Assignment 3

Fashion MNIST Dataset

Date : 01 April 2022

Loadind Data

In [31]:
```
#importing libraries
import time
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb

from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.cluster import DBSCAN
from sklearn.neighbors import NearestNeighbors
from sklearn.manifold import TSNE

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.utils import to_categorical

from tensorflow.keras.models import Sequential, load_model, Model
from tensorflow.keras.layers import Dense, Dropout, Flatten, Lambda, Input,
Activation, Conv2D, MaxPooling2D, BatchNormalization, GlobalAveragePooling2D,
Add ,TimeDistributed,LSTM
from tensorflow.keras.optimizers import Adam,SGD,Adagrad,Adadelta,RMSprop
#from tensorflow.keras.callbacks import ReduceLROnPlateau,
LearningRateScheduler
#from tensorflow.keras.layers import LeakyReLU
#from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

In [32]:
```
#Constants
BATCH_SIZE = 500
EPOCH = 10
n_components = 2
random_state = 27
```

In [33]:
```
#loading files into dataframe from mounted google drive
df_x_train = pd.read_csv("/content/drive/MyDrive/ece657a-1221-asg3-
fashionmnist-datafiles/x_train.csv")
df_y_train = pd.read_csv("/content/drive/MyDrive/ece657a-1221-asg3-
fashionmnist-datafiles/y_train.csv")
df_x_test = pd.read_csv("/content/drive/MyDrive/ece657a-1221-asg3-
fashionmnist-datafiles/x_test.csv")
df_y_test = pd.read_csv("/content/drive/MyDrive/ece657a-1221-asg3-
fashionmnist-datafiles/y_test.csv")
```

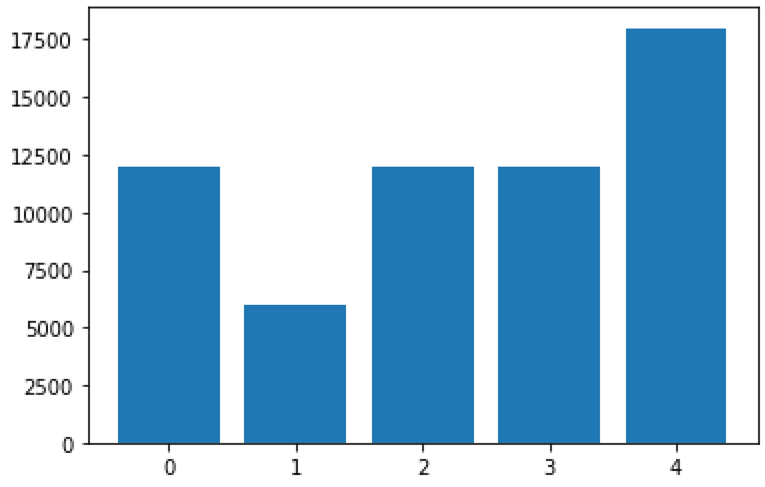
In [34]:
```
#shapes of train and test dataset
print(df_x_test.shape,df_y_test.shape)
print(df_x_train.shape,df_y_train.shape)
```

```
(10000, 784) (10000, 1)
(60000, 784) (60000, 1)
```

In [35]:
```
#number of unique classes and their class wise count
classes = np.unique(df_y_train)
nClasses = len(classes)
print('Total number of outputs : ', nClasses)
print('Output classes : ', classes)

plt.bar(df_y_train['0'].unique(),df_y_train.value_counts())
```

```
Total number of outputs :  5
Output classes :  [0 1 2 3 4]
```

Out[35]:
```
<BarContainer object of 5 artists>
```



Data Preprocessing

- Dividing training data into training and validation dataset in ratio of 80:20
- Reshaping features in a 28*28 array and 1 channel(Grayscale)
- Scaling features(x) in (0,1) by dividing by 255 [pixel range : 0-256]
- Converting label into categorical variable [5 classes]

In [36]:
```
#splitting df_train in training and validation dataset
x_train, x_val, y_train, y_val = train_test_split(df_x_train, df_y_train,
test_size=0.2, random_state=random_state)
print("Shape of train, validation and test dataset are :
",x_train.shape,x_val.shape, df_x_test.shape)

x_train = x_train.values.reshape((-1, 28, 28, 1))
x_val = x_val.values.reshape((-1, 28, 28, 1))
x_test = df_x_test.values.reshape((-1, 28, 28, 1))

x_train = x_train.astype("float32")/255
x_val = x_val.astype("float32")/255
x_test = x_test.astype("float32")/255
print("Shape of train, validation and test dataset are :
",x_train.shape,x_val.shape,x_test.shape)

y_train = to_categorical(y_train, num_classes=5)
y_val = to_categorical(y_val, num_classes=5)
y_test = to_categorical(df_y_test, num_classes=5)
print("Shape of train, validation and test for dependent variable are :
",y_train.shape,y_val.shape,y_test.shape)
```

```
Shape of train, validation and test dataset are :  (48000, 784) (12000, 784) (10000, 784)
Shape of train, validation and test dataset are :  (48000, 28, 28, 1) (12000, 28, 28, 1)
(10000, 28, 28, 1)
Shape of train, validation and test for dependent variable are :  (48000, 5) (12000, 5) (1
0000, 5)
```

In [ ]:
```
#Initial approach for creating validatio dataset but scikit in-bulit method
(train_test_split)
#provided a nice implementation and hence skipped this approach
#x_val = x_train[-10000:]
#y_val = y_train[-10000:]
#x_train = x_train[:-10000]
#y_train = y_train[:-10000]
```

CM1 : Default CNN

Convolution Neural Network

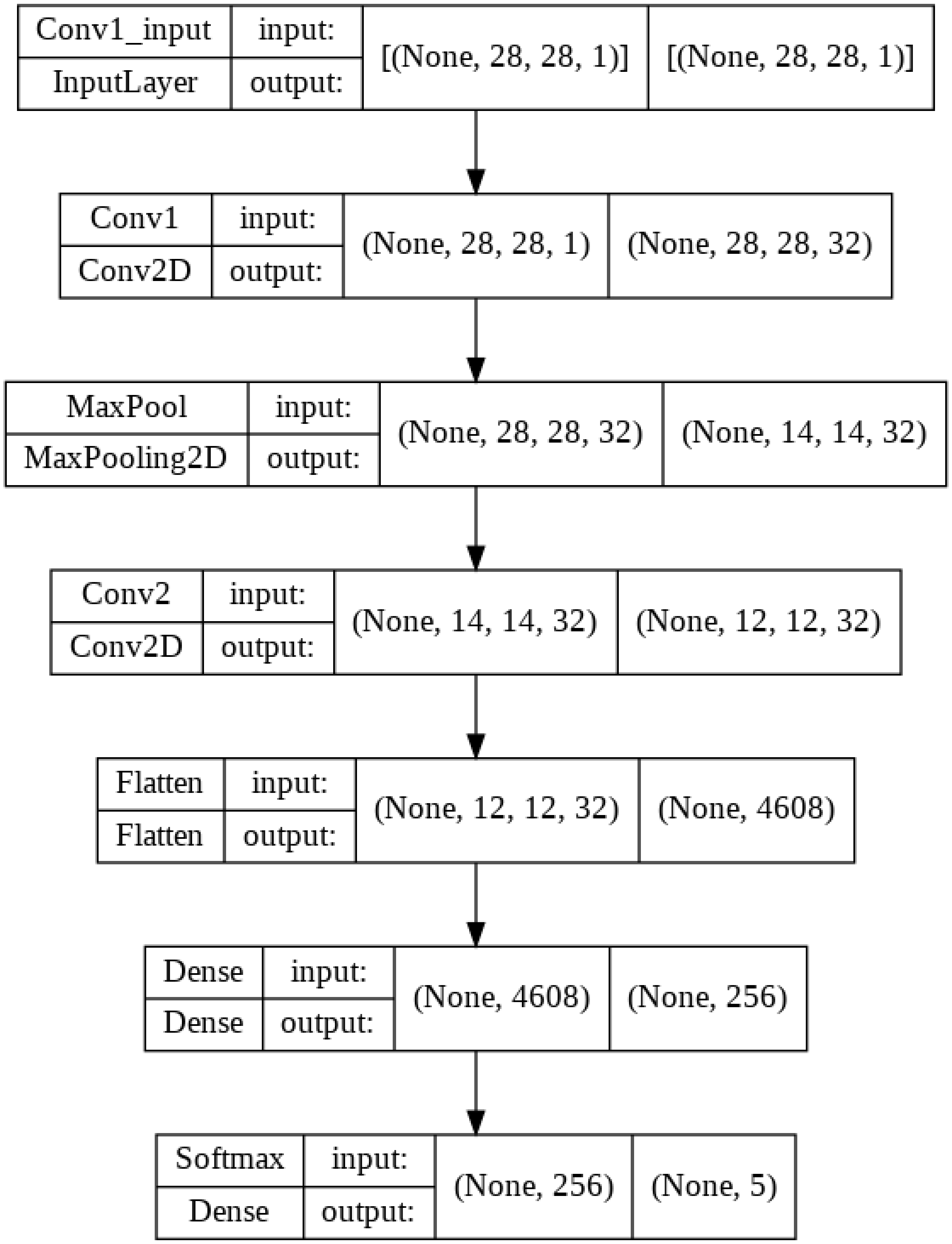
In [37]:
```
#CM1 Model as defined in A3
model= Sequential(name="CM1")
model.add(Conv2D(32, kernel_size=(3, 3),
                 strides=(1, 1),
                 activation='relu',
                     input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool'))
model.add(Conv2D(32, (3, 3), activation='relu',name = 'Conv2'))
model.add(Flatten(name='Flatten'))
model.add(Dense(256, activation='relu',name = 'Dense'))
model.add(Dense(5, activation='softmax',name = 'Softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam',metrics=
['accuracy'])
```

In [38]:
```
model.summary()
```

```
Model: "CM1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 Conv1 (Conv2D)              (None, 28, 28, 32)        320       
                                                                 
 MaxPool (MaxPooling2D)      (None, 14, 14, 32)        0         
                                                                 
 Conv2 (Conv2D)              (None, 12, 12, 32)        9248      
                                                                 
 Flatten (Flatten)           (None, 4608)              0         
                                                                 
 Dense (Dense)               (None, 256)               1179904   
                                                                 
 Softmax (Dense)             (None, 5)                 1285      
                                                                 
=================================================================
Total params: 1,190,757
Trainable params: 1,190,757
Non-trainable params: 0
_________________________________________________________________
```

In [39]:
```
#Just another wway to visualize model architecture
tf.keras.utils.plot_model(model, to_file='CM1.png', show_shapes=True)
```

Out[39]:



In [40]:

