916467530

November 24, 2023

[1]:
```
import numpy as np
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, fpmax, fpgrowth
from mlxtend.frequent_patterns import association_rules
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
import glob
import cv2
import imageio.v3 as iio
import random
import tensorflow as tf
from tensorflow.keras import datasets
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
class CNN:
    def __init__(self,path):
        self.path=path
    def list_filenames(self):
        files=glob.glob(f'{self.path}/*/*')
        return files
    def array_hist(self,files):
        img_array=[iio.imread(uri=i, mode="L") for i in files]
        class_n=[str(i).split('/')[-2].split('-')[1] for i in files]
        length = len(class_n)
        shuffled_indices = random.sample(range(length), length)
        class_n = [class_n[i] for i in shuffled_indices]
        img_array = [img_array[i] for i in shuffled_indices]
        return class_n,img_array
```

[3]:
```
image_cls=CNN('/Users/Jishnu/Cropped')
files=image_cls.list_filenames()
class_n,img_array=image_cls.array_hist(files)
```

[4]:
```
train_data=np.expand_dims(np.array(img_array), -1)
```

[5]:
```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
class_n=label_encoder.fit_transform(class_n)
```

1 StudentID-916467530

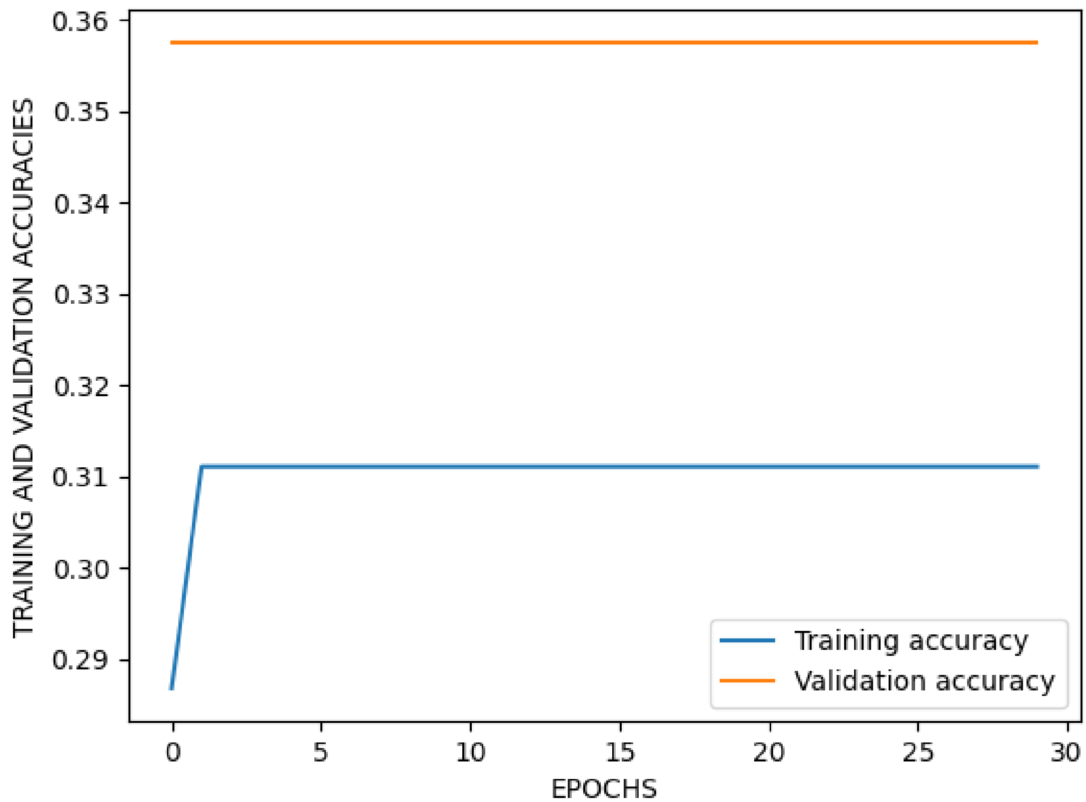
[6]:
```
batch_size = 16
nb_classes =4
nb_epochs = 30
from tensorflow.keras import models
def model(i):
    model = models.Sequential()
    model.add(layers.Conv2D(8, (i, i), activation='relu', input_shape=(100,␣
 ↪100, 1)))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Flatten())
    model.add(layers.Dense(16, activation='relu'))
    model.add(layers.Dense(4, activation='softmax'))
    model.
 ↪compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
    HISTORY=model.fit(train_data, class_n, batch_size = batch_size, epochs =␣
 ↪nb_epochs, verbose = 1, validation_split=0.2)
    plt.plot(HISTORY.history['accuracy'], label='Training accuracy')
    plt.plot(HISTORY.history['val_accuracy'], label='Validation accuracy')
    plt.xlabel('EPOCHS')
    plt.ylabel('TRAINING AND VALIDATION ACCURACIES')
    plt.legend()
    plt.show()
```

