124250	0.010500	0.106870	0.860123	-0.001708	0.980541	-0.152789
1	(other vegetables)	(whole milk)	0.12425	0.161875	0.015500	0.124748	0.770647	-0.004613	0.957582	-0.253640
2	(rolls/buns)	(whole milk)	0.11125	0.161875	0.014750	0.132584	0.819053	-0.003259	0.966232	-0.199087
3	(soda)	(whole milk)	0.09825	0.161875	0.013500	0.137405	0.848831	-0.002404	0.971632	-0.164923
4	(yogurt)	(whole milk)	0.08650	0.161875	0.011875	0.137283	0.848082	-0.002127	0.971495	-0.163945

In [22]:

```
filtered_rules = association_rules(itemsets, metric="confidence", min_threshold=0.1)
filtered_rules = filtered_rules[filtered_rules['support'] >= 0.01]

print(filtered_rules[['antecedents', 'consequents', 'support', 'confidence']])
```

```
           antecedents          consequents   support  confidence
11              (soda)  (other vegetables)  0.010500    0.106870
12  (other vegetables)        (whole milk)  0.015500    0.124748
17        (rolls/buns)        (whole milk)  0.014750    0.132584
22              (soda)        (whole milk)  0.013500    0.137405
24            (yogurt)        (whole milk)  0.011875    0.137283
```

: These rules represent associations between different items based on the specified minimum support and confidence threshold.

In [17]:

```
Confidence_counts = pd.DataFrame(columns=['msv', 'mct', 'counts'])

min_support_ = []
min_confidence_ = []
counts = []
for min_support in [0.001, 0.005, 0.01, 0.05]:
    for min_confidence in [0.05, 0.075, 0.1]:
        frequent_itemsets = apriori(df, min_support=min_support, use_colnames=True)
        association_rules_df = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.1)
        min_support_.append(min_support)
        min_confidence_.append(min_confidence)
        counts.append(len(association_rules_df))

Confidence_counts['msv'] = min_support_
Confidence_counts['mct'] = min_confidence_
Confidence_counts['counts'] = counts
Confidence_counts
```

Out[17]:

	msv	mct	counts
0	0.001	0.050	162
1	0.001	0.075	162
2	0.001	0.100	162
3	0.005	0.050	25
4	0.005	0.075	25
5	0.005	0.100	25
6	0.010	0.050	5
7	0.010	0.075	5
8	0.010	0.100	5
9	0.050	0.050	0
10	0.050	0.075	0
11	0.050	0.100	0

In [18]:

```
table = pd.pivot_table(Confidence_counts, values='counts', index='mct', columns='msv', fill_value=0)
table
```

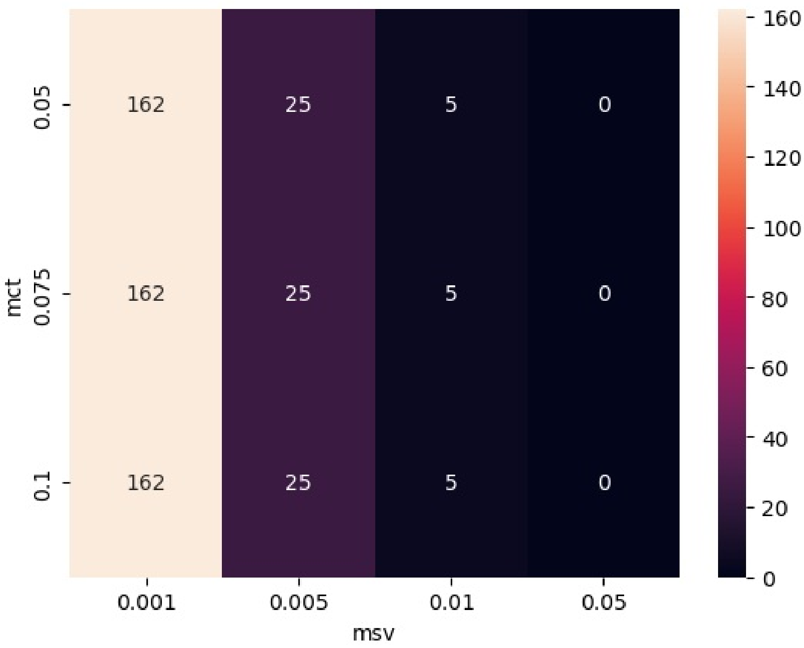
Out[18]:

msv mct	0.001	0.005	0.010	0.050
0.050	162	25	5	0
0.075	162	25	5	0
0.100	162	25	5	0