```
#To include early stopping (depends on patience or loss)
#es = EarlyStopping(monitor='val_loss', mode='min', verbose=1)
#Time perfromance for train dataset
start = time.time()
#Fitting the model
cm1_history = model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=50,
          shuffle = True,
          #callbacks=[es],
          validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

```
Epoch 1/50
96/96 [==============================] - 42s 429ms/step - loss: 0.4832 - accuracy: 0.8102
- val_loss: 0.3401 - val_accuracy: 0.8763
Epoch 2/50
96/96 [==============================] - 41s 424ms/step - loss: 0.2926 - accuracy: 0.8950
- val_loss: 0.2787 - val_accuracy: 0.9006
Epoch 3/50
96/96 [==============================] - 41s 422ms/step - loss: 0.2504 - accuracy: 0.9103
- val_loss: 0.2400 - val_accuracy: 0.9154
Epoch 4/50
96/96 [==============================] - 40s 414ms/step - loss: 0.2158 - accuracy: 0.9241
- val_loss: 0.2148 - val_accuracy: 0.9236
Epoch 5/50
96/96 [==============================] - 40s 416ms/step - loss: 0.1947 - accuracy: 0.9304
- val_loss: 0.2119 - val_accuracy: 0.9273
Epoch 6/50
96/96 [==============================] - 39s 409ms/step - loss: 0.1769 - accuracy: 0.9369
- val_loss: 0.2041 - val_accuracy: 0.9258
Epoch 7/50
96/96 [==============================] - 40s 413ms/step - loss: 0.1656 - accuracy: 0.9408
- val_loss: 0.2022 - val_accuracy: 0.9288
Epoch 8/50
96/96 [==============================] - 41s 424ms/step - loss: 0.1532 - accuracy: 0.9454
- val_loss: 0.2008 - val_accuracy: 0.9277
Epoch 9/50
96/96 [==============================] - 40s 420ms/step - loss: 0.1420 - accuracy: 0.9486
- val_loss: 0.1834 - val_accuracy: 0.9345
Epoch 10/50
96/96 [==============================] - 40s 415ms/step - loss: 0.1349 - accuracy: 0.9516
- val_loss: 0.1844 - val_accuracy: 0.9371
Epoch 11/50
96/96 [==============================] - 40s 422ms/step - loss: 0.1241 - accuracy: 0.9554
- val_loss: 0.1891 - val_accuracy: 0.9343
Epoch 12/50
96/96 [==============================] - 41s 425ms/step - loss: 0.1133 - accuracy: 0.9605
- val_loss: 0.1799 - val_accuracy: 0.9350
Epoch 13/50
96/96 [==============================] - 41s 429ms/step - loss: 0.1093 - accuracy: 0.9607
- val_loss: 0.1776 - val_accuracy: 0.9392
Epoch 14/50
96/96 [==============================] - 41s 423ms/step - loss: 0.0968 - accuracy: 0.9661
- val_loss: 0.1746 - val_accuracy: 0.9389
Epoch 15/50
96/96 [==============================] - 40s 421ms/step - loss: 0.0895 - accuracy: 0.9696
- val_loss: 0.1782 - val_accuracy: 0.9407
Epoch 16/50
96/96 [==============================] - 40s 422ms/step - loss: 0.0849 - accuracy: 0.9708
- val_loss: 0.1917 - val_accuracy: 0.9382
Epoch 17/50
96/96 [==============================] - 40s 418ms/step - loss: 0.0785 - accuracy: 0.9727
- val_loss: 0.1868 - val_accuracy: 0.9389
Epoch 18/50
96/96 [==============================] - 40s 419ms/step - loss: 0.0722 - accuracy: 0.9748
- val_loss: 0.1917 - val_accuracy: 0.9391
Epoch 19/50
96/96 [==============================] - 40s 413ms/step - loss: 0.0686 - accuracy: 0.9763
- val_loss: 0.1970 - val_accuracy: 0.9377
Epoch 20/50
```

```
96/96 [==============================] - 40s 415ms/step - loss: 0.0612 - accuracy: 0.9792
- val_loss: 0.2050 - val_accuracy: 0.9373
Epoch 21/50
96/96 [==============================] - 40s 417ms/step - loss: 0.0560 - accuracy: 0.9810
- val_loss: 0.2050 - val_accuracy: 0.9386
Epoch 22/50
96/96 [==============================] - 40s 417ms/step - loss: 0.0507 - accuracy: 0.9831
- val_loss: 0.2064 - val_accuracy: 0.9391
Epoch 23/50
96/96 [==============================] - 40s 415ms/step - loss: 0.0485 - accuracy: 0.9840
- val_loss: 0.2147 - val_accuracy: 0.9380
Epoch 24/50
96/96 [==============================] - 41s 424ms/step - loss: 0.0434 - accuracy: 0.9857
- val_loss: 0.1990 - val_accuracy: 0.9409
Epoch 25/50
96/96 [==============================] - 40s 418ms/step - loss: 0.0396 - accuracy: 0.9870
- val_loss: 0.2063 - val_accuracy: 0.9404
Epoch 26/50
96/96 [==============================] - 40s 413ms/step - loss: 0.0318 - accuracy: 0.9904
- val_loss: 0.2218 - val_accuracy: 0.9408
Epoch 27/50
96/96 [==============================] - 40s 416ms/step - loss: 0.0306 - accuracy: 0.9900
- val_loss: 0.2193 - val_accuracy: 0.9434
Epoch 28/50
96/96 [==============================] - 40s 417ms/step - loss: 0.0264 - accuracy: 0.9920
- val_loss: 0.2381 - val_accuracy: 0.9436
Epoch 29/50
96/96 [==============================] - 40s 419ms/step - loss: 0.0242 - accuracy: 0.9927
- val_loss: 0.2285 - val_accuracy: 0.9418
Epoch 30/50
96/96 [==============================] - 40s 417ms/step - loss: 0.0217 - accuracy: 0.9934
- val_loss: 0.2387 - val_accuracy: 0.9413
Epoch 31/50
96/96 [==============================] - 47s 486ms/step - loss: 0.0174 - accuracy: 0.9950
- val_loss: 0.2518 - val_accuracy: 0.9414
Epoch 32/50
96/96 [==============================] - 40s 415ms/step - loss: 0.0145 - accuracy: 0.9961
- val_loss: 0.2528 - val_accuracy: 0.9433
Epoch 33/50
96/96 [==============================] - 40s 414ms/step - loss: 0.0132 - accuracy: 0.9967
- val_loss: 0.2634 - val_accuracy: 0.9394
Epoch 34/50
96/96 [==============================] - 40s 415ms/step - loss: 0.0142 - accuracy: 0.9959
- val_loss: 0.2727 - val_accuracy: 0.9404
Epoch 35/50
96/96 [==============================] - 40s 414ms/step - loss: 0.0111 - accuracy: 0.9973
- val_loss: 0.3108 - val_accuracy: 0.9401
Epoch 36/50
96/96 [==============================] - 40s 415ms/step - loss: 0.0131 - accuracy: 0.9962
- val_loss: 0.2890 - val_accuracy: 0.9416
Epoch 37/50
96/96 [==============================] - 40s 416ms/step - loss: 0.0068 - accuracy: 0.9986
- val_loss: 0.2889 - val_accuracy: 0.9413
Epoch 38/50
96/96 [==============================] - 40s 413ms/step - loss: 0.0060 - accuracy: 0.9988
- val_loss: 0.2919 - val_accuracy: 0.9417
Epoch 39/50
96/96 [==============================] - 40s 413ms/step - loss: 0.0036 - accuracy: 0.9997
```

```
- val_loss: 0.3074 - val_accuracy: 0.9421
Epoch 40/50
96/96 [==============================] - 40s 413ms/step - loss: 0.0034 - accuracy: 0.9996
- val_loss: 0.3106 - val_accuracy: 0.9414
Epoch 41/50
96/96 [==============================] - 40s 419ms/step - loss: 0.0039 - accuracy: 0.9994
- val_loss: 0.3080 - val_accuracy: 0.9441
Epoch 42/50
96/96 [==============================] - 40s 419ms/step - loss: 0.0030 - accuracy: 0.9996
- val_loss: 0.3146 - val_accuracy: 0.9427
Epoch 43/50
96/96 [==============================] - 40s 414ms/step - loss: 0.0048 - accuracy: 0.9988
- val_loss: 0.3757 - val_accuracy: 0.9327
Epoch 44/50
96/96 [==============================] - 40s 412ms/step - loss: 0.0346 - accuracy: 0.9873
- val_loss: 0.2917 - val_accuracy: 0.9358
Epoch 45/50
96/96 [==============================] - 40s 412ms/step - loss: 0.0145 - accuracy: 0.9950
- val_loss: 0.3042 - val_accuracy: 0.9414
Epoch 46/50
96/96 [==============================] - 40s 414ms/step - loss: 0.0060 - accuracy: 0.9986
- val_loss: 0.3177 - val_accuracy: 0.9436
Epoch 47/50
96/96 [==============================] - 40s 417ms/step - loss: 0.0019 - accuracy: 0.9999
- val_loss: 0.3296 - val_accuracy: 0.9447
Epoch 48/50
96/96 [==============================] - 40s 418ms/step - loss: 9.5341e-04 - accuracy: 1.0
000 - val_loss: 0.3394 - val_accuracy: 0.9437
Epoch 49/50
96/96 [==============================] - 40s 418ms/step - loss: 8.4584e-04 - accuracy: 1.0
000 - val_loss: 0.3445 - val_accuracy: 0.9446
Epoch 50/50
96/96 [==============================] - 40s 414ms/step - loss: 6.3437e-04 - accuracy: 1.0
000 - val_loss: 0.3502 - val_accuracy: 0.9449
Total time:  2063.238160133362 seconds
```

In [41]:

```python
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100,
test_acc*100))
```

```
Train: 100.000, Val: 94.492,Test: 93.960
```

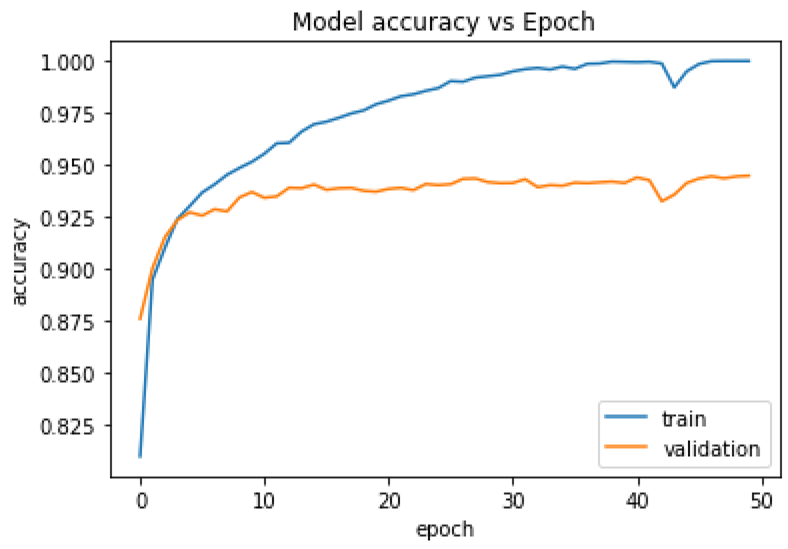
In [42]:

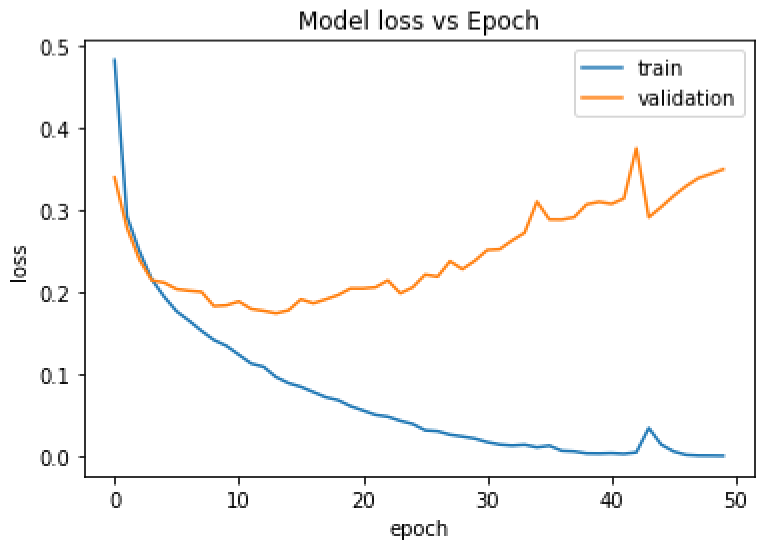
```python
#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

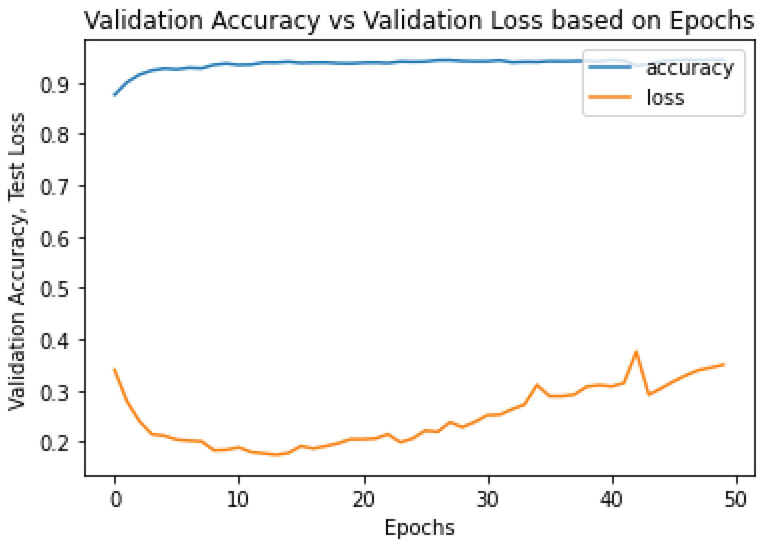
```
Testing time :  3.376964807510376
```

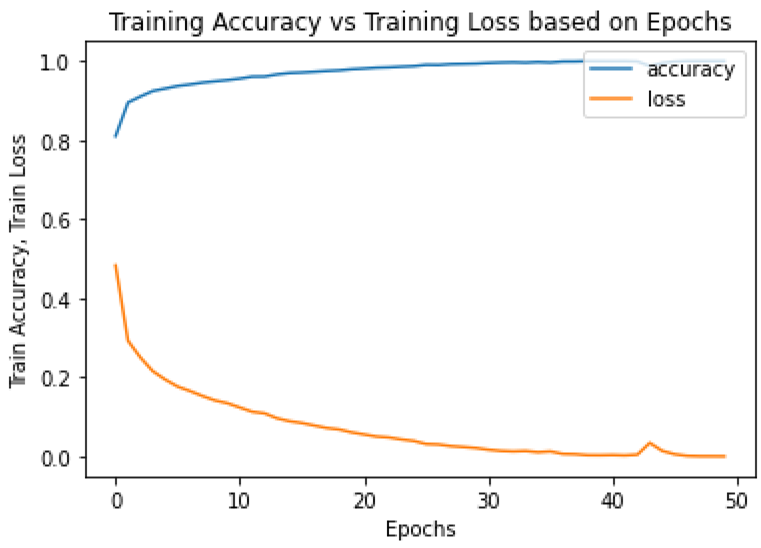
In [43]:

```
#Plots: Visualization of accuracy vs epoch and loss vs epoch

plt.plot(cm1_history.history['accuracy'])
plt.plot(cm1_history.history['val_accuracy'])
plt.title('Model accuracy vs Epoch')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='lower right')
plt.show()
# summarize history for loss
plt.plot(cm1_history.history['loss'])
plt.plot(cm1_history.history['val_loss'])
plt.title('Model loss vs Epoch')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()

plt.plot(cm1_history.history['val_accuracy'])
plt.plot(cm1_history.history['val_loss'])
plt.title('Validation Accuracy vs Validation Loss based on Epochs')
plt.ylabel('Validation Accuracy, Test Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()

plt.plot(cm1_history.history['accuracy'])
plt.plot(cm1_history.history['loss'])
plt.title('Training Accuracy vs Training Loss based on Epochs')
plt.ylabel('Train Accuracy, Train Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()
```


Model accuracy vs Epoch
accuracy
epoch
train
validation
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0
10
20
30
40
50


Model loss vs Epoch
loss
epoch
train
validation
0.5
0.4
0.3
0.2
0.1
0.0
0
10
20
30
40
50


Validation Accuracy vs Validation Loss based on Epochs
Validation Accuracy, Test Loss
Epochs
accuracy
loss
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
10
20
30
40
50



Comments:

- We obtain ~94% accuracy on test dataset for this simple CNN model.
- We tried with different epochs to see the impact of local minima and observed that validation loss started increasing and validation accuracy fluctuated in small increments but on both sides of scale. The data gave significant accuracy in few epochs (as low as 5).
- Adam Optimizer yielded better accuracy comapred to SGD.
- Categorical_crossentropy loss function gave better accuracy measure compared to other loss functions.
- Runtime for training and testing suggests good performance (quite fast).

CM2 : Own Network

> We implememt a simple CNN model , a variant of CM1 model byy adding a conv layer and dense layer. We implement more spohisticated CNN architectures in subsequent sections to compare the impact of different components in architecture.

CNN1

To experiment with the imapct of iterative increase and decrease in filter size(increasing and decreasing volume) and an added dense layer (better relationship in features)

- We use Adaptive Moment Estimation (Adam) optimizer with default value
- We make use of categorical cross entrpy as loss function
- We make use of 3 Conv2D layer but with different kernel sizes (32,64 and 32 respectively) followed by a flatten layer and 2 Dense layers with 256 and 128 neurons and finally a softmax max function to give probabilities in (0,1) range for our 5 class classification task. Complete model architecture is given below.
- We make use of ReLU activation function (Leaky ReLU yielded similar performance)
- Model converged faster with Adam Optimizer than SGD.

In [ ]:
```
model= Sequential(name="CNN1")
model.add(Conv2D(32, kernel_size=(3, 3),strides=(1, 1),activation='relu',
                 input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(Conv2D(64, (3, 3), activation='relu',name = 'Conv2'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool'))
model.add(Conv2D(32, (3, 3), activation='relu',name = 'Conv3'))
model.add(Flatten(name='Flatten'))
model.add(Dense(256, activation='relu',name = 'Dense1'))
model.add(Dense(128, activation='relu',name = 'Dense2'))
model.add(Dense(5, activation='softmax',name = 'Softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam',metrics=
['accuracy'])
```

In [ ]:

```
model.summary()
```

```
Model: "CNN1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 Conv1 (Conv2D)              (None, 28, 28, 32)        320       
                                                                 
 Conv2 (Conv2D)              (None, 26, 26, 64)        18496     
                                                                 
 MaxPool (MaxPooling2D)      (None, 13, 13, 64)        0         
                                                                 
 Conv3 (Conv2D)              (None, 11, 11, 32)        18464     
                                                                 
 Flatten (Flatten)           (None, 3872)              0         
                                                                 
 Dense1 (Dense)              (None, 256)               991488    
                                                                 
 Dense2 (Dense)              (None, 128)               32896     
                                                                 
 Softmax (Dense)             (None, 5)                 645       
                                                                 
=================================================================
Total params: 1,062,309
Trainable params: 1,062,309
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
start = time.time()
CNN1_history = model.fit(x_train, y_train,
            batch_size=BATCH_SIZE,
            epochs=EPOCH,
            shuffle = True,
            validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

```
Epoch 1/10
96/96 [==============================] - 152s 2s/step - loss: 0.5250 - accuracy: 0.7914 -
val_loss: 0.3352 - val_accuracy: 0.8779
Epoch 2/10
96/96 [==============================] - 120s 1s/step - loss: 0.2822 - accuracy: 0.8986 -
val_loss: 0.2608 - val_accuracy: 0.9069
Epoch 3/10
96/96 [==============================] - 120s 1s/step - loss: 0.2262 - accuracy: 0.9187 -
val_loss: 0.2260 - val_accuracy: 0.9189
Epoch 4/10
```

```
96/96 [==============================] - 119s 1s/step - loss: 0.1879 - accuracy: 0.9334 -
val_loss: 0.2146 - val_accuracy: 0.9225
Epoch 5/10
96/96 [==============================] - 119s 1s/step - loss: 0.1669 - accuracy: 0.9395 -
val_loss: 0.1893 - val_accuracy: 0.9324
Epoch 6/10
96/96 [==============================] - 118s 1s/step - loss: 0.1508 - accuracy: 0.9456 -
val_loss: 0.1865 - val_accuracy: 0.9327
Epoch 7/10
96/96 [==============================] - 116s 1s/step - loss: 0.1307 - accuracy: 0.9534 -
val_loss: 0.1840 - val_accuracy: 0.9328
Epoch 8/10
96/96 [==============================] - 117s 1s/step - loss: 0.1179 - accuracy: 0.9566 -
val_loss: 0.1804 - val_accuracy: 0.9387
Epoch 9/10
96/96 [==============================] - 115s 1s/step - loss: 0.0996 - accuracy: 0.9638 -
val_loss: 0.1665 - val_accuracy: 0.9426
Epoch 10/10
96/96 [==============================] - 115s 1s/step - loss: 0.0896 - accuracy: 0.9679 -
val_loss: 0.1828 - val_accuracy: 0.9397
Total time:  1222.489366531372 seconds
```

In [ ]:

```
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100,
test_acc*100))
```

```
Train: 97.206, Val: 93.967,Test: 93.820
```

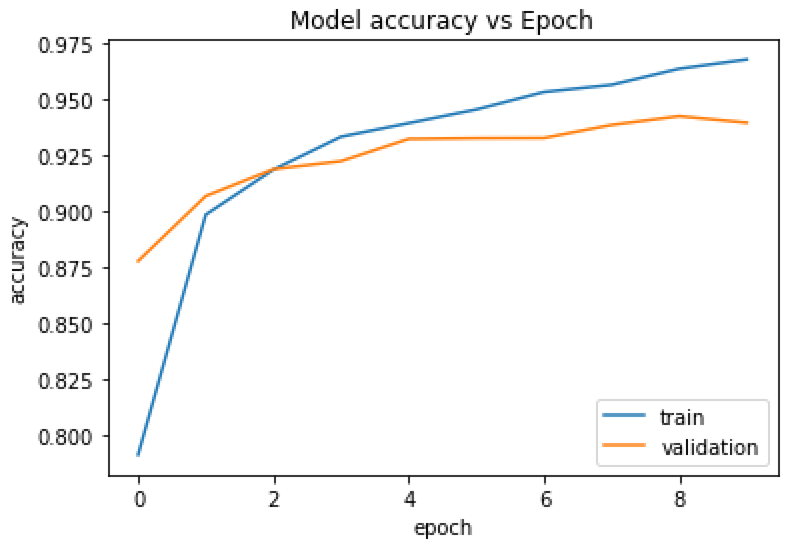
In [ ]:

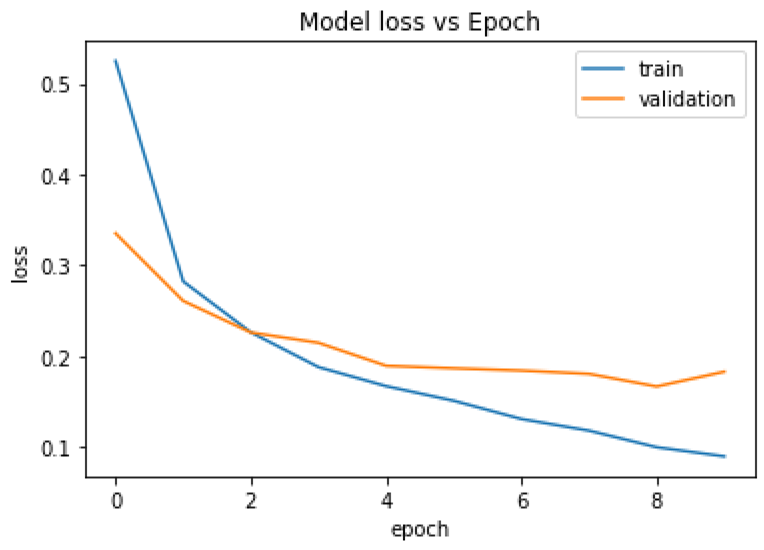
```
#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

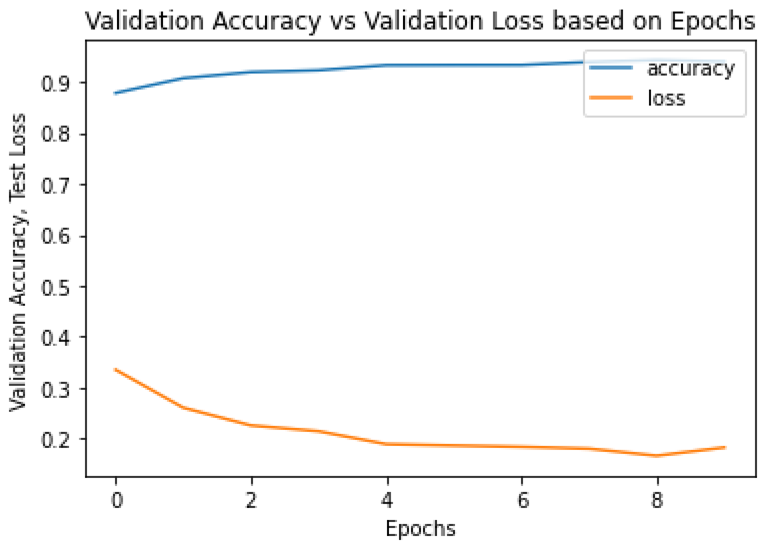
```
Testing time :  5.968332529067993
```

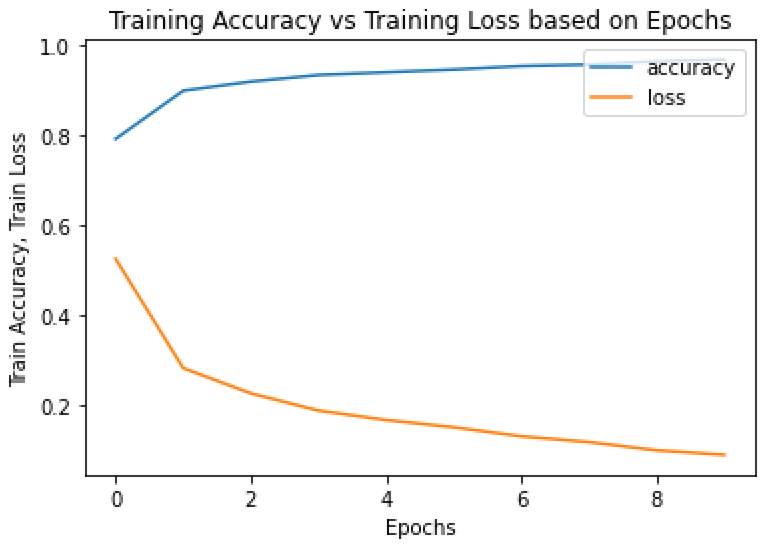
In [ ]:

```
#Plots: Visualization of accuracy vs epoch and loss vs epoch
plt.plot(CNN1_history.history['accuracy'])
plt.plot(CNN1_history.history['val_accuracy'])
plt.title('Model accuracy vs Epoch')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='lower right')
plt.show()
# summarize history for loss
plt.plot(CNN1_history.history['loss'])
plt.plot(CNN1_history.history['val_loss'])
plt.title('Model loss vs Epoch')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()

plt.plot(CNN1_history.history['val_accuracy'])
plt.plot(CNN1_history.history['val_loss'])
plt.title('Validation Accuracy vs Validation Loss based on Epochs')
plt.ylabel('Validation Accuracy, Test Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()

plt.plot(CNN1_history.history['accuracy'])
plt.plot(CNN1_history.history['loss'])
plt.title('Training Accuracy vs Training Loss based on Epochs')
plt.ylabel('Train Accuracy, Train Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()
```









Comments

We observed ~94% accuracy with our own CNN model.

CM3 : Own Network

- CNN2 : Adding Dropout layers
- CNN3 : Experimenting imapct of Optimizers (SGD)
- CNN4 : Experimention with activation function (Leaky ReLU)

- CNN_VGG : Inspiration from VGG16 (focusing on increasing volume)
- LSTM : Long Short term memory architecture

CNN2

> We added Dropout layers to see the imapct of regularization.We use rate=0.3 as argument i.e, the fraction of the input units to be dropped at each layer. It is a fraction between 0 and 1 and is used to prevent overfitting

In [ ]:

```
model = Sequential(name="CNN_2")

model.add(Conv2D(32, kernel_size=(3, 3),
                 strides=(1, 1),
                 activation='relu',
                 input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool1'))
model.add(Dropout(0.3))



model.add(Conv2D(32, (3, 3), activation='relu',name = 'Conv2'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool2'))
model.add(Dropout(0.3))

model.add(Flatten(name = 'Flatten'))

model.add(Dense(256, activation='relu',name = 'Dense1'))
model.add(Dropout(0.5))

model.add(Dense(64, activation='relu',name = 'Dense2'))

model.add(Dense(5, activation='softmax',name = 'Softmax'))