[7]:
```
model(3)
```

```
Epoch 1/30
42/42 [==============================] - 1s 11ms/step - loss: 127.6481 -
accuracy: 0.2868 - val_loss: 1.3829 - val_accuracy: 0.3576
Epoch 2/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3843 - accuracy:
0.3111 - val_loss: 1.3813 - val_accuracy: 0.3576
Epoch 3/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3829 - accuracy:
0.3111 - val_loss: 1.3802 - val_accuracy: 0.3576
Epoch 4/30
```

```
42/42 [==============================] - 0s 9ms/step - loss: 1.3814 - accuracy:
0.3111 - val_loss: 1.3785 - val_accuracy: 0.3576
Epoch 5/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3800 - accuracy:
0.3111 - val_loss: 1.3771 - val_accuracy: 0.3576
Epoch 6/30
42/42 [==============================] - 0s 11ms/step - loss: 1.3788 - accuracy:
0.3111 - val_loss: 1.3758 - val_accuracy: 0.3576
Epoch 7/30
42/42 [==============================] - 1s 10ms/step - loss: 1.3779 - accuracy:
0.3111 - val_loss: 1.3753 - val_accuracy: 0.3576
Epoch 8/30
42/42 [==============================] - 0s 10ms/step - loss: 1.3769 - accuracy:
0.3111 - val_loss: 1.3741 - val_accuracy: 0.3576
Epoch 9/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3762 - accuracy:
0.3111 - val_loss: 1.3729 - val_accuracy: 0.3576
Epoch 10/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3753 - accuracy:
0.3111 - val_loss: 1.3721 - val_accuracy: 0.3576
Epoch 11/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3745 - accuracy:
0.3111 - val_loss: 1.3713 - val_accuracy: 0.3576
Epoch 12/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3740 - accuracy:
0.3111 - val_loss: 1.3707 - val_accuracy: 0.3576
Epoch 13/30
42/42 [==============================] - 0s 10ms/step - loss: 1.3734 - accuracy:
0.3111 - val_loss: 1.3695 - val_accuracy: 0.3576
Epoch 14/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3728 - accuracy:
0.3111 - val_loss: 1.3695 - val_accuracy: 0.3576
Epoch 15/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3723 - accuracy:
0.3111 - val_loss: 1.3692 - val_accuracy: 0.3576
Epoch 16/30
42/42 [==============================] - 0s 9ms/step - loss: 1.3720 - accuracy:
0.3111 - val_loss: 1.3686 - val_accuracy: 0.3576
Epoch 17/30
42/42 [==============================] - 1s 13ms/step - loss: 1.3716 - accuracy:
0.3111 - val_loss: 1.3684 - val_accuracy: 0.3576
Epoch 18/30
42/42 [==============================] - 1s 16ms/step - loss: 1.3714 - accuracy:
0.3111 - val_loss: 1.3681 - val_accuracy: 0.3576
Epoch 19/30
42/42 [==============================] - 1s 18ms/step - loss: 1.3712 - accuracy:
0.3111 - val_loss: 1.3679 - val_accuracy: 0.3576
Epoch 20/30
```

```
42/42 [==============================] - 1s 18ms/step - loss: 1.3711 - accuracy:
0.3111 - val_loss: 1.3676 - val_accuracy: 0.3576
Epoch 21/30
42/42 [==============================] - 1s 18ms/step - loss: 1.3709 - accuracy:
0.3111 - val_loss: 1.3674 - val_accuracy: 0.3576
Epoch 22/30
42/42 [==============================] - 1s 21ms/step - loss: 1.3708 - accuracy:
0.3111 - val_loss: 1.3676 - val_accuracy: 0.3576
Epoch 23/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3708 - accuracy:
0.3111 - val_loss: 1.3670 - val_accuracy: 0.3576
Epoch 24/30
42/42 [==============================] - 1s 17ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3668 - val_accuracy: 0.3576
Epoch 25/30
42/42 [==============================] - 1s 25ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3669 - val_accuracy: 0.3576
Epoch 26/30
42/42 [==============================] - 1s 22ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3672 - val_accuracy: 0.3576
Epoch 27/30
42/42 [==============================] - 1s 19ms/step - loss: 1.3705 - accuracy:
0.3111 - val_loss: 1.3666 - val_accuracy: 0.3576
Epoch 28/30
42/42 [==============================] - 1s 19ms/step - loss: 1.3704 - accuracy:
0.3111 - val_loss: 1.3662 - val_accuracy: 0.3576
Epoch 29/30
42/42 [==============================] - 1s 16ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3663 - val_accuracy: 0.3576
Epoch 30/30
42/42 [==============================] - 1s 18ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3660 - val_accuracy: 0.3576
```