In [19]:

```
sns.heatmap(table, annot=True, fmt='g')
```

Out[19]: <Axes: xlabel='msv', ylabel='mct'>



In [20]:

```
itemsets = apriori(df, min_support=0.005, use_colnames=True)
itemsets
```

Out[20]:

	support	itemsets
0	0.020250	(UHT-milk)
1	0.008000	(baking powder)
2	0.033750	(beef)
3	0.021625	(berries)
4	0.015375	(beverages)
...	...	...
125	0.005250	(soda, tropical fruit)
126	0.013500	(whole milk, soda)
127	0.006250	(yogurt, soda)
128	0.009000	(whole milk, tropical fruit)
129	0.011875	(yogurt, whole milk)

130 rows × 2 columns

In [25]:
```
max_confidence_rule = association_rules(itemsets, metric="confidence", min_threshold=0.1)
max_confidence_rule = max_confidence_rule[max_confidence_rule['support'] >= 0.005].sort_values(by='confidence',

print(max_confidence_rule[['antecedents', 'consequents', 'confidence']])
```

```
      antecedents    consequents  confidence
1  (bottled beer)  (whole milk)    0.159091
```

The association rule with the highest confidence for a minimum support of 0.005 is: Rule: (bottled beer) ->(whole milk) confidence: 0.159091

Image Classification using CNN

In [30]:
```
#Loading assigned dataset
dataset_path = Path("/Users/alokkumarjha/Downloads/Images")
```

In [31]:
```
datagen = ImageDataGenerator(
    rescale=1./255,
    validation_split=0.2
)
```

In [32]:
```
train_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(256, 256),
    batch_size=20,
    class_mode='categorical',
    subset='training'
)
```

```
Found 529 images belonging to 4 classes.
```

In [33]:
```
validation_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(256, 256),
    batch_size=20,
    class_mode='categorical',
    subset='validation'
)
```

```
Found 130 images belonging to 4 classes.
```

Reference: https://www.learndatasci.com/tutorials/convolutional-neural-networks-image-classification/

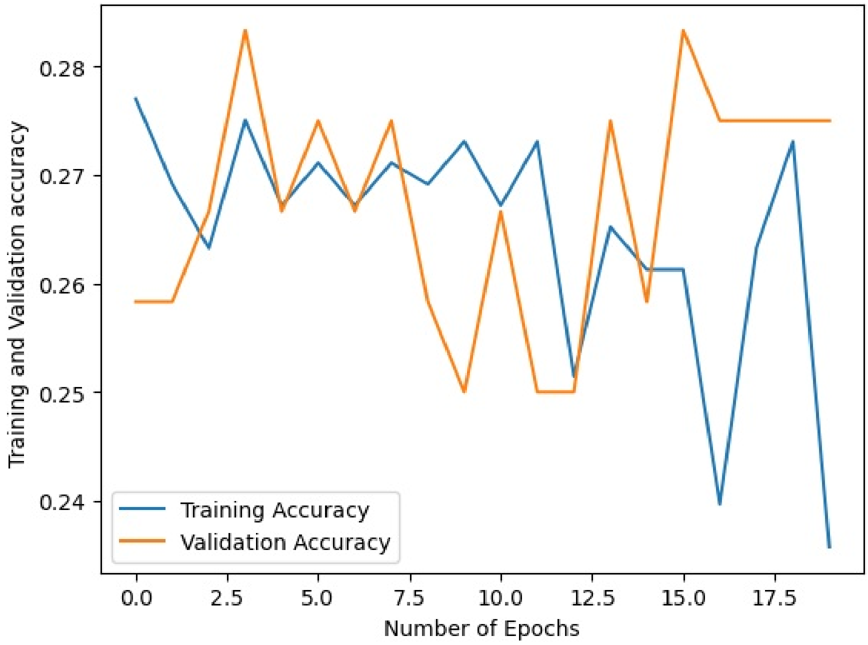
In [34]:
```
# Convolutional Layer with 8 3 × 3 filters, max pooling with 2 × 2 pool size.

model = Sequential()
model.add(Conv2D(8, (3, 3), activation='relu', input_shape=(256, 256, 3)))
model.add(MaxPooling2D((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'])
```