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

In [ ]:

```
model.summary()
```

```
Model: "CNN_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 Conv1 (Conv2D)              (None, 28, 28, 32)        320

 MaxPool1 (MaxPooling2D)     (None, 14, 14, 32)        0

 dropout (Dropout)           (None, 14, 14, 32)        0
 Conv2 (Conv2D)              (None, 12, 12, 32)        9248

 MaxPool2 (MaxPooling2D)     (None, 6, 6, 32)          0

 dropout_1 (Dropout)         (None, 6, 6, 32)          0

 Flatten (Flatten)           (None, 1152)              0

 Dense1 (Dense)              (None, 256)               295168

 dropout_2 (Dropout)         (None, 256)               0

 Dense2 (Dense)              (None, 64)                16448

 Softmax (Dense)             (None, 5)                 325

=================================================================
Total params: 321,509
Trainable params: 321,509
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
start = time.time()
CNN_2_history = model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=EPOCH,
          shuffle = True,
          validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

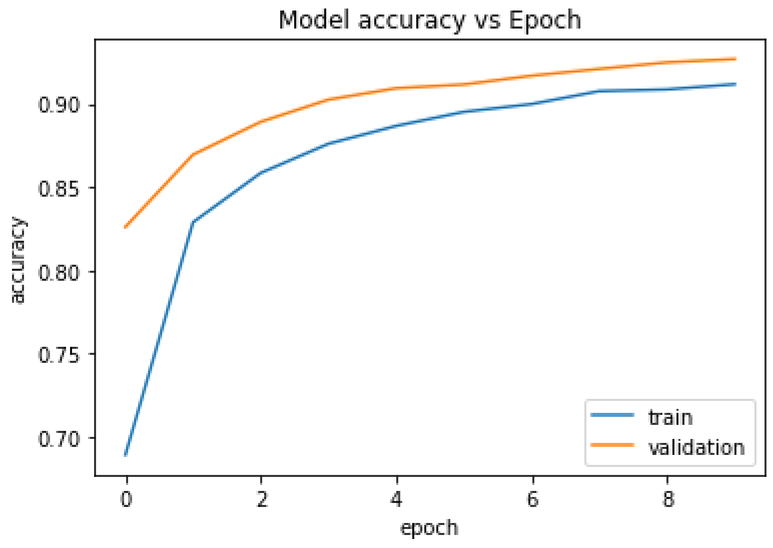
```
Epoch 1/10
96/96 [==============================] - 31s 318ms/step - loss: 0.7341 - accuracy: 0.6894
- val_loss: 0.4416 - val_accuracy: 0.8261
Epoch 2/10
96/96 [==============================] - 31s 318ms/step - loss: 0.4404 - accuracy: 0.8289
- val_loss: 0.3444 - val_accuracy: 0.8695
Epoch 3/10
96/96 [==============================] - 31s 320ms/step - loss: 0.3754 - accuracy: 0.8585
- val_loss: 0.2996 - val_accuracy: 0.8892
Epoch 4/10
96/96 [==============================] - 31s 320ms/step - loss: 0.3337 - accuracy: 0.8760
- val_loss: 0.2678 - val_accuracy: 0.9025
Epoch 5/10
96/96 [==============================] - 30s 317ms/step - loss: 0.3094 - accuracy: 0.8867
- val_loss: 0.2470 - val_accuracy: 0.9093
Epoch 6/10
96/96 [==============================] - 31s 319ms/step - loss: 0.2866 - accuracy: 0.8951
- val_loss: 0.2342 - val_accuracy: 0.9116
Epoch 7/10
96/96 [==============================] - 31s 319ms/step - loss: 0.2725 - accuracy: 0.8998
- val_loss: 0.2223 - val_accuracy: 0.9168
Epoch 8/10
96/96 [==============================] - 30s 317ms/step - loss: 0.2577 - accuracy: 0.9076
- val_loss: 0.2118 - val_accuracy: 0.9209
Epoch 9/10
96/96 [==============================] - 30s 318ms/step - loss: 0.2476 - accuracy: 0.9086
```

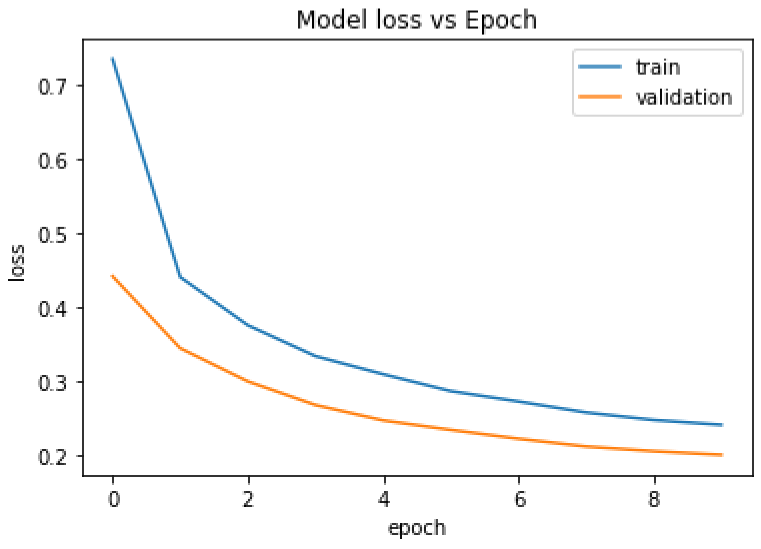
```
- val_loss: 0.2055 - val_accuracy: 0.9248
Epoch 10/10
96/96 [==============================] - 30s 317ms/step - loss: 0.2410 - accuracy: 0.9117
- val_loss: 0.2006 - val_accuracy: 0.9268
Total time:  322.5631422996521 seconds
```

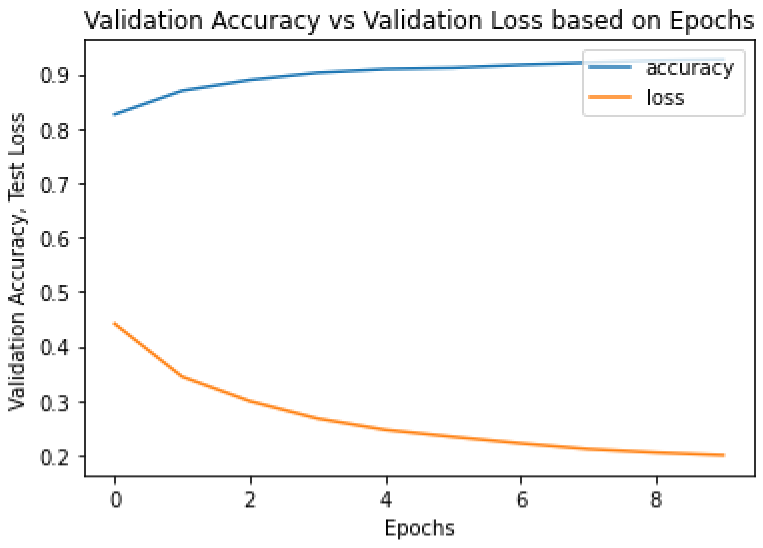
In [ ]:
```
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100,
test_acc*100))

#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

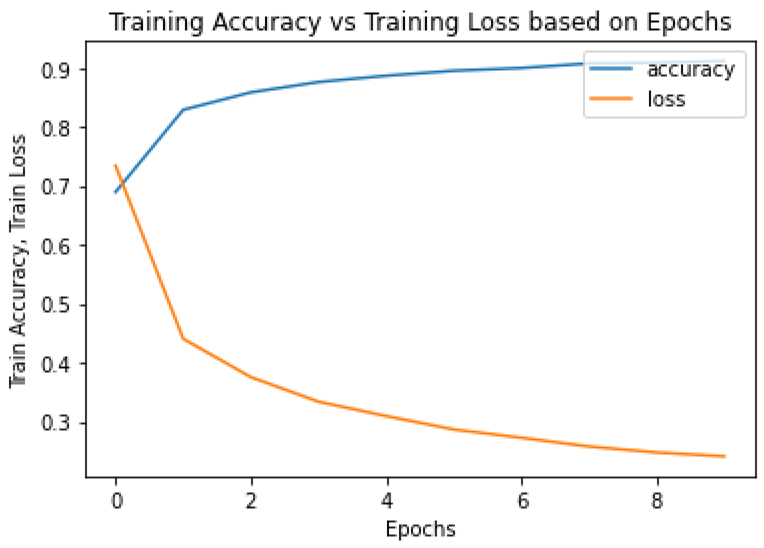
```
Train: 93.448, Val: 92.683,Test: 92.420
Testing time :  1.8049075603485107
```

In [ ]:
```
plt.plot(CNN_2_history.history['accuracy'])
plt.plot(CNN_2_history.history['val_accuracy'])
plt.title('Model accuracy vs Epoch')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='lower right')
plt.show()
# summarize history for loss
plt.plot(CNN_2_history.history['loss'])
plt.plot(CNN_2_history.history['val_loss'])
plt.title('Model loss vs Epoch')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()

plt.plot(CNN_2_history.history['val_accuracy'])
plt.plot(CNN_2_history.history['val_loss'])
plt.title('Validation Accuracy vs Validation Loss based on Epochs')
plt.ylabel('Validation Accuracy, Test Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()
plt.plot(CNN_2_history.history['accuracy'])
plt.plot(CNN_2_history.history['loss'])
plt.title('Training Accuracy vs Training Loss based on Epochs')
plt.ylabel('Train Accuracy, Train Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()
```









CNN3

> Trained the model with Stochastic Gradient Descent (SGD) Optimizer.

In [ ]:

```
model = Sequential(name="CNN_3")

model.add(Conv2D(32, kernel_size=(3, 3),
                 strides=(1, 1),
                 activation='relu',
                 input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool1'))
model.add(Conv2D(32, (3, 3), activation='relu',name = 'Conv2'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool2'))
model.add(Dropout(0.3))
model.add(Flatten(name = 'Flatten'))
model.add(Dense(256, activation='relu',name = 'Dense1'))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu',name = 'Dense2'))
model.add(Dense(5, activation='softmax',name = 'Softmax'))
model.compile(loss='categorical_crossentropy', optimizer='SGD',
              metrics=['accuracy'])
```

In [ ]:

```
start = time.time()
CNN_3_history = model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=EPOCH,
          shuffle = True,
          validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

```
Epoch 1/10
96/96 [==============================] - 28s 292ms/step - loss: 1.5011 - accuracy: 0.3079
```

```
- val_loss: 1.3404 - val_accuracy: 0.5020
Epoch 2/10
96/96 [==============================] - 28s 292ms/step - loss: 1.2983 - accuracy: 0.4315
- val_loss: 1.0609 - val_accuracy: 0.6069
Epoch 3/10
96/96 [==============================] - 29s 306ms/step - loss: 1.1244 - accuracy: 0.5020
- val_loss: 0.9144 - val_accuracy: 0.6252
Epoch 4/10
96/96 [==============================] - 30s 311ms/step - loss: 1.0229 - accuracy: 0.5493
- val_loss: 0.8435 - val_accuracy: 0.6422
Epoch 5/10
96/96 [==============================] - 28s 294ms/step - loss: 0.9528 - accuracy: 0.5888
- val_loss: 0.7829 - val_accuracy: 0.6808
Epoch 6/10
96/96 [==============================] - 28s 296ms/step - loss: 0.9059 - accuracy: 0.6157
- val_loss: 0.7398 - val_accuracy: 0.7044
Epoch 7/10
96/96 [==============================] - 29s 298ms/step - loss: 0.8619 - accuracy: 0.6402
- val_loss: 0.7052 - val_accuracy: 0.7117
Epoch 8/10
96/96 [==============================] - 28s 296ms/step - loss: 0.8276 - accuracy: 0.6572
- val_loss: 0.6736 - val_accuracy: 0.7303
Epoch 9/10
96/96 [==============================] - 29s 298ms/step - loss: 0.7942 - accuracy: 0.6740
- val_loss: 0.6409 - val_accuracy: 0.7535
Epoch 10/10
96/96 [==============================] - 28s 295ms/step - loss: 0.7686 - accuracy: 0.6839
- val_loss: 0.6189 - val_accuracy: 0.7540
Total time:  322.4274568557739 seconds
```

In [ ]:

```
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100,
test_acc*100))

#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

```
Train: 75.352, Val: 75.400,Test: 75.210
Testing time :  1.7907054424285889
```

CNN4

> We trained the model with LeakyReLu activation function. It is a variant of ReLU and introduces a small gradient for negative value instead of) as in ReLU. Both are similar in that their derivative is monotonic and continous, They both are able to solve the problem of exploding and vanishing gradients.

In [ ]:
```
model = Sequential(name="CNN_4")

model.add(Conv2D(32, kernel_size=(3, 3),
                 strides=(1, 1),
                 activation=tf.keras.layers.LeakyReLU(alpha=0.2),
                 input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool1'))
model.add(Conv2D(32, (3, 3),
activation=tf.keras.layers.LeakyReLU(alpha=0.2),name = 'Conv2'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool2'))
model.add(Dropout(0.3))
model.add(Flatten(name = 'Flatten'))
model.add(Dense(256, activation=tf.keras.layers.LeakyReLU(alpha=0.2),name =
'Dense1'))
model.add(Dropout(0.5))
model.add(Dense(64, activation=tf.keras.layers.LeakyReLU(alpha=0.2),name =
'Dense2'))
model.add(Dense(5, activation='softmax',name = 'Softmax'))
model.compile(loss='categorical_crossentropy', optimizer='Adam',
              metrics=['accuracy'])
```

In [ ]:
```
start = time.time()
CNN_4_history = model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=EPOCH,
          shuffle = True,
          validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

```
Epoch 1/10
96/96 [==============================] - 32s 327ms/step - loss: 0.6416 - accuracy: 0.7396
- val_loss: 0.3685 - val_accuracy: 0.8621
Epoch 2/10
96/96 [==============================] - 31s 324ms/step - loss: 0.3715 - accuracy: 0.8617
- val_loss: 0.3028 - val_accuracy: 0.8909
Epoch 3/10
96/96 [==============================] - 31s 322ms/step - loss: 0.3203 - accuracy: 0.8828
- val_loss: 0.2707 - val_accuracy: 0.9013
Epoch 4/10
96/96 [==============================] - 31s 322ms/step - loss: 0.2886 - accuracy: 0.8949
- val_loss: 0.2443 - val_accuracy: 0.9107
Epoch 5/10
96/96 [==============================] - 31s 322ms/step - loss: 0.2645 - accuracy: 0.9022
- val_loss: 0.2264 - val_accuracy: 0.9176
Epoch 6/10
96/96 [==============================] - 31s 322ms/step - loss: 0.2501 - accuracy: 0.9099
- val_loss: 0.2211 - val_accuracy: 0.9201
Epoch 7/10
```

```
96/96 [==============================] - 31s 322ms/step - loss: 0.2366 - accuracy: 0.9143
- val_loss: 0.2096 - val_accuracy: 0.9241
Epoch 8/10
96/96 [==============================] - 31s 324ms/step - loss: 0.2230 - accuracy: 0.9204
- val_loss: 0.2012 - val_accuracy: 0.9262
Epoch 9/10
96/96 [==============================] - 31s 323ms/step - loss: 0.2147 - accuracy: 0.9211
- val_loss: 0.1912 - val_accuracy: 0.9307
Epoch 10/10
96/96 [==============================] - 31s 325ms/step - loss: 0.2042 - accuracy: 0.9262
- val_loss: 0.1843 - val_accuracy: 0.9326
Total time:  322.5065915584564 seconds
```

In [ ]:

```
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100,
test_acc*100))

#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

```
Train: 94.356, Val: 93.258,Test: 92.960
Testing time :  2.2175590991973877
```

CNN_VGG

> VGG is an popular image classifictaion model using fewer CNN layers compared to other image classification algorithms such as AleXNet, LeNet and others. It successively increases the volume by addinD CNN layers with a larger filter size and finally using multiple fully connected layers to learn relationship between features.