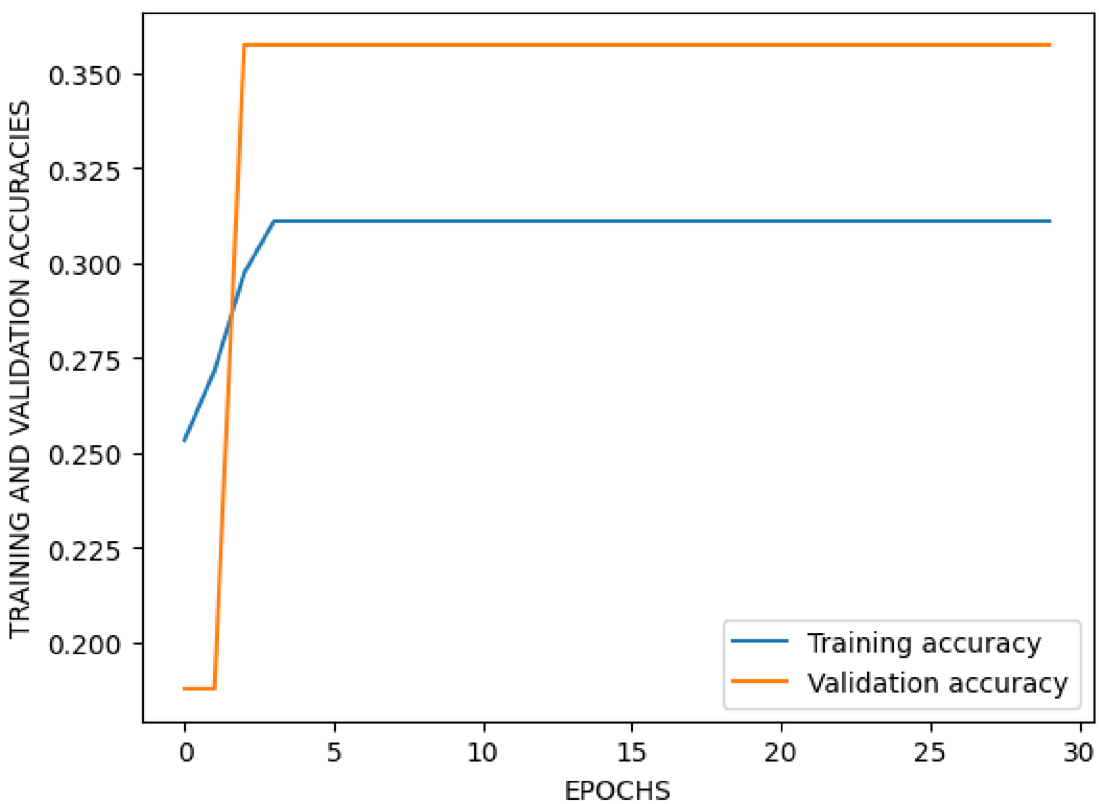



```
[8]: model(5)
```

```
Epoch 1/30
42/42 [==============================] - 1s 25ms/step - loss: 12.6449 -
accuracy: 0.2534 - val_loss: 1.3851 - val_accuracy: 0.1879
Epoch 2/30
42/42 [==============================] - 1s 25ms/step - loss: 1.3846 - accuracy:
0.2716 - val_loss: 1.3838 - val_accuracy: 0.1879
Epoch 3/30
42/42 [==============================] - 1s 28ms/step - loss: 1.3830 - accuracy:
0.2974 - val_loss: 1.3819 - val_accuracy: 0.3576
Epoch 4/30
42/42 [==============================] - 1s 26ms/step - loss: 1.3812 - accuracy:
0.3111 - val_loss: 1.3803 - val_accuracy: 0.3576
Epoch 5/30
42/42 [==============================] - 1s 30ms/step - loss: 1.3798 - accuracy:
0.3111 - val_loss: 1.3788 - val_accuracy: 0.3576
Epoch 6/30
42/42 [==============================] - 2s 36ms/step - loss: 1.3785 - accuracy:
0.3111 - val_loss: 1.3771 - val_accuracy: 0.3576
Epoch 7/30
```

```
42/42 [==============================] - 1s 27ms/step - loss: 1.3774 - accuracy:
0.3111 - val_loss: 1.3761 - val_accuracy: 0.3576
Epoch 8/30
42/42 [==============================] - 1s 25ms/step - loss: 1.3764 - accuracy:
0.3111 - val_loss: 1.3746 - val_accuracy: 0.3576
Epoch 9/30
42/42 [==============================] - 1s 26ms/step - loss: 1.3756 - accuracy:
0.3111 - val_loss: 1.3741 - val_accuracy: 0.3576
Epoch 10/30
42/42 [==============================] - 1s 29ms/step - loss: 1.3747 - accuracy:
0.3111 - val_loss: 1.3730 - val_accuracy: 0.3576
Epoch 11/30
42/42 [==============================] - 1s 27ms/step - loss: 1.3739 - accuracy:
0.3111 - val_loss: 1.3717 - val_accuracy: 0.3576
Epoch 12/30
42/42 [==============================] - 1s 26ms/step - loss: 1.3733 - accuracy:
0.3111 - val_loss: 1.3708 - val_accuracy: 0.3576
Epoch 13/30
42/42 [==============================] - 1s 23ms/step - loss: 1.3727 - accuracy:
0.3111 - val_loss: 1.3700 - val_accuracy: 0.3576
Epoch 14/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3724 - accuracy:
0.3111 - val_loss: 1.3694 - val_accuracy: 0.3576
Epoch 15/30
42/42 [==============================] - 1s 27ms/step - loss: 1.3720 - accuracy:
0.3111 - val_loss: 1.3691 - val_accuracy: 0.3576
Epoch 16/30
42/42 [==============================] - 1s 27ms/step - loss: 1.3717 - accuracy:
0.3111 - val_loss: 1.3688 - val_accuracy: 0.3576
Epoch 17/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3716 - accuracy:
0.3111 - val_loss: 1.3683 - val_accuracy: 0.3576
Epoch 18/30
42/42 [==============================] - 1s 23ms/step - loss: 1.3713 - accuracy:
0.3111 - val_loss: 1.3680 - val_accuracy: 0.3576
Epoch 19/30
42/42 [==============================] - 1s 23ms/step - loss: 1.3711 - accuracy:
0.3111 - val_loss: 1.3676 - val_accuracy: 0.3576
Epoch 20/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3709 - accuracy:
0.3111 - val_loss: 1.3677 - val_accuracy: 0.3576
Epoch 21/30
42/42 [==============================] - 1s 27ms/step - loss: 1.3707 - accuracy:
0.3111 - val_loss: 1.3676 - val_accuracy: 0.3576
Epoch 22/30
42/42 [==============================] - 1s 26ms/step - loss: 1.3707 - accuracy:
0.3111 - val_loss: 1.3671 - val_accuracy: 0.3576
Epoch 23/30
```