In [35]:
```
history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // train_generator.batch_size,
    epochs=20,
    validation_data=validation_generator,
    validation_steps=validation_generator.samples // validation_generator.batch_size
)
```

```
Epoch 1/20
26/26 [==============================] - 12s 420ms/step - loss: 2.2547 - accuracy: 0.2770 - val_loss: 1.3862 -
val_accuracy: 0.2583
Epoch 2/20
26/26 [==============================] - 10s 369ms/step - loss: 1.3860 - accuracy: 0.2692 - val_loss: 1.3860 -
val_accuracy: 0.2583
Epoch 3/20
26/26 [==============================] - 9s 332ms/step - loss: 1.3858 - accuracy: 0.2633 - val_loss: 1.3852 - v
al_accuracy: 0.2667
Epoch 4/20
26/26 [==============================] - 9s 347ms/step - loss: 1.3852 - accuracy: 0.2750 - val_loss: 1.3856 - v
al_accuracy: 0.2833
Epoch 5/20
26/26 [==============================] - 10s 367ms/step - loss: 1.3852 - accuracy: 0.2672 - val_loss: 1.3852 -
val_accuracy: 0.2667
Epoch 6/20
26/26 [==============================] - 9s 352ms/step - loss: 1.3848 - accuracy: 0.2711 - val_loss: 1.3836 - v
al_accuracy: 0.2750
Epoch 7/20
26/26 [==============================] - 10s 371ms/step - loss: 1.3850 - accuracy: 0.2672 - val_loss: 1.3849 -
val_accuracy: 0.2667
Epoch 8/20
26/26 [==============================] - 9s 356ms/step - loss: 1.3846 - accuracy: 0.2711 - val_loss: 1.3844 - v
al_accuracy: 0.2750
Epoch 9/20
26/26 [==============================] - 9s 334ms/step - loss: 1.3844 - accuracy: 0.2692 - val_loss: 1.3848 - v
al_accuracy: 0.2583
Epoch 10/20
26/26 [==============================] - 10s 358ms/step - loss: 1.3840 - accuracy: 0.2731 - val_loss: 1.3858 -
val_accuracy: 0.2500
Epoch 11/20
26/26 [==============================] - 9s 353ms/step - loss: 1.3842 - accuracy: 0.2672 - val_loss: 1.3846 - v
al_accuracy: 0.2667
Epoch 12/20
26/26 [==============================] - 10s 365ms/step - loss: 1.3832 - accuracy: 0.2731 - val_loss: 1.3851 -
val_accuracy: 0.2500
Epoch 13/20
26/26 [==============================] - 10s 385ms/step - loss: 1.3837 - accuracy: 0.2515 - val_loss: 1.3850 -
val_accuracy: 0.2500
Epoch 14/20
26/26 [==============================] - 10s 375ms/step - loss: 1.3834 - accuracy: 0.2652 - val_loss: 1.3836 -
val_accuracy: 0.2750
Epoch 15/20
26/26 [==============================] - 10s 391ms/step - loss: 1.3830 - accuracy: 0.2613 - val_loss: 1.3834 -
val_accuracy: 0.2583
Epoch 16/20
26/26 [==============================] - 10s 375ms/step - loss: 1.3837 - accuracy: 0.2613 - val_loss: 1.3833 -
val_accuracy: 0.2833
Epoch 17/20
26/26 [==============================] - 11s 425ms/step - loss: 1.3840 - accuracy: 0.2397 - val_loss: 1.3806 -
val_accuracy: 0.2750
Epoch 18/20
26/26 [==============================] - 10s 370ms/step - loss: 1.3824 - accuracy: 0.2633 - val_loss: 1.3816 -
val_accuracy: 0.2750
Epoch 19/20
26/26 [==============================] - 9s 340ms/step - loss: 1.3828 - accuracy: 0.2731 - val_loss: 1.3820 - v
al_accuracy: 0.2750
Epoch 20/20
26/26 [==============================] - 10s 363ms/step - loss: 1.3827 - accuracy: 0.2358 - val_loss: 1.3821 -
val_accuracy: 0.2750
```