In [ ]:

```
model = Sequential(name="CNN_VGG")

model.add(Conv2D(32, kernel_size=(3, 3),
                 strides=(1, 1),
                 activation='relu',
                 input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool1'))
model.add(Conv2D(64, (3, 3), activation='relu',name = 'Conv2'))

model.add(Conv2D(128, (3, 3), activation='relu',name = 'Conv3'))
model.add(Conv2D(128, (3, 3), activation='relu',name = 'Conv4'))
model.add(Conv2D(256, (3, 3), activation='relu',name = 'Conv5'))
model.add(Conv2D(256, (3, 3), activation='relu',name = 'Conv6'))

model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool4'))
model.add(Flatten(name = 'Flatten'))

model.add(Dense(1024, activation='relu',name = 'Dense1'))
model.add(Dropout(0.5))
model.add(Dense(512, activation='relu',name = 'Dense2'))
model.add(Dropout(0.5))
model.add(Dense(256, activation='relu',name = 'Dense3'))
model.add(Dropout(0.5))
model.add(Dense(5, activation='softmax',name = 'Softmax'))

model.compile(loss='categorical_crossentropy', optimizer=
tf.keras.optimizers.Adam(0.003),metrics=['accuracy'])
```

In [ ]:
```
model.summary()
```

```
Model: "CNN_VGG"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 Conv1 (Conv2D)              (None, 28, 28, 32)        320

 MaxPool1 (MaxPooling2D)     (None, 14, 14, 32)        0

 Conv2 (Conv2D)              (None, 12, 12, 64)        18496

 Conv3 (Conv2D)              (None, 10, 10, 128)       73856

 Conv4 (Conv2D)              (None, 8, 8, 128)         147584

 Conv5 (Conv2D)              (None, 6, 6, 256)         295168

 Conv6 (Conv2D)              (None, 4, 4, 256)         590080

 MaxPool4 (MaxPooling2D)     (None, 2, 2, 256)         0

 Flatten (Flatten)           (None, 1024)              0

 Dense1 (Dense)              (None, 1024)              1049600

 dropout_7 (Dropout)         (None, 1024)              0

 Dense2 (Dense)              (None, 512)               524800

 dropout_8 (Dropout)         (None, 512)               0

 Dense3 (Dense)              (None, 256)               131328
 dropout_9 (Dropout)         (None, 256)               0

 Softmax (Dense)             (None, 5)                 1285

=================================================================
Total params: 2,832,517
Trainable params: 2,832,517
Non-trainable params: 0
_________________________________________________________________
```

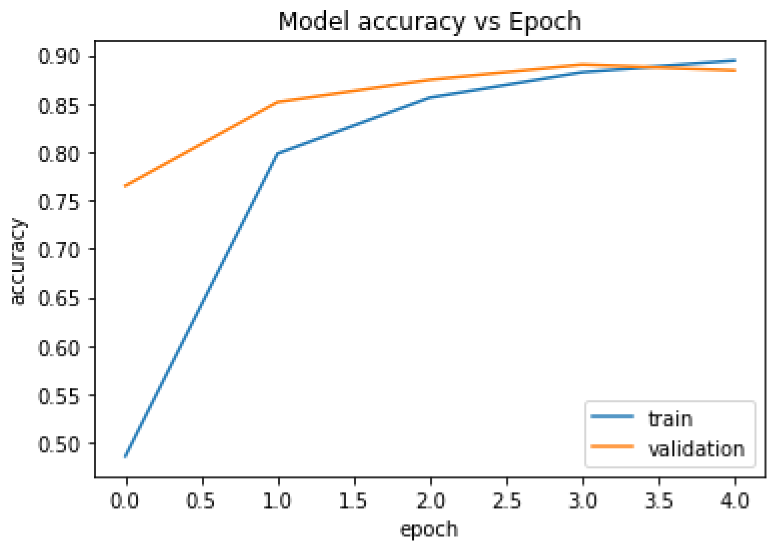
In [ ]:
```python
start = time.time()
CNN_VGG_history = model.fit(x_train, y_train,
          batch_size=400,
          epochs=5,
          shuffle = True,
          validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

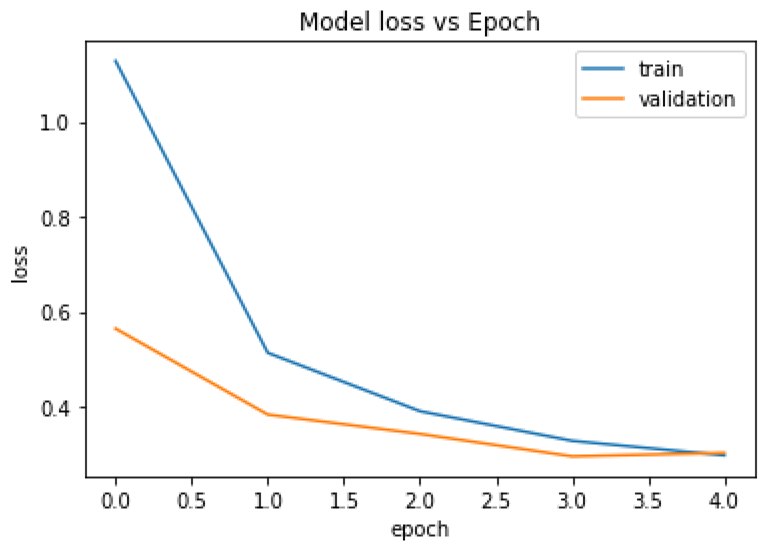
```
Epoch 1/5
120/120 [==============================] - 290s 2s/step - loss: 1.1276 - accuracy: 0.4862
- val_loss: 0.5640 - val_accuracy: 0.7650
Epoch 2/5
120/120 [==============================] - 283s 2s/step - loss: 0.5131 - accuracy: 0.7983
- val_loss: 0.3830 - val_accuracy: 0.8514
Epoch 3/5
120/120 [==============================] - 281s 2s/step - loss: 0.3902 - accuracy: 0.8560
- val_loss: 0.3422 - val_accuracy: 0.8744
Epoch 4/5
120/120 [==============================] - 288s 2s/step - loss: 0.3277 - accuracy: 0.8822
- val_loss: 0.2951 - val_accuracy: 0.8902
Epoch 5/5
120/120 [==============================] - 303s 3s/step - loss: 0.2972 - accuracy: 0.8944
- val_loss: 0.3023 - val_accuracy: 0.8842
Total time:  1462.7450199127197 seconds
```

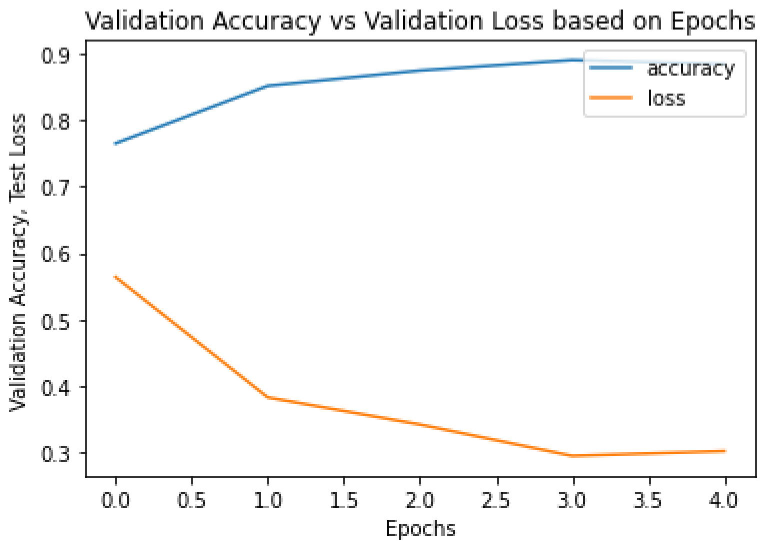
In [ ]:
```python
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100,
test_acc*100))

#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

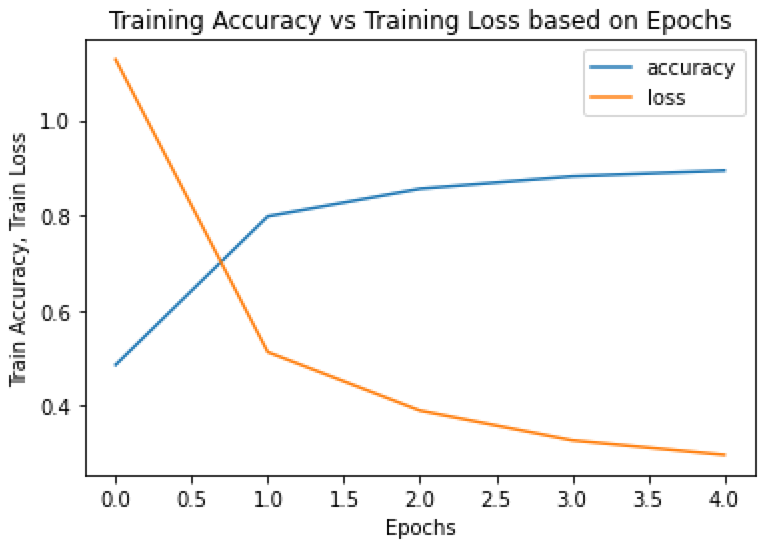
```
Train: 89.415, Val: 88.417,Test: 88.040
Testing time :  13.466981887817383
```

In [ ]:
```
plt.plot(CNN_VGG_history.history['accuracy'])
plt.plot(CNN_VGG_history.history['val_accuracy'])
plt.title('Model accuracy vs Epoch')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='lower right')
plt.show()
# summarize history for loss
plt.plot(CNN_VGG_history.history['loss'])
plt.plot(CNN_VGG_history.history['val_loss'])
plt.title('Model loss vs Epoch')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()

plt.plot(CNN_VGG_history.history['val_accuracy'])
plt.plot(CNN_VGG_history.history['val_loss'])
plt.title('Validation Accuracy vs Validation Loss based on Epochs')
plt.ylabel('Validation Accuracy, Test Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()

plt.plot(CNN_VGG_history.history['accuracy'])
plt.plot(CNN_VGG_history.history['loss'])
plt.title('Training Accuracy vs Training Loss based on Epochs')
plt.ylabel('Train Accuracy, Train Loss')
plt.xlabel('Epochs')
plt.legend(['accuracy', 'loss'], loc='upper right')
plt.show()
```









LSTM

> Long Short Term Memory are special type of Recurrent Neural network (RNN) architecture i sable to learn long range dependencies. It has input and forget gate whose values are calculated based on previous cell state and previous hidden state.

In [ ]:
```
row_hidden = 128
col_hidden = 128
```

```
num_classes = 5
row, col, pixel = x_train.shape[1:]
x = Input(shape=(row, col, pixel))
encoded_rows = TimeDistributed(LSTM(row_hidden))(x)
encoded_columns = LSTM(col_hidden)(encoded_rows)
prediction = Dense(num_classes, activation='softmax')(encoded_columns)
model = Model(x, prediction)
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

In [ ]:
```
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 28, 28, 1)]       0

 time_distributed (TimeDistr  (None, 28, 128)          66560
 ibuted)

 lstm_1 (LSTM)               (None, 128)               131584

 dense (Dense)               (None, 5)                 645

=================================================================
Total params: 198,789
Trainable params: 198,789
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:
```
start = time.time()
model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=EPOCH,
          verbose=1,
          validation_data=(x_val, y_val))
print("Total time: ", time.time() - start, "seconds")
```

```
Epoch 1/10
96/96 [==============================] - 457s 5s/step - loss: 1.0675 - accuracy: 0.5205 -
val_loss: 0.7682 - val_accuracy: 0.6822
Epoch 2/10
96/96 [==============================] - 447s 5s/step - loss: 0.7299 - accuracy: 0.6923 -
val_loss: 0.6500 - val_accuracy: 0.7227
Epoch 3/10
96/96 [==============================] - 481s 5s/step - loss: 0.6108 - accuracy: 0.7523 -
val_loss: 0.5363 - val_accuracy: 0.7925
Epoch 4/10
96/96 [==============================] - 489s 5s/step - loss: 0.5445 - accuracy: 0.7859 -
val_loss: 0.5266 - val_accuracy: 0.7949
```

```
Epoch 5/10
96/96 [==============================] - 515s 5s/step - loss: 0.4983 - accuracy: 0.8077 -
val_loss: 0.4239 - val_accuracy: 0.8419
Epoch 6/10
96/96 [==============================] - 512s 5s/step - loss: 0.4539 - accuracy: 0.8259 -
val_loss: 0.4301 - val_accuracy: 0.8392
Epoch 7/10
96/96 [==============================] - 514s 5s/step - loss: 0.4164 - accuracy: 0.8430 -
val_loss: 0.3707 - val_accuracy: 0.8652
Epoch 8/10
96/96 [==============================] - 539s 6s/step - loss: 0.3834 - accuracy: 0.8572 -
val_loss: 0.3659 - val_accuracy: 0.8696
Epoch 9/10
96/96 [==============================] - 535s 6s/step - loss: 0.3596 - accuracy: 0.8654 -
val_loss: 0.3619 - val_accuracy: 0.8675
Epoch 10/10
96/96 [==============================] - 535s 6s/step - loss: 0.3394 - accuracy: 0.8729 -
val_loss: 0.3818 - val_accuracy: 0.8575
Total time:  5064.516736030579 seconds
```

In [ ]:

```
#evaluation
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, val_acc = model.evaluate(x_val, y_val, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train: %.3f, Val: %.3f,Test: %.3f' % (train_acc*100, val_acc*100, 
test_acc*100))
```

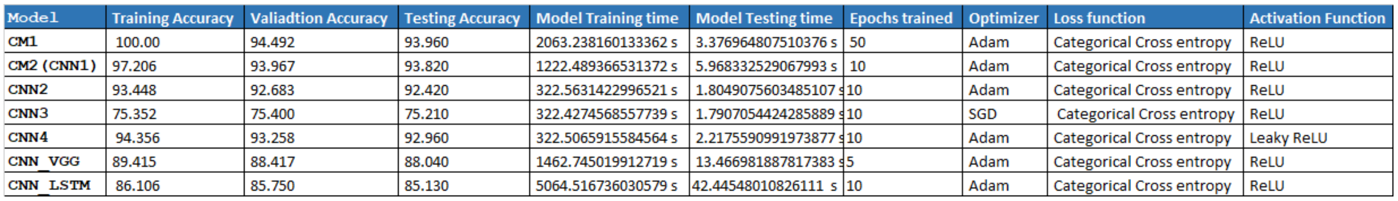
```
Train: 86.106, Val: 85.750,Test: 85.130
```

In [ ]:

```
#Time perfrormance for test dataset
start_time = time.time()
y_pred = model.predict(x_test)
end_time = time.time()
time_taken = end_time - start_time
print("Testing time : ", time_taken)
```

```
Testing time :  42.44548010826111
```

Comparisons



Model	Training Accuracy	Valiadtion Accuracy	Testing Accuracy	Model Training time	Model Testing time	Epochs trained	Optimizer	Loss function	Activation Function
CM1	100.00	94.492	93.960	2063.238160133362 s	3.376964807510376 s	50	Adam	Categorical Cross entropy	ReLU
CM2 (CNN1)	97.206	93.967	93.820	1222.489366531372 s	5.968332529067993 s	10	Adam	Categorical Cross entropy	ReLU
CNN2	93.448	92.683	92.420	322.5631422996521 s	1.8049075603485107 s	10	Adam	Categorical Cross entropy	ReLU
CNN3	75.352	75.400	75.210	322.4274568557739 s	1.7907054424285889 s	10	SGD	Categorical Cross entropy	ReLU
CNN4	94.356	93.258	92.960	322.5065915584564 s	2.2175590991973877 s	10	Adam	Categorical Cross entropy	Leaky ReLU
CNN_VGG	89.415	88.417	88.040	1462.745019912719 s	13.466981887817383 s	5	Adam	Categorical Cross entropy	ReLU
CNN_LSTM	86.106	85.750	85.130	5064.516736030579 s	42.44548010826111 s	10	Adam	Categorical Cross entropy	ReLU

Observations:

> When trained with same Epoch =10 and batch size of 500 images , the models performed similar except CNN3(SGD optimizer) and CNN_VGG and LSTM architectures. This is possibly as SGD takes longer to converge but generalizes better(argued in various papers). LSTM and CNN_VGG are complex models with greater number of parameters to learn. This is also apparent through the runtime performance for these models. THe plots for model accuracy vs epochs and model loss vs

> epoch are plotted above and it is observed that in complex models it doe snot each its optimal trainng accuracy and loss did not start increasing whereas in simpler models , models trained much faster and tend to overfit (as apparen by increase in loss function).