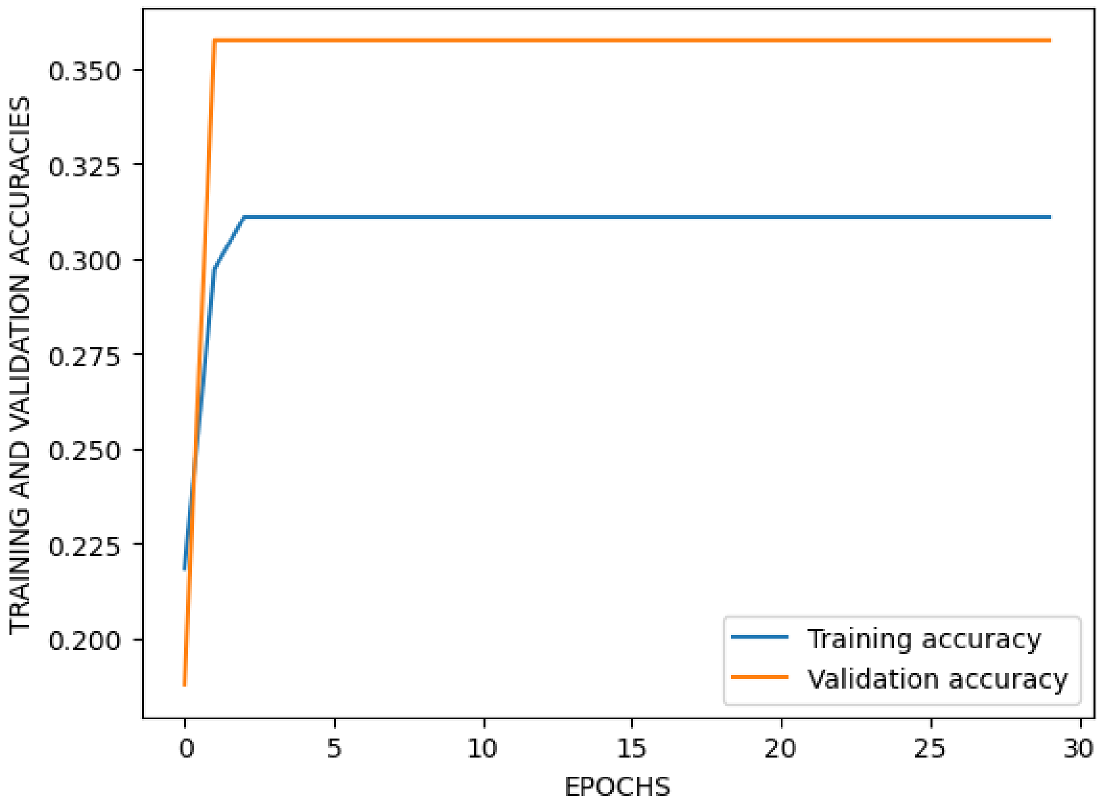
```
42/42 [==============================] - 1s 28ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3679 - val_accuracy: 0.3576
Epoch 24/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3676 - val_accuracy: 0.3576
Epoch 25/30
42/42 [==============================] - 1s 23ms/step - loss: 1.3704 - accuracy:
0.3111 - val_loss: 1.3666 - val_accuracy: 0.3576
Epoch 26/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3664 - val_accuracy: 0.3576
Epoch 27/30
42/42 [==============================] - 1s 23ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3663 - val_accuracy: 0.3576
Epoch 28/30
42/42 [==============================] - 1s 24ms/step - loss: 1.3704 - accuracy:
0.3111 - val_loss: 1.3660 - val_accuracy: 0.3576
Epoch 29/30
42/42 [==============================] - 1s 27ms/step - loss: 1.3702 - accuracy:
0.3111 - val_loss: 1.3661 - val_accuracy: 0.3576
Epoch 30/30
42/42 [==============================] - 1s 22ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3656 - val_accuracy: 0.3576
```