In [36]:

```
plt.plot(history.history["accuracy"], label="Training Accuracy")
plt.plot(history.history["val_accuracy"], label="Validation Accuracy")
plt.xlabel("Number of Epochs")
plt.ylabel("Training and Validation accuracy ")
plt.legend()
plt.show()
```



In [37]:
```
score = model.evaluate(validation_generator, verbose=0)
print("Model - Validation Loss:", score[0])
print("Model - Validation Accuracy:", score[1])
```

```
Model - Validation Loss: 1.383488655090332
Model - Validation Accuracy: 0.26923078298568726
```

In [38]:
```
Banner_id = '916462010'
print('Banner id: ', Banner_id)
```

```
Banner id:  916462010
```

Banner id last digit is 0. So, Training the CNN using 2 other filter sizes: 5 × 5 and 7 × 7 for the convolution layer with all other parameters unchanged.

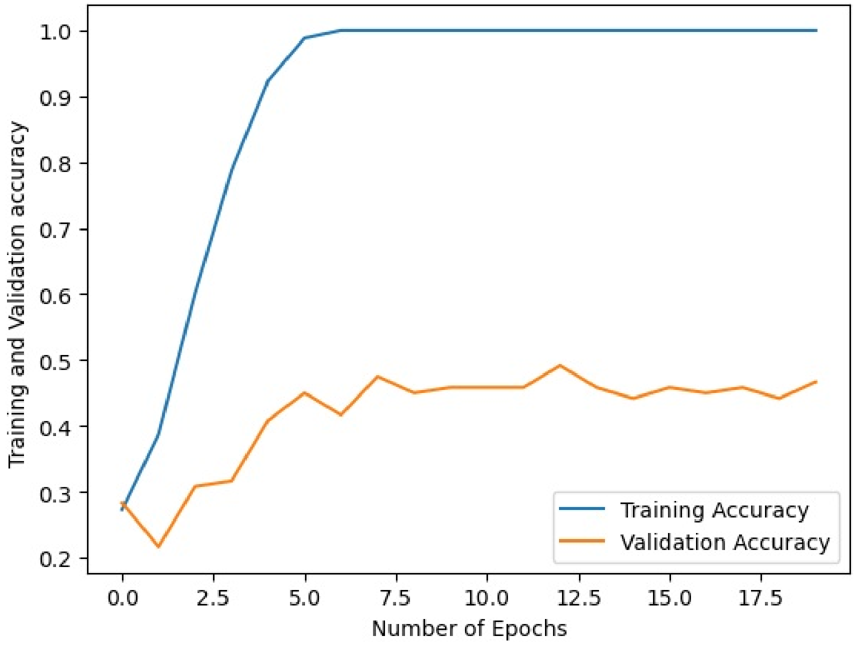
In [39]:
```
#CNN using filter sizes: 5 × 5

model_5x5 = Sequential()
model_5x5.add(Conv2D(8, (5, 5), activation='relu', input_shape=(256, 256, 3)))
model_5x5.add(MaxPooling2D((2, 2)))
model_5x5.add(Flatten())
model_5x5.add(Dense(16, activation='relu'))
model_5x5.add(Dense(4, activation='softmax'))

model_5x5.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

In [40]:
```
history_5x5 = model_5x5.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // train_generator.batch_size,
    epochs=20,
    validation_data=validation_generator,
    validation_steps=validation_generator.samples // validation_generator.batch_size
)
```