CM4 : Using your own encoding

In [ ]:
```
model = Sequential(name="CNN_2")

model.add(Conv2D(32, kernel_size=(3, 3),
                 strides=(1, 1),
                 activation='relu',
                 input_shape=(28,28,1), padding = 'same',name = 'Conv1'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool1'))
#model.add(Dropout(0.3))


model.add(Conv2D(32, (3, 3), activation='relu',name = 'Conv2'))
model.add(MaxPooling2D(pool_size=(2, 2),name = 'MaxPool2'))
model.add(Dropout(0.3))

model.add(Flatten(name = 'Flatten'))

model.add(Dense(256, activation='relu',name = 'Dense1'))
model.add(Dropout(0.5))

model.add(Dense(64, activation='relu',name = 'Dense2'))

model.add(Dense(5, activation='softmax',name = 'Softmax'))

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

In [ ]:
```
CNN_2_history = model.fit(x_train, y_train,
          batch_size=BATCH_SIZE,
          epochs=3,
          shuffle = True,
          validation_data=(x_val, y_val))
```

```
Epoch 1/3
96/96 [==============================] - 39s 388ms/step - loss: 0.6579 - accuracy: 0.7325
- val_loss: 0.3782 - val_accuracy: 0.8569
Epoch 2/3
96/96 [==============================] - 32s 338ms/step - loss: 0.3884 - accuracy: 0.8553
- val_loss: 0.3047 - val_accuracy: 0.8897
Epoch 3/3
```

```
96/96 [==============================] - 32s 337ms/step - loss: 0.3304 - accuracy: 0.8783
- val_loss: 0.2699 - val_accuracy: 0.8997
```

Intermediate Layer Model

In [ ]:
```
dense_layer_output = [layer.output for layer in model.layers if layer.name ==
'Dense2']
extractor = Model(inputs=model.inputs,outputs=dense_layer_output)
features = extractor(x_test)
```

In [ ]:
```
print(type(features))
print(len(features))
print(len(x_test))
```

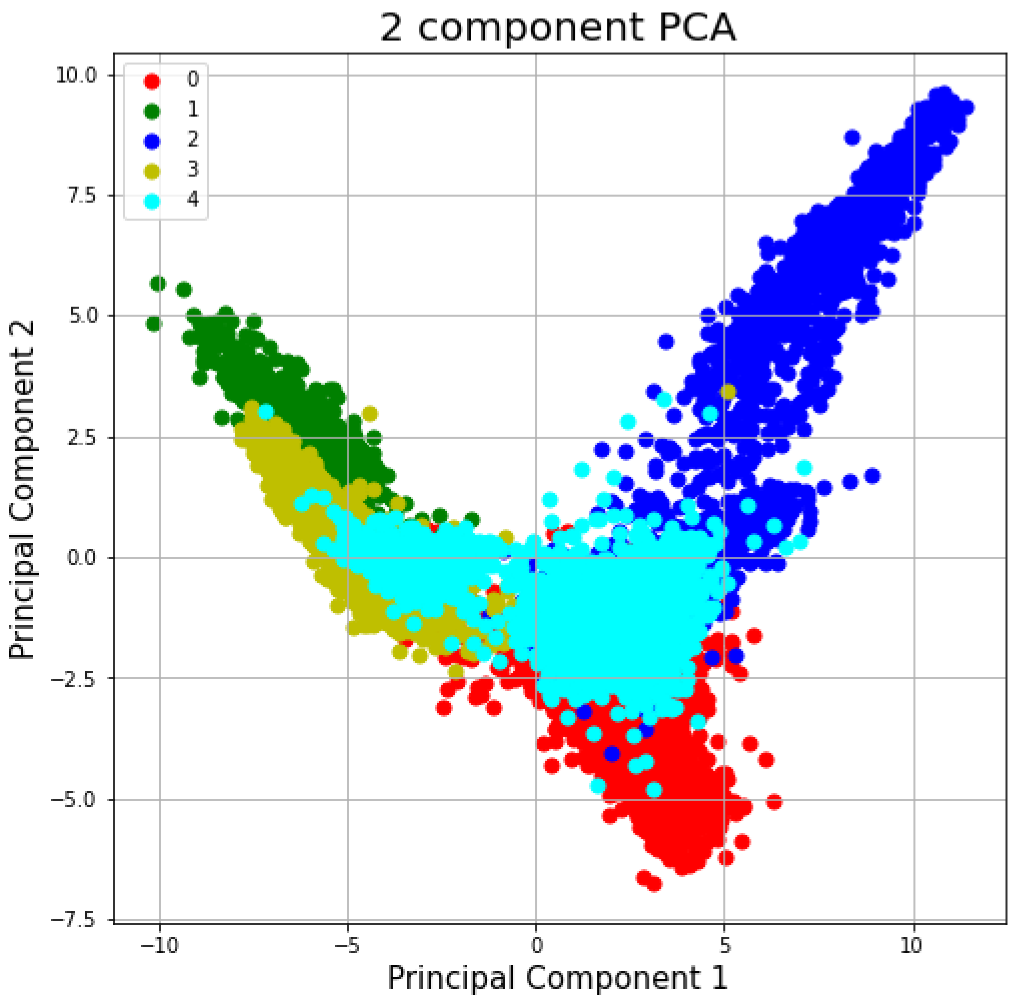
```
<class 'tensorflow.python.framework.ops.EagerTensor'>
10000
10000
```

PCA on extracted features

In [ ]:
```
pca = PCA(n_components=n_components, random_state=random_state)
pca.fit(features)
x = pca.transform(features)
```

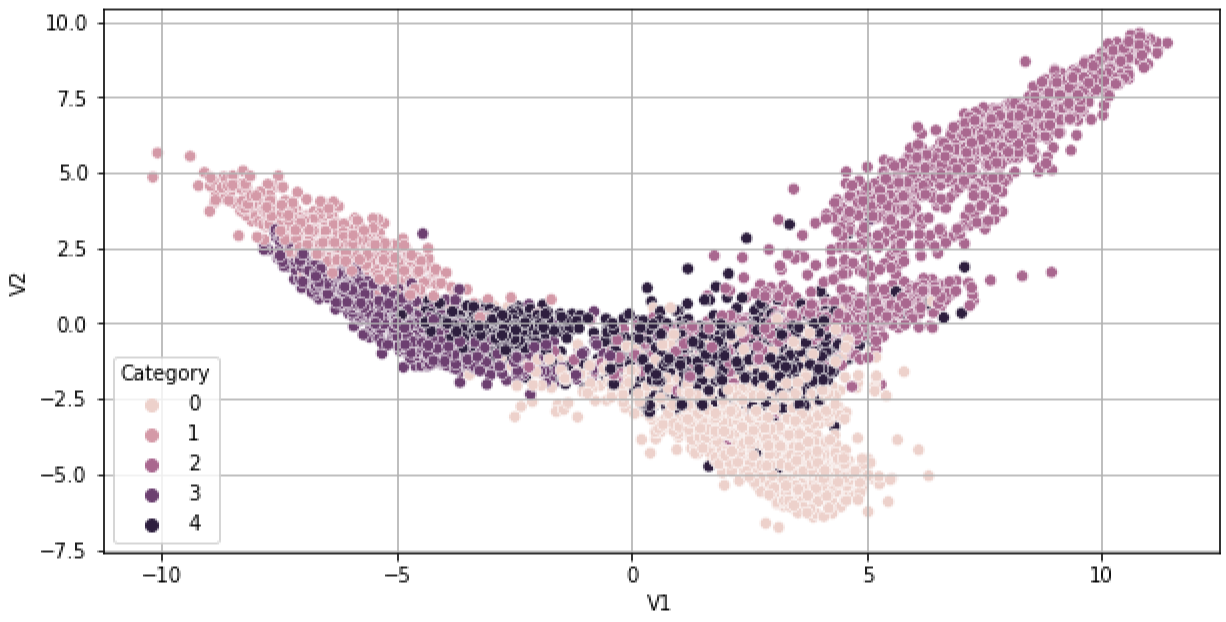
In [ ]:
```
principalDf = pd.DataFrame(data = x
             , columns = ['principal component 1', 'principal component 2'])
finalDf = pd.concat([principalDf, df_y_test[['0']]], axis = 1)
```

In [ ]:
```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
targets = classes
colors = ['r', 'g', 'b','y','cyan']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf['0'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(targets)
ax.grid()
```



In [ ]:

```
dimReducedDataFrame = pd.DataFrame(x)
dimReducedDataFrame = dimReducedDataFrame.rename(columns = { 0: 'V1', 1 :
'V2'})
dimReducedDataFrame['Category'] = df_y_test['0']
plt.figure(figsize = (10, 5))
sb.scatterplot(data = dimReducedDataFrame, x = 'V1', y = 'V2',hue =
'Category')
plt.grid(True)
plt.show()
```



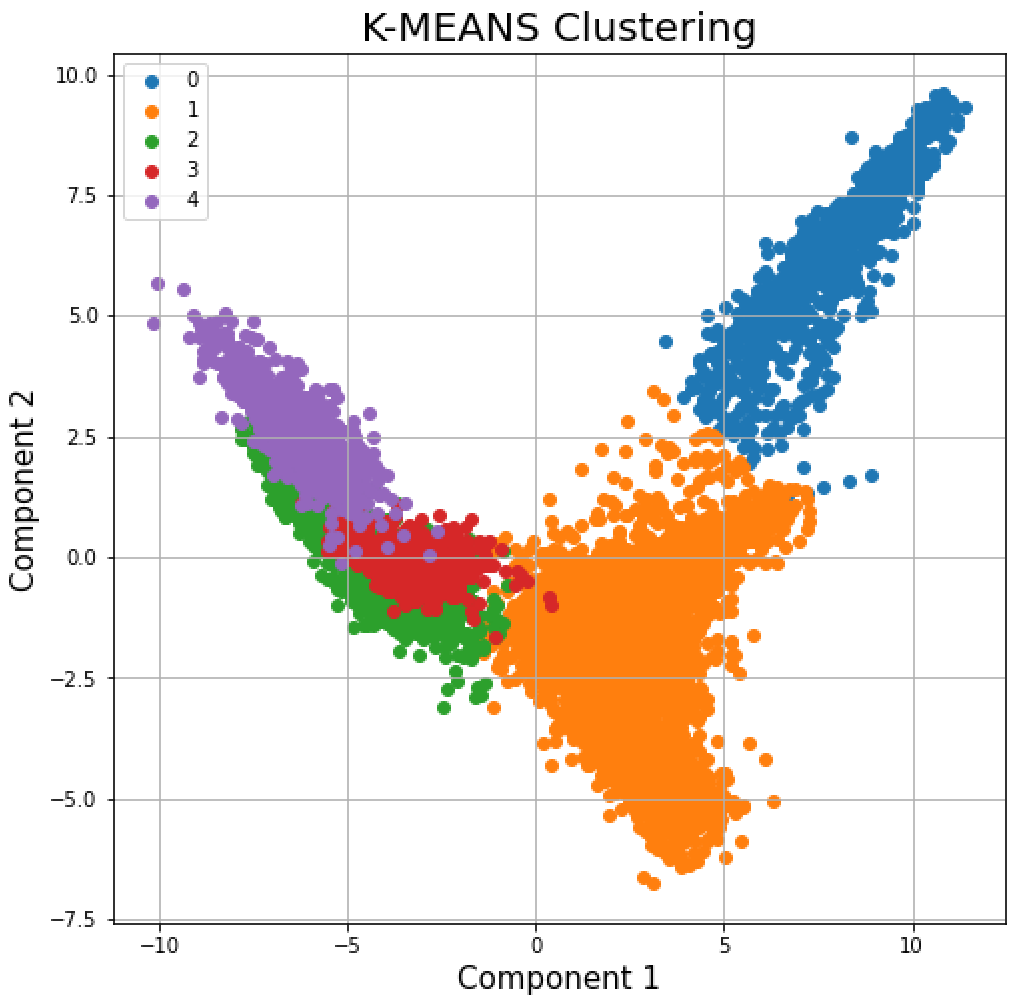
KMeans

In [ ]:
```
kmeans = KMeans(n_clusters=5, random_state=22)
kmeans.fit(features)
```

Out[ ]:
```
KMeans(n_clusters=5, random_state=22)
```

In [ ]:
```
#kmeans = KMeans(n_clusters=5, random_state=random_state)
#z=kmeans.fit_transform(features)
```

In [ ]:
```
label = kmeans.fit_predict(features)
u_labels = np.unique(label)
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Component 1', fontsize = 15)
ax.set_ylabel('Component 2', fontsize = 15)
ax.set_title('K-MEANS Clustering', fontsize = 20)
fig = plt.figure(figsize = (8,8))
for i in u_labels:
    ax.scatter(x[label == i , 0] , x[label == i , 1] , label = i)
ax.legend()
ax.grid()
```