[9]:
```
model(7)
```

```
Epoch 1/30
42/42 [==============================] - 2s 36ms/step - loss: 13.2280 -
accuracy: 0.2185 - val_loss: 1.3858 - val_accuracy: 0.1879
Epoch 2/30
42/42 [==============================] - 2s 36ms/step - loss: 1.3847 - accuracy:
0.2974 - val_loss: 1.3834 - val_accuracy: 0.3576
Epoch 3/30
42/42 [==============================] - 1s 32ms/step - loss: 1.3829 - accuracy:
0.3111 - val_loss: 1.3816 - val_accuracy: 0.3576
Epoch 4/30
42/42 [==============================] - 1s 36ms/step - loss: 1.3813 - accuracy:
0.3111 - val_loss: 1.3796 - val_accuracy: 0.3576
Epoch 5/30
42/42 [==============================] - 1s 33ms/step - loss: 1.3798 - accuracy:
0.3111 - val_loss: 1.3776 - val_accuracy: 0.3576
Epoch 6/30
42/42 [==============================] - 2s 38ms/step - loss: 1.3782 - accuracy:
0.3111 - val_loss: 1.3762 - val_accuracy: 0.3576
Epoch 7/30
42/42 [==============================] - 2s 40ms/step - loss: 1.3771 - accuracy:
0.3111 - val_loss: 1.3755 - val_accuracy: 0.3576
Epoch 8/30
42/42 [==============================] - 2s 47ms/step - loss: 1.3759 - accuracy:
0.3111 - val_loss: 1.3742 - val_accuracy: 0.3576
Epoch 9/30
42/42 [==============================] - 2s 40ms/step - loss: 1.3752 - accuracy:
0.3111 - val_loss: 1.3731 - val_accuracy: 0.3576
Epoch 10/30
42/42 [==============================] - 2s 39ms/step - loss: 1.3744 - accuracy:
0.3111 - val_loss: 1.3719 - val_accuracy: 0.3576
Epoch 11/30
42/42 [==============================] - 2s 37ms/step - loss: 1.3739 - accuracy:
0.3111 - val_loss: 1.3713 - val_accuracy: 0.3576
Epoch 12/30
42/42 [==============================] - 2s 37ms/step - loss: 1.3733 - accuracy:
0.3111 - val_loss: 1.3709 - val_accuracy: 0.3576
Epoch 13/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3729 - accuracy:
0.3111 - val_loss: 1.3699 - val_accuracy: 0.3576
Epoch 14/30
42/42 [==============================] - 2s 39ms/step - loss: 1.3724 - accuracy:
0.3111 - val_loss: 1.3703 - val_accuracy: 0.3576
Epoch 15/30
```

```
42/42 [==============================] - 1s 35ms/step - loss: 1.3718 - accuracy:
0.3111 - val_loss: 1.3694 - val_accuracy: 0.3576
Epoch 16/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3715 - accuracy:
0.3111 - val_loss: 1.3687 - val_accuracy: 0.3576
Epoch 17/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3714 - accuracy:
0.3111 - val_loss: 1.3688 - val_accuracy: 0.3576
Epoch 18/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3711 - accuracy:
0.3111 - val_loss: 1.3679 - val_accuracy: 0.3576
Epoch 19/30
42/42 [==============================] - 2s 40ms/step - loss: 1.3708 - accuracy:
0.3111 - val_loss: 1.3681 - val_accuracy: 0.3576
Epoch 20/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3708 - accuracy:
0.3111 - val_loss: 1.3679 - val_accuracy: 0.3576
Epoch 21/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3678 - val_accuracy: 0.3576
Epoch 22/30
42/42 [==============================] - 2s 36ms/step - loss: 1.3706 - accuracy:
0.3111 - val_loss: 1.3674 - val_accuracy: 0.3576
Epoch 23/30
42/42 [==============================] - 1s 36ms/step - loss: 1.3705 - accuracy:
0.3111 - val_loss: 1.3678 - val_accuracy: 0.3576
Epoch 24/30
42/42 [==============================] - 2s 36ms/step - loss: 1.3704 - accuracy:
0.3111 - val_loss: 1.3671 - val_accuracy: 0.3576
Epoch 25/30
42/42 [==============================] - 2s 38ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3666 - val_accuracy: 0.3576
Epoch 26/30
42/42 [==============================] - 1s 33ms/step - loss: 1.3702 - accuracy:
0.3111 - val_loss: 1.3662 - val_accuracy: 0.3576
Epoch 27/30
42/42 [==============================] - 2s 40ms/step - loss: 1.3703 - accuracy:
0.3111 - val_loss: 1.3662 - val_accuracy: 0.3576
Epoch 28/30
42/42 [==============================] - 1s 34ms/step - loss: 1.3704 - accuracy:
0.3111 - val_loss: 1.3663 - val_accuracy: 0.3576
Epoch 29/30
42/42 [==============================] - 2s 37ms/step - loss: 1.3702 - accuracy:
0.3111 - val_loss: 1.3665 - val_accuracy: 0.3576
Epoch 30/30
42/42 [==============================] - 2s 36ms/step - loss: 1.3702 - accuracy:
0.3111 - val_loss: 1.3657 - val_accuracy: 0.3576
```