```
Epoch 1/20
26/26 [==============================] - 17s 628ms/step - loss: 2.1277 - accuracy: 0.2731 - val_loss: 1.4004
- val_accuracy: 0.2833
Epoch 2/20
26/26 [==============================] - 15s 588ms/step - loss: 1.3315 - accuracy: 0.3870 - val_loss: 1.3789
- val_accuracy: 0.2167
Epoch 3/20
26/26 [==============================] - 16s 606ms/step - loss: 1.1458 - accuracy: 0.6012 - val_loss: 1.4664
- val_accuracy: 0.3083
Epoch 4/20
26/26 [==============================] - 17s 629ms/step - loss: 0.8025 - accuracy: 0.7878 - val_loss: 1.4682
- val_accuracy: 0.3167
Epoch 5/20
26/26 [==============================] - 16s 606ms/step - loss: 0.4076 - accuracy: 0.9234 - val_loss: 1.5656
- val_accuracy: 0.4083
Epoch 6/20
26/26 [==============================] - 18s 679ms/step - loss: 0.1597 - accuracy: 0.9882 - val_loss: 1.4571
- val_accuracy: 0.4500
Epoch 7/20
26/26 [==============================] - 15s 592ms/step - loss: 0.0682 - accuracy: 1.0000 - val_loss: 1.6827
- val_accuracy: 0.4167
Epoch 8/20
26/26 [==============================] - 16s 621ms/step - loss: 0.0282 - accuracy: 1.0000 - val_loss: 1.5129
- val_accuracy: 0.4750
Epoch 9/20
26/26 [==============================] - 15s 577ms/step - loss: 0.0192 - accuracy: 1.0000 - val_loss: 1.7277
- val_accuracy: 0.4500
Epoch 10/20
26/26 [==============================] - 15s 555ms/step - loss: 0.0093 - accuracy: 1.0000 - val_loss: 1.6906
- val_accuracy: 0.4583
Epoch 11/20
26/26 [==============================] - 15s 562ms/step - loss: 0.0062 - accuracy: 1.0000 - val_loss: 1.6867
- val_accuracy: 0.4583
Epoch 12/20
26/26 [==============================] - 14s 550ms/step - loss: 0.0045 - accuracy: 1.0000 - val_loss: 1.6591
- val_accuracy: 0.4583
Epoch 13/20
26/26 [==============================] - 15s 560ms/step - loss: 0.0036 - accuracy: 1.0000 - val_loss: 1.7032
- val_accuracy: 0.4917
Epoch 14/20
26/26 [==============================] - 15s 587ms/step - loss: 0.0029 - accuracy: 1.0000 - val_loss: 1.6679
- val_accuracy: 0.4583
Epoch 15/20
26/26 [==============================] - 15s 570ms/step - loss: 0.0025 - accuracy: 1.0000 - val_loss: 1.7064
- val_accuracy: 0.4417
Epoch 16/20
26/26 [==============================] - 16s 595ms/step - loss: 0.0020 - accuracy: 1.0000 - val_loss: 1.6910
- val_accuracy: 0.4583
Epoch 17/20
26/26 [==============================] - 15s 593ms/step - loss: 0.0018 - accuracy: 1.0000 - val_loss: 1.7690
- val_accuracy: 0.4500
Epoch 18/20
26/26 [==============================] - 15s 569ms/step - loss: 0.0016 - accuracy: 1.0000 - val_loss: 1.6499
- val_accuracy: 0.4583
Epoch 19/20
26/26 [==============================] - 16s 617ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 1.8726
- val_accuracy: 0.4417
Epoch 20/20
26/26 [==============================] - 17s 635ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 1.7711
- val_accuracy: 0.4667
```

In [41]:

```
plt.plot(history_5x5.history["accuracy"], label="Training Accuracy")
plt.plot(history_5x5.history["val_accuracy"], label="Validation Accuracy")
plt.xlabel("Number of Epochs")
plt.ylabel("Training and Validation accuracy ")
plt.legend()
plt.show()
```



In [42]:
```
score_5x5 = model_5x5.evaluate(validation_generator, verbose=0)
print("Filter Size 5x5 Model - Validation Loss:", score_5x5[0])
print("Filter Size 5x5 Model - Validation Accuracy:", score_5x5[1])
```

```
Filter Size 5x5 Model - Validation Loss: 1.7159208059310913
Filter Size 5x5 Model - Validation Accuracy: 0.48461538553237915
```

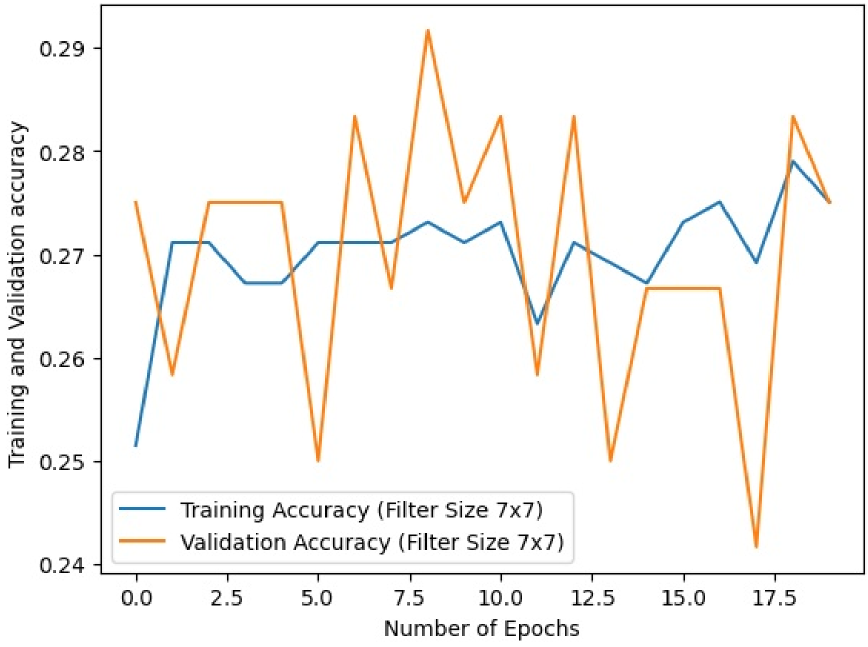
In [43]:
```
#CNN using filter sizes: 7 × 7
model_7x7 = Sequential()
model_7x7.add(Conv2D(8, (7, 7), activation='relu', input_shape=(256, 256, 3)))
model_7x7.add(MaxPooling2D((2, 2)))
model_7x7.add(Flatten())
model_7x7.add(Dense(16, activation='relu'))
model_7x7.add(Dense(4, activation='softmax'))