```
<Figure size 576x576 with 0 Axes>
```

In [ ]:

```
#unique, counts = np.unique(label, return_counts=True)
#print(unique, counts)
```

```
[0 1 2 3 4] [4951 2113  848 1022 1066]
```

In [ ]:

```
#df_y_test['0'].value_counts()
```

Out[ ]:

```
4    3000
2    2000
0    2000
3    2000
1    1000
Name: 0, dtype: int64
```

DBSCAN

Finding optimal value of epsilon

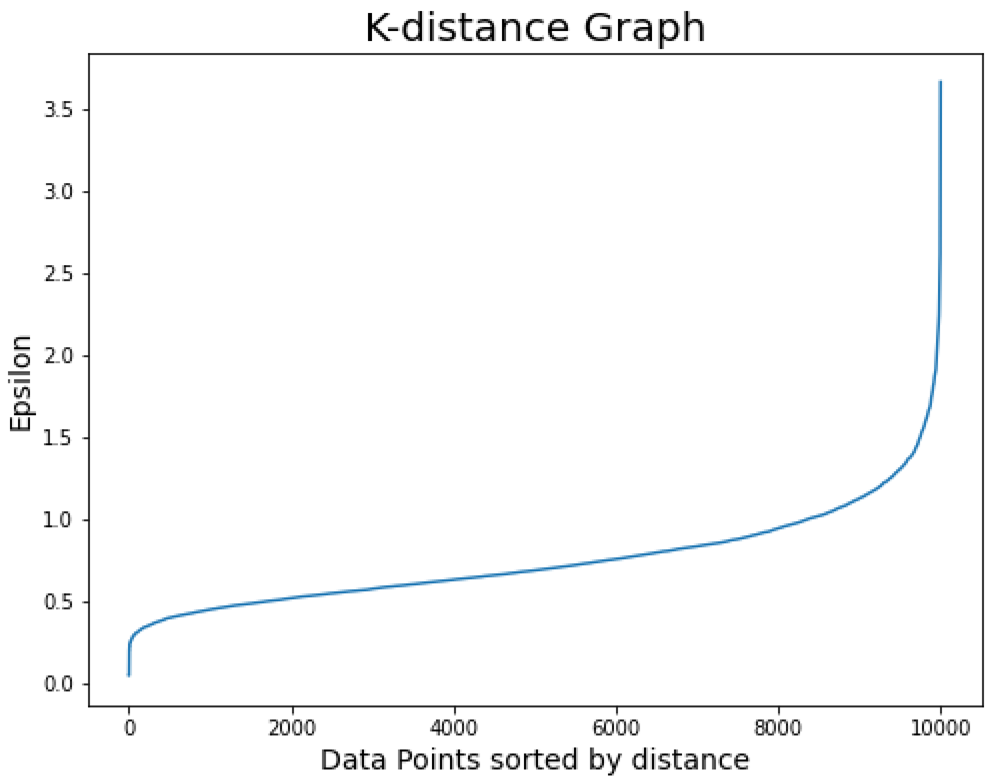
In [ ]:

```
neigh = NearestNeighbors(n_neighbors=2)
nbrs = neigh.fit(features)
distances, indices = nbrs.kneighbors(features)
```

In [ ]:

```
distances = np.sort(distances, axis=0)
distances = distances[:,1]
```

```
plt.figure(figsize=(8,6))
plt.plot(distances)
plt.title('K-distance Graph',fontsize=20)
plt.xlabel('Data Points sorted by distance',fontsize=14)
plt.ylabel('Epsilon',fontsize=14)
plt.show()
```



DBSCAN using extracted features

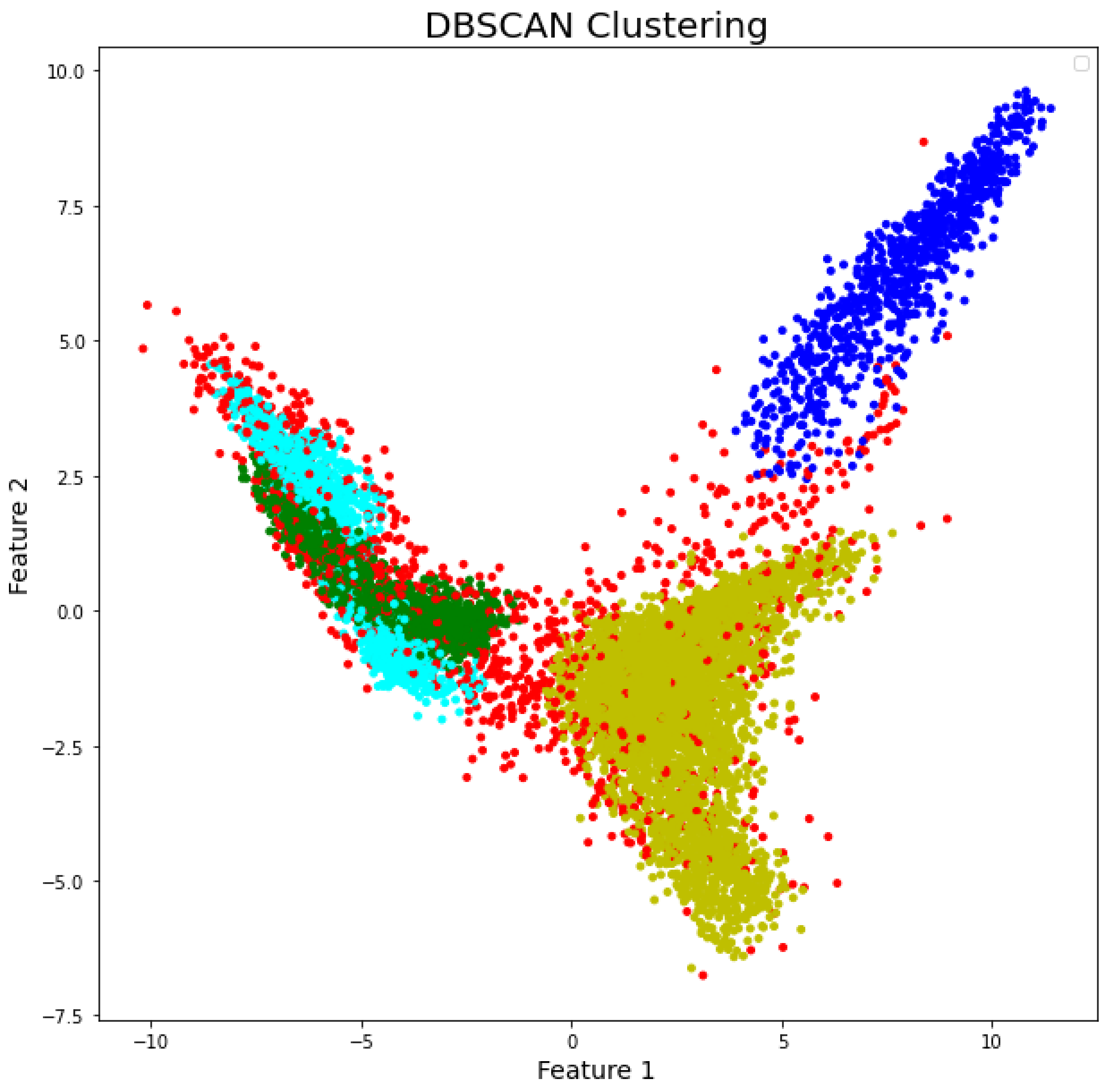
In [ ]:
```
dbscan_opt=DBSCAN(eps=1.6,min_samples=60)
#d = dbscan_opt.fit_predict(features)
d = dbscan_opt.fit(features)
```

In [ ]:
```
principalDf['DBSCAN_opt_labels'] = dbscan_opt.labels_
print(dbscan_opt.labels_)
print(np.unique(dbscan_opt.labels_))
print(principalDf['DBSCAN_opt_labels'].value_counts())
```

```
[ 0 -1  1 ... -1  1  0]
[-1  0  1  2  3  4]
 2    4626
 0    1975
-1    1281
 1     839
 3     699
 4     580
Name: DBSCAN_opt_labels, dtype: int64
```

In [ ]:
```
import matplotlib
plt.figure(figsize=(10,10))
plt.scatter(principalDf['principal component 1'],principalDf['principal
component 2'],c=principalDf['DBSCAN_opt_labels'],
            cmap=matplotlib.colors.ListedColormap(colors),s=15)
plt.title('DBSCAN Clustering',fontsize=20)
plt.xlabel('Feature 1',fontsize=14)
plt.ylabel('Feature 2',fontsize=14)
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```



T-SNE

In [ ]:
```
tsne = TSNE(n_components=n_components,  random_state=random_state) #verbose=1
z = tsne.fit_transform(features)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:783: FutureWarning: The
default initialization in TSNE will change from 'random' to 'pca' in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:793: FutureWarning: The
```

```
default learning rate in TSNE will change from 200.0 to 'auto' in 1.2.
  FutureWarning,
```

In [ ]:

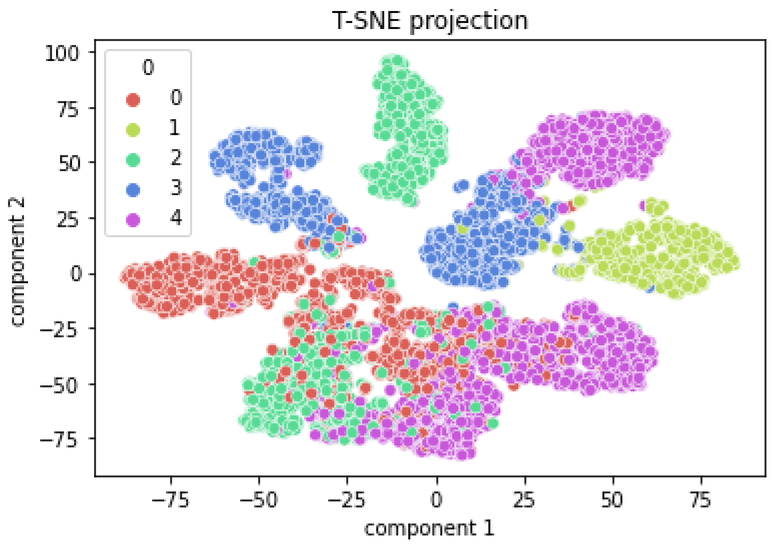
```
tsneDf = pd.DataFrame(data = z
             , columns = ['component 1', 'component 2'])
finalDf = pd.concat([tsneDf, df_y_test[['0']]], axis = 1)
```

In [ ]:

```
sb.scatterplot(x="component 1", y="component 2", hue=finalDf['0'],
                palette=sb.color_palette("hls", 5),
                data=finalDf).set(title="T-SNE projection")
```

Out[ ]:

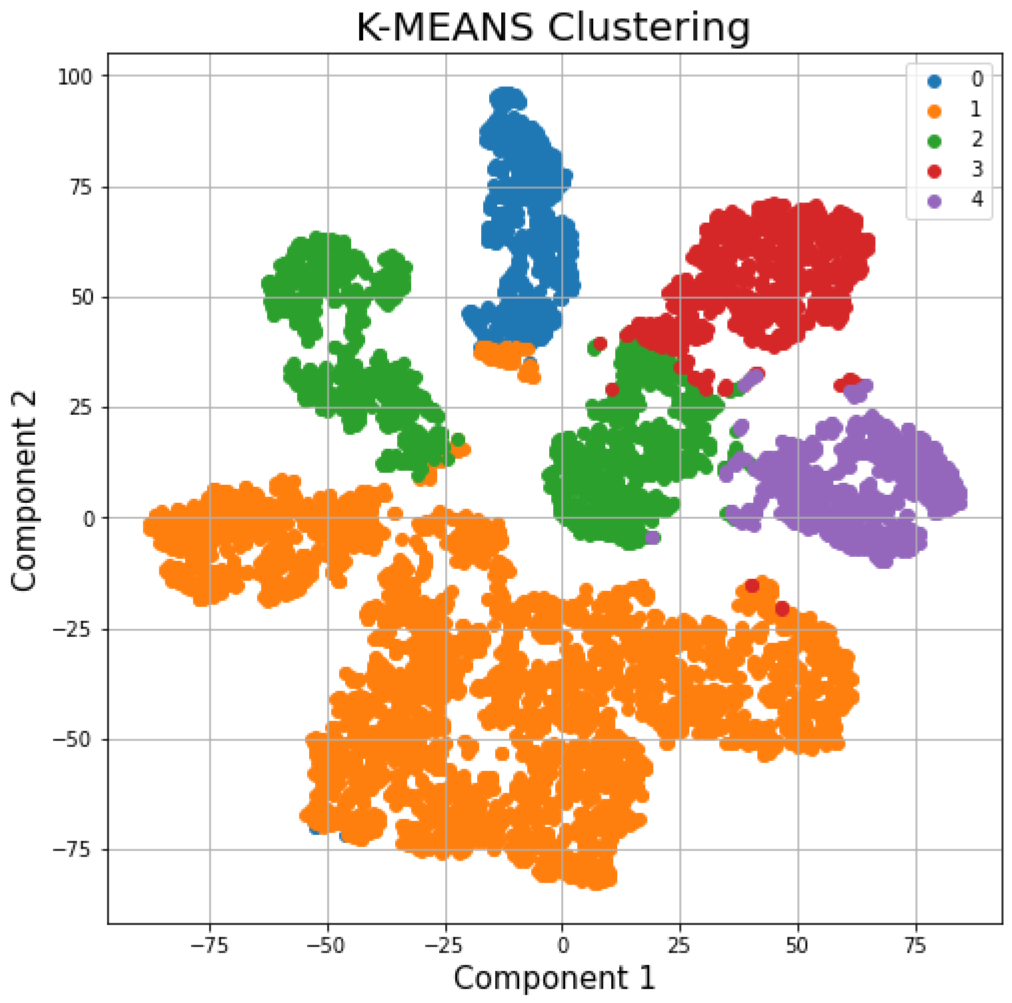
```
[Text(0.5, 1.0, 'T-SNE projection')]
```



K-Means Clustering

In [ ]:

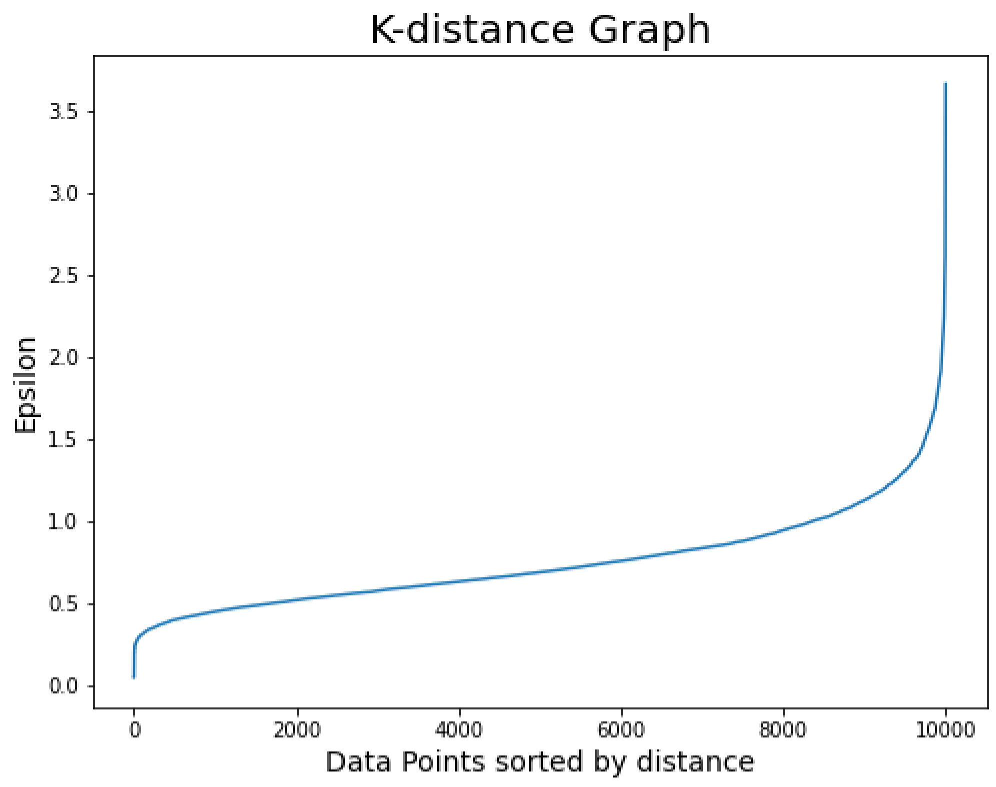
```
kmeans = KMeans(n_clusters=5, random_state=22)
kmeans.fit(features)
label = kmeans.fit_predict(features)
u_labels = np.unique(label)
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Component 1', fontsize = 15)
ax.set_ylabel('Component 2', fontsize = 15)
ax.set_title('K-MEANS Clustering', fontsize = 20)
fig = plt.figure(figsize = (8,8))
for i in u_labels:
    ax.scatter(z[label == i , 0] , z[label == i , 1] , label = i)
ax.legend()
ax.grid()
```



```
<Figure size 576x576 with 0 Axes>
```

DBSCAN Clustering

In [ ]:
```
neigh = NearestNeighbors(n_neighbors=2)
nbrs = neigh.fit(features)
distances, indices = nbrs.kneighbors(features)
distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.figure(figsize=(8,6))
plt.plot(distances)
plt.title('K-distance Graph',fontsize=20)
plt.xlabel('Data Points sorted by distance',fontsize=14)
plt.ylabel('Epsilon',fontsize=14)
plt.show()
```

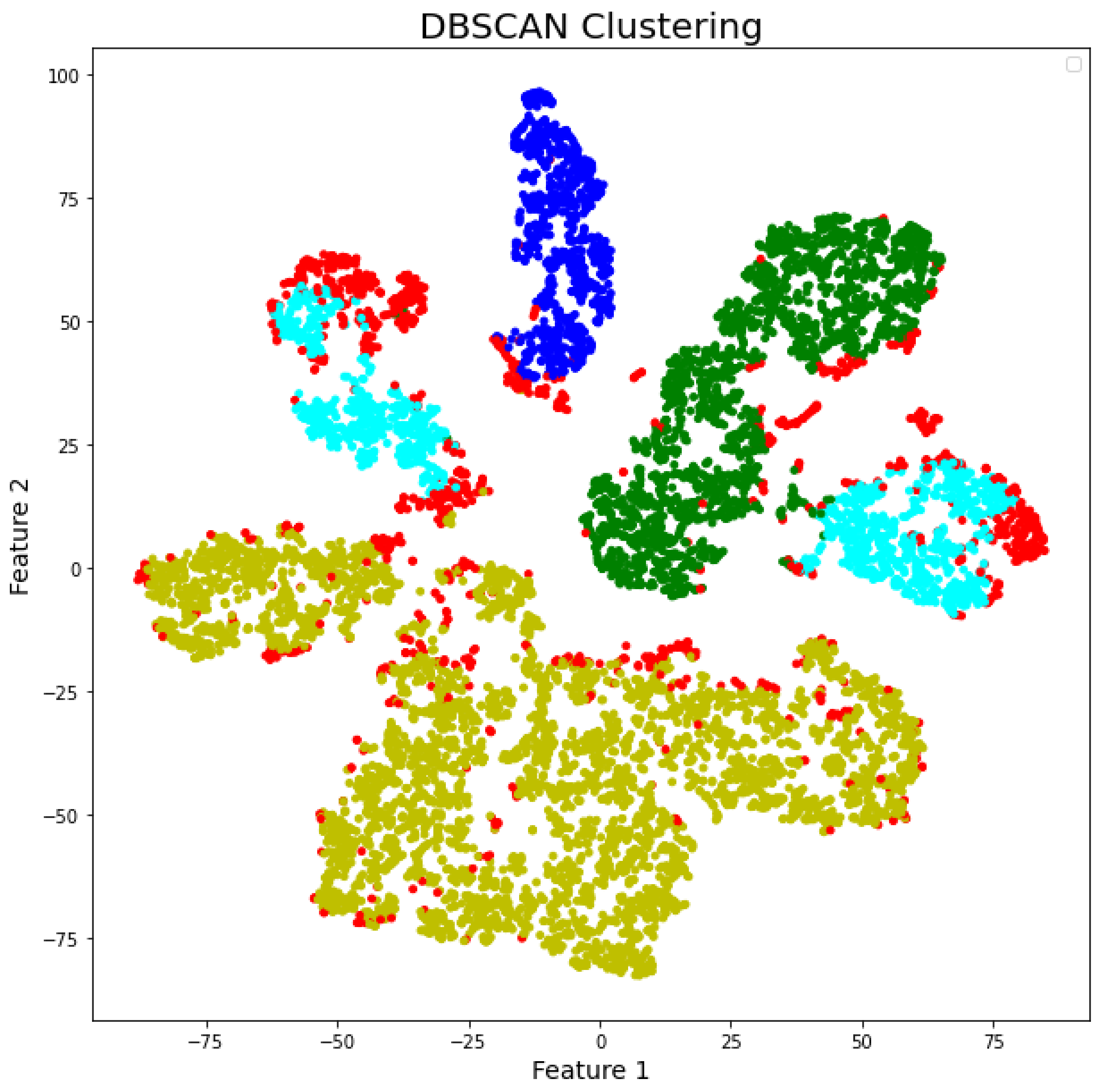


In [ ]:
```
dbscan_opt=DBSCAN(eps=1.6,min_samples=60)
#d = dbscan_opt.fit_predict(features)
d = dbscan_opt.fit(features)
finalDf['DBSCAN_opt_labels'] = dbscan_opt.labels_
print(dbscan_opt.labels_)
print(np.unique(dbscan_opt.labels_))
print(finalDf['DBSCAN_opt_labels'].value_counts())
```

```
[ 0 -1  1 ... -1  1  0]
[-1  0  1  2  3  4]
 2    4626
 0    1975
-1    1281
 1     839
 3     699
 4     580
Name: DBSCAN_opt_labels, dtype: int64
```

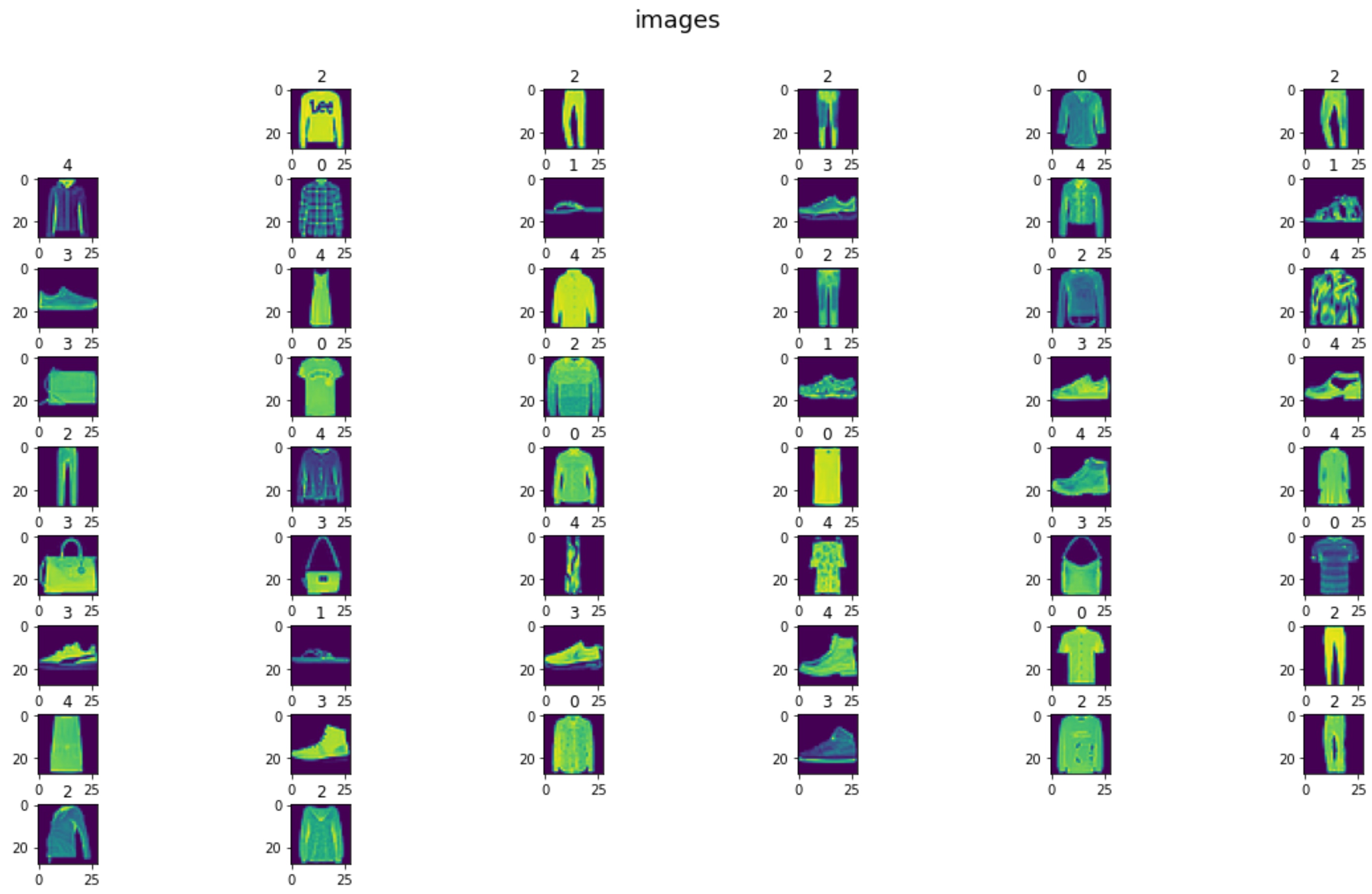
In [ ]:
```
plt.figure(figsize=(10,10))
plt.scatter(finalDf['component 1'],finalDf['component
2'],c=finalDf['DBSCAN_opt_labels'],
              cmap=matplotlib.colors.ListedColormap(colors),s=15)
plt.title('DBSCAN Clustering',fontsize=20)
plt.xlabel('Feature 1',fontsize=14)
plt.ylabel('Feature 2',fontsize=14)
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```



Decoding mystery labels

In [24]:
```python
from PIL import Image
rows=10
plt.figure(figsize=(20, 12))
plt.subplots_adjust(hspace=0.5)
plt.suptitle("images", fontsize=18, y=0.95)

for i in range(1,50):
  #print(i)
  #print(df_x_test[:i].shape)
  img=df_x_test.iloc[i].values.reshape((28,28,1))
  pil_img = tf.keras.preprocessing.image.array_to_img(img)
  plt.subplot(rows,6,i+1)
  plt.title(df_y_test['0'].iloc[i])
  plt.imshow(pil_img)
  #plt.show()
```



Mystery Labels Decoded

We plotted images with their true labels from test dataset and with predicted labels using KMeans on features encoding applied on test dataset. These are the major classes/ labels that are associated with category, although broader category (Summer wear, Winterwear or clothing material) is hard to define because of certain labels having mixed classes, we define grouped labels on the granular/ initial fashion mnist dataset labels that could have been represented by our mystery labels.

- Label 0 : Tshirt/Top and Shirt
- Label 1 : Sandals
- Label 2 : Trouser , Coat and Pullover
- Label 3 : Sneakers and Handbags
- Label 4 : Dress and Ankle Boots

References

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