2 Model 2 performs well(5x5), as no overfitting occurs as the number of epochs increases. For Model 1 and model 3 both underfitting and overfitting occurs

3 Model2 perfroms better than other two models

[10]:
```
class Association_Rules:
    def __init__(self,path):
        self.path=path
    def data(self):
        df = pd.read_csv(self.path)
        df = df.fillna('0')

        print(df)
        te = TransactionEncoder()
        df = te.fit(df.values).transform(df.values)
        return df, te
    def Ass_rules(self,df,msv,mct):
        frequent_itemsets = fpgrowth(df, min_support=msv, use_colnames=True)
```

```
        associa_rules,shape=association_rules(frequent_itemsets,␣
↪metric="confidence", min_threshold=mct),association_rules(frequent_itemsets,␣
↪metric="confidence", min_threshold=mct).shape[0]
        return associa_rules, len(associa_rules.index),shape
```

[11]:
```
ar=Association_Rules('/Users/Jishnu/Grocery_Items_55.csv')
df,te=ar.data()
df=pd.DataFrame(df,columns=te.columns_)
df = df.drop('0', axis=1)

rules,s,e=ar.Ass_rules(df,0.01,0.1)
```

```
                          0                  1  2  3  4  5  6  7  8  9  10
0                   mustard               soda  0  0  0  0  0  0  0  0   0
1           root vegetables      sweet spreads  0  0  0  0  0  0  0  0   0
2                      soda             spices  0  0  0  0  0  0  0  0   0
3                   sausage             yogurt  0  0  0  0  0  0  0  0   0
4                   chicken             onions  0  0  0  0  0  0  0  0   0
…                         …                  … .. .. .. .. .. .. .. ..  ..
7995  fruit/vegetable juice  seasonal products  0  0  0  0  0  0  0  0   0
7996                 pastry          chocolate  0  0  0  0  0  0  0  0   0
7997             whole milk         rolls/buns  0  0  0  0  0  0  0  0   0
7998             whole milk          margarine  0  0  0  0  0  0  0  0   0
7999       other vegetables            napkins  0  0  0  0  0  0  0  0   0

[8000 rows x 11 columns]
```

[12]:
```
rules
```

[12]:
```
           antecedents   consequents  antecedent support  consequent support  \
0               (soda)  (whole milk)            0.096250            0.156125
1             (yogurt)  (whole milk)            0.087250            0.156125
2   (other vegetables)  (whole milk)            0.120875            0.156125
3         (rolls/buns)  (whole milk)            0.110125            0.156125

    support  confidence      lift  leverage  conviction  zhangs_metric
0  0.010250    0.106494  0.682104 -0.004777    0.944453      -0.340233
1  0.010625    0.121777  0.779994 -0.002997    0.960889      -0.236072
2  0.014750    0.122027  0.781597 -0.004122    0.961163      -0.241189
3  0.013625    0.123723  0.792461 -0.003568    0.963023      -0.227382
```

[13]:
```
print(f'number of rules---{e}')
```

```
number of rules---4
```

[14]:
```
val=pd.DataFrame(np.ones((3, 4)),columns=[0.001, 0.005, 0.01, 0.05],index=[0.
 ↪05, 0.075, 0.1], dtype=float)
val
```

[14]:

	0.001	0.005	0.010	0.050
0.050	1.0	1.0	1.0	1.0
0.075	1.0	1.0	1.0	1.0
0.100	1.0	1.0	1.0	1.0

[15]:
```
i=0
while i<3:
    j=0
    while j<4:
        mct=list(val.index)[i]
        msv=list(val.columns)[j]
        print(f'msv{msv},mct{mct}')
        rules,s,e=ar.Ass_rules(df,msv,mct)
        if msv==0.005:
            r=rules
        print('rulescount----',s)
        val.iloc[i,j]=s
        j+=1
    i+=1
```

```
msv0.001,mct0.05
rulescount---- 542
msv0.005,mct0.05
rulescount---- 61
msv0.01,mct0.05
rulescount---- 8
msv0.05,mct0.05
rulescount---- 0
msv0.001,mct0.075
rulescount---- 295
msv0.005,mct0.075
rulescount---- 42
msv0.01,mct0.075
rulescount---- 6
msv0.05,mct0.075
rulescount---- 0
msv0.001,mct0.1
rulescount---- 155
msv0.005,mct0.1
rulescount---- 18
msv0.01,mct0.1
```

```
rulescount---- 4
msv0.05,mct0.1
rulescount---- 0
```