model_7x7.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

In [44]:
```
history_7x7 = model_7x7.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // train_generator.batch_size,
    epochs=20,
    validation_data=validation_generator,
    validation_steps=validation_generator.samples // validation_generator.batch_size
)
```

```
Epoch 1/20
26/26 [==============================] - 31s 1s/step - loss: 2.6719 - accuracy: 0.2515 - val_loss: 1.3860 - val
_accuracy: 0.2750
Epoch 2/20
26/26 [==============================] - 29s 1s/step - loss: 1.3860 - accuracy: 0.2711 - val_loss: 1.3860 - val
_accuracy: 0.2583
Epoch 3/20
26/26 [==============================] - 29s 1s/step - loss: 1.3858 - accuracy: 0.2711 - val_loss: 1.3856 - val
_accuracy: 0.2750
Epoch 4/20
26/26 [==============================] - 29s 1s/step - loss: 1.3855 - accuracy: 0.2672 - val_loss: 1.3854 - val
_accuracy: 0.2750
Epoch 5/20
26/26 [==============================] - 30s 1s/step - loss: 1.3854 - accuracy: 0.2672 - val_loss: 1.3849 - val
_accuracy: 0.2750
Epoch 6/20
26/26 [==============================] - 30s 1s/step - loss: 1.3851 - accuracy: 0.2711 - val_loss: 1.3853 - val
_accuracy: 0.2500
Epoch 7/20
26/26 [==============================] - 29s 1s/step - loss: 1.3848 - accuracy: 0.2711 - val_loss: 1.3837 - val
_accuracy: 0.2833
Epoch 8/20
26/26 [==============================] - 29s 1s/step - loss: 1.3844 - accuracy: 0.2711 - val_loss: 1.3839 - val
_accuracy: 0.2667
Epoch 9/20
26/26 [==============================] - 29s 1s/step - loss: 1.3842 - accuracy: 0.2731 - val_loss: 1.3828 - val
_accuracy: 0.2917
Epoch 10/20
26/26 [==============================] - 29s 1s/step - loss: 1.3846 - accuracy: 0.2711 - val_loss: 1.3828 - val
_accuracy: 0.2750
Epoch 11/20
26/26 [==============================] - 30s 1s/step - loss: 1.3835 - accuracy: 0.2731 - val_loss: 1.3843 - val
_accuracy: 0.2833
Epoch 12/20
26/26 [==============================] - 29s 1s/step - loss: 1.3841 - accuracy: 0.2633 - val_loss: 1.3851 - val
_accuracy: 0.2583
Epoch 13/20
26/26 [==============================] - 29s 1s/step - loss: 1.3838 - accuracy: 0.2711 - val_loss: 1.3835 - val
_accuracy: 0.2833
Epoch 14/20
26/26 [==============================] - 29s 1s/step - loss: 1.3833 - accuracy: 0.2692 - val_loss: 1.3839 - val
_accuracy: 0.2500
Epoch 15/20
26/26 [==============================] - 29s 1s/step - loss: 1.3833 - accuracy: 0.2672 - val_loss: 1.3838 - val
_accuracy: 0.2667
Epoch 16/20
26/26 [==============================] - 29s 1s/step - loss: 1.3834 - accuracy: 0.2731 - val_loss: 1.3834 - val
_accuracy: 0.2667
Epoch 17/20
26/26 [==============================] - 29s 1s/step - loss: 1.3837 - accuracy: 0.2750 - val_loss: 1.3826 - val
_accuracy: 0.2667
Epoch 18/20
26/26 [==============================] - 29s 1s/step - loss: 1.3831 - accuracy: 0.2692 - val_loss: 1.3843 - val
_accuracy: 0.2417
Epoch 19/20
26/26 [==============================] - 30s 1s/step - loss: 1.3829 - accuracy: 0.2790 - val_loss: 1.3830 - val
_accuracy: 0.2833
Epoch 20/20
26/26 [==============================] - 29s 1s/step - loss: 1.3836 - accuracy: 0.2750 - val_loss: 1.3832 - val
_accuracy: 0.2750
```

In [45]:

```
plt.plot(history_7x7.history["accuracy"], label="Training Accuracy (Filter Size 7x7)")
plt.plot(history_7x7.history["val_accuracy"], label="Validation Accuracy (Filter Size 7x7)")
plt.xlabel("Number of Epochs")
plt.ylabel("Training and Validation accuracy ")
plt.legend()
plt.show()
```



In [46]:

```
score_7x7 = model_7x7.evaluate(validation_generator, verbose=0)
print("Filter Size 7x7 Model - Validation Loss:", score_7x7[0])
print("Filter Size 7x7 Model - Validation Accuracy:", score_7x7[1])
```

```
Filter Size 7x7 Model - Validation Loss: 1.383507251739502
Filter Size 7x7 Model - Validation Accuracy: 0.26923078298568726
```

From the 3 above graph, CNN using 3 × 3 filters is underfitting, CNN using 5×5 filters is overfitting. CNN using 7×7 filters is Good fit model as Towards the end, both training and validation accuracies have increased, and there is a small gap between them. Based on performance of the models, Validation accuracy is more for 5×5 filters (0.484). So, it is the best model.