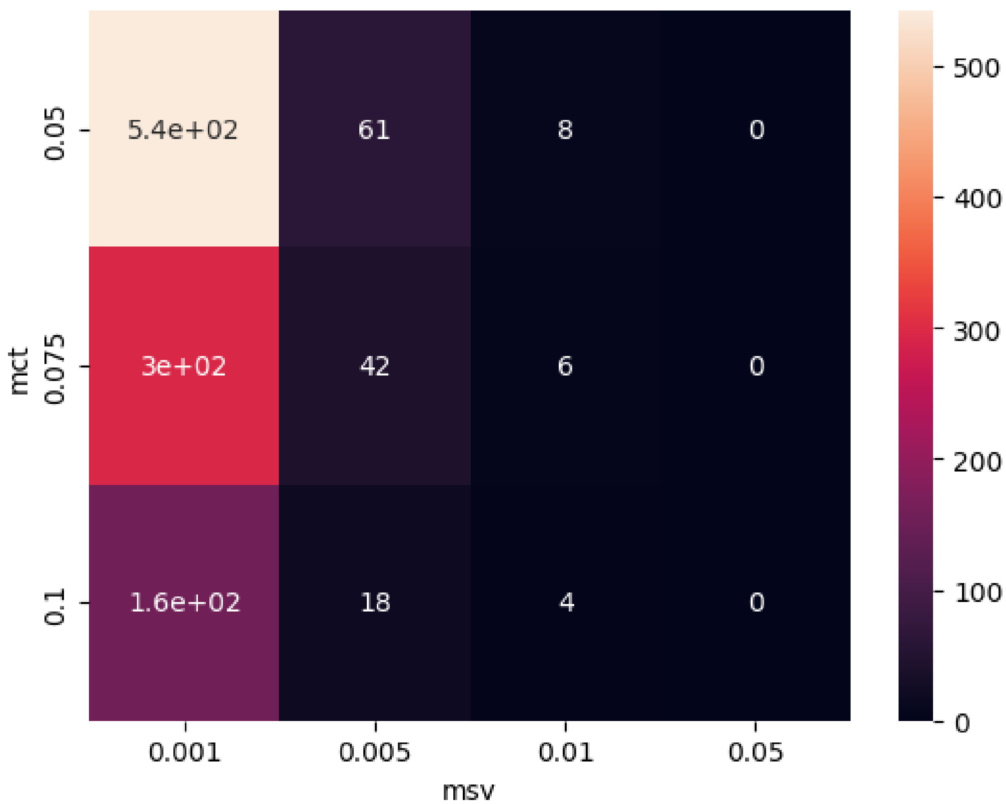
[16]:
```
val
```

[16]:

	0.001	0.005	0.010	0.050
0.050	542.0	61.0	8.0	0.0
0.075	295.0	42.0	6.0	0.0
0.100	155.0	18.0	4.0	0.0

[17]:
```
ax=sns.heatmap(val, annot=True)
ax.set(xlabel="msv", ylabel="mct")
```

[17]:
```
[Text(0.5, 23.52222222222222, 'msv'), Text(50.722222222222214, 0.5, 'mct')]
```



r

[19]:
```
r=pd.DataFrame(ar.Ass_rules(df,0.005,0.001)[0])
```

[20]:
```
max(r['confidence'])
```

[20]: 0.16024340770791076

[25]:
```
r[r['confidence']==max(r['confidence'])]
```

[25]:
```
    antecedents   consequents  antecedent support  consequent support  \
25   (sausage)  (whole milk)            0.061625            0.156125

     support  confidence      lift  leverage  conviction  zhangs_metric
25  0.009875    0.160243  1.026379  0.000254    1.004904       0.027389
```

4 References

5 http://rasbt.github.io/mlxtend/user_guide/frequent_patterns/associatio

6 https://datagen.tech/guides/image-classification/image-classification-using-cnn/

7 https://keras.io/examples/vision/mnist_convnet/

8 https://seaborn.pydata.org/generated/seaborn.heatmap.html

9 https://www.geeksforgeeks.org/image-classifier-using-cnn/

[ ]: