FASHION CLASS CLASSIFICATION

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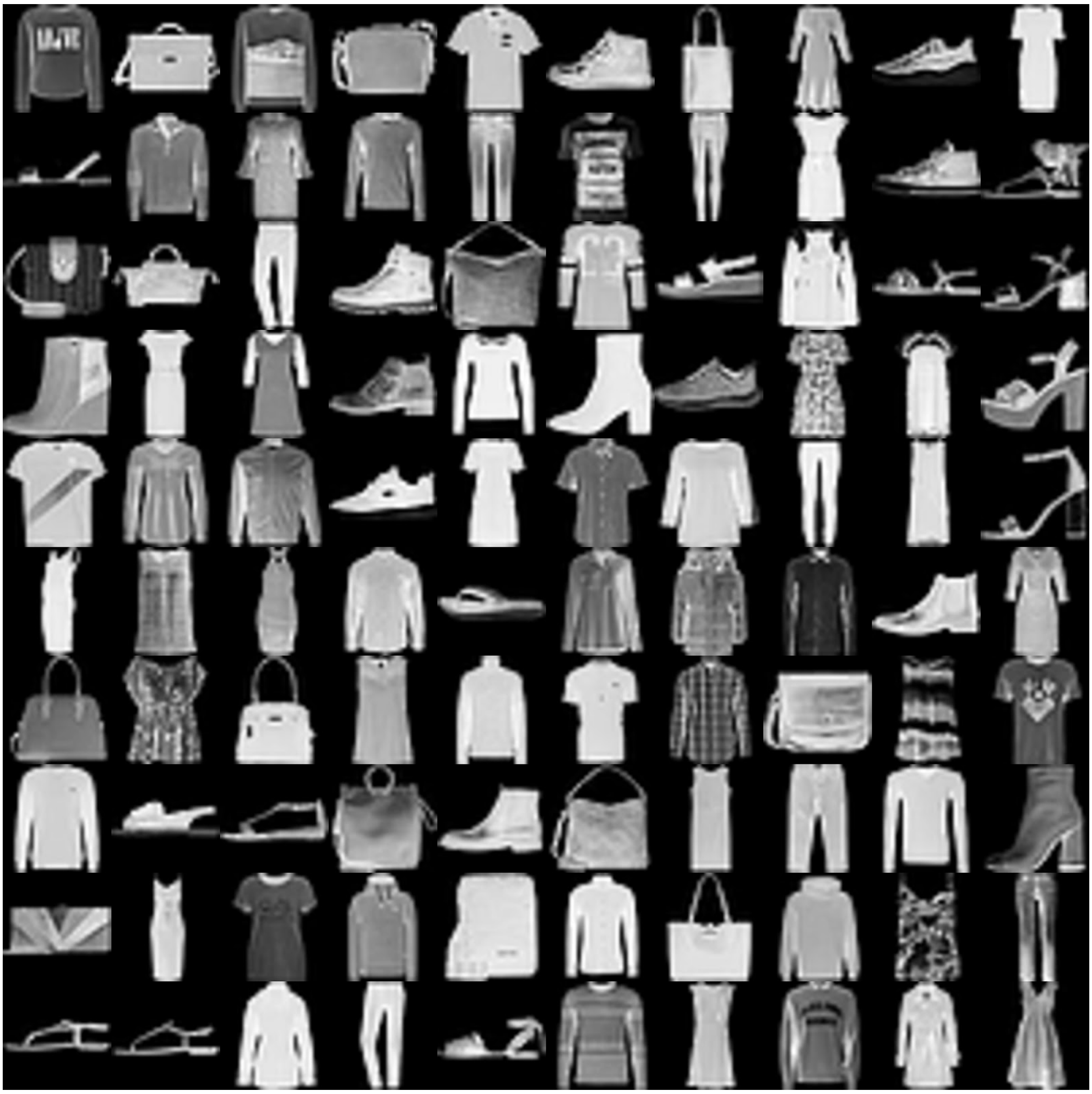
1. PROBLEM STATEMENT AND BUSINESS CASE UNDERSTANDING

Fashion training set consists of 70,000 images divided into 60,000 training and 10,000 testing samples. Dataset sample consists of 28x28 grayscale image, associated with a label from 10 classes.

The 10 classes are as follows:
0 => T-shirt/top 1 => Trouser 2 => Pullover 3 => Dress 4 => Coat 5 => Sandal 6 => Shirt 7 => Sneaker 8 => Bag 9 => Ankle boot

Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel-value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker. This pixel-value is an integer between 0 and 255.



2. Importing Essential Libraries & Our Fashion Mnist Data

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
train_df = pd.read_csv('fashion-mnist_train.csv', sep = ',')
test_df = pd.read_csv('fashion-mnist_test.csv', sep = ',')
```

In [3]:
```
train_df.head(10)
```

Out[3]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel77
0	2	0	0	0	0	0	0	0	0	0	...	0	
1	9	0	0	0	0	0	0	0	0	0	...	0	
2	6	0	0	0	0	0	0	0	5	0	...	0	

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel77
3	0	0	0	0	1	2	0	0	0	0	...	3	
4	3	0	0	0	0	0	0	0	0	0	...	0	
5	4	0	0	0	5	4	5	5	3	5	...	7	
6	4	0	0	0	0	0	0	0	0	0	...	14	
7	5	0	0	0	0	0	0	0	0	0	...	0	
8	4	0	0	0	0	0	0	3	2	0	...	1	
9	8	0	0	0	0	0	0	0	0	0	...	203	21

10 rows × 785 columns

In [4]:
```
test_df.head(10)
```

Out[4]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel77
0	0	0	0	0	0	0	0	0	9	8	...	103	8
1	1	0	0	0	0	0	0	0	0	0	...	34	
2	2	0	0	0	0	0	0	14	53	99	...	0	
3	2	0	0	0	0	0	0	0	0	0	...	137	12
4	3	0	0	0	0	0	0	0	0	0	...	0	
5	2	0	0	0	0	0	44	105	44	10	...	105	6
6	8	0	0	0	0	0	0	0	0	0	...	0	
7	6	0	0	0	0	0	0	0	1	0	...	174	13
8	5	0	0	0	0	0	0	0	0	0	...	0	
9	0	0	0	0	0	0	0	0	0	0	...	57	7

10 rows × 785 columns

In [5]:
```
train_df.shape
```

Out[5]:
```
(60000, 785)
```

In [6]:
```
test_df.shape
```

Out[6]:
```
(10000, 785)
```

3. Data Visualization

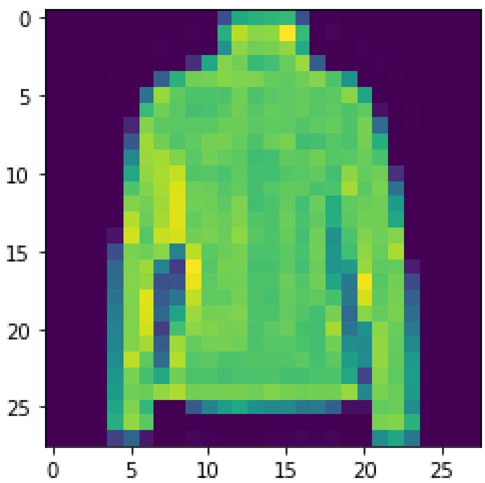
Converting our data from 'dataframe' to an 'array' so that we can visualize our data.

In [7]:
```
training = np.array(train_df, dtype = 'float32')
```

In [8]:
```
test = np.array(test_df, dtype = 'float32')
```

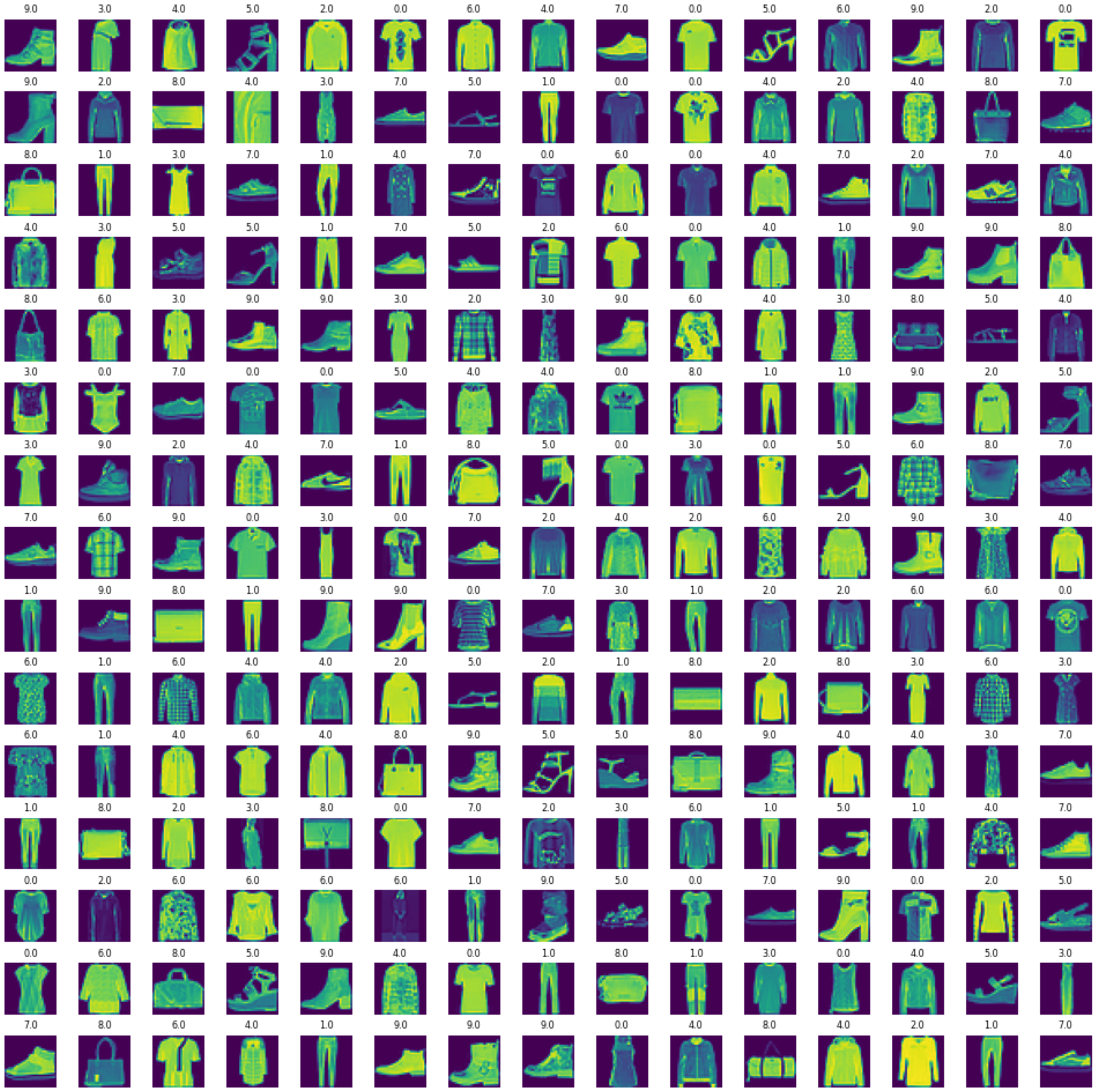
In [9]:
```python
plt.imshow(training[55, 1:].reshape(28,28))
#plt.savefig('Example Image.png')
```

Out[9]: <matplotlib.image.AxesImage at 0x1b2b7395f40>



Moreover, we can use a for loop and create a grid of random images.

In [10]:
```python
W_grid = 15
L_grid = 15
fig, axes = plt.subplots(L_grid, W_grid, figsize = (17,17))
axes = axes.ravel()
n_training = len(training)
for i in np.arange(0, W_grid * L_grid):
    index = np.random.randint(0, n_training)
    axes[i].imshow(training[index, 1:].reshape(28,28))
    axes[i].set_title(training[index, 0], fontsize = 8)
    axes[i].axis('off')
plt.subplots_adjust(hspace=0.4)
#fig.savefig('Grid Image.png')
```



Model Building & Training

In [11]:
```
# Splitting the Training Set
X_train = training[:, 1:]/255
y_train = training[:, 0]

# Splitting the Test Set
X_test = test[:, 1:]/255
y_test = test[:, 0]
```

In [12]:
```
from sklearn.model_selection import train_test_split
X_train, X_validate, y_train, y_validate = train_test_split(X_train, y_train, test_s
```

In [13]:
```
X_train.shape
```

Out[13]: (48000, 784)

In [14]:
```
y_train.shape
```

Out[14]: (48000,)

In [15]:
```
# Remember that * unpacks the tuple
```

```
X_train = X_train.reshape(X_train.shape[0], *(28, 28 ,1))
X_test = X_test.reshape(X_test.shape[0], *(28, 28 ,1))
X_validate = X_validate.reshape(X_validate.shape[0], *(28, 28 ,1))
```

In [16]:
```
X_train.shape
```

Out[16]: (48000, 28, 28, 1)

In [17]:
```
X_test.shape
```

Out[17]: (10000, 28, 28, 1)

In [18]:
```
X_validate.shape
```

Out[18]: (12000, 28, 28, 1)

In [19]:
```
import tensorflow
```

In [20]:
```
tensorflow.__version__
```

Out[20]: '2.3.1'

In [21]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import TensorBoard
```

In [22]:
```
cnn = Sequential()
```

In [23]:
```
# Was first run with filter = 32 and then later changed it to 64 for better accuracy
cnn.add(Conv2D(filters = 64, kernel_size = 3, input_shape = [28, 28, 1], activation
```

In [24]:
```
cnn.add(MaxPooling2D(pool_size = (2, 2)))
```

In [25]:
```
cnn.add(Flatten())
```

In [26]:
```
cnn.add(Dense(units = 32, activation = 'relu'))
```

In [27]:
```
cnn.add(Dense(units = 10, activation = 'sigmoid'))
```

In [ ]:
```
#cnn.add(Dropout(0.25))
```

In [28]:
```
cnn.compile(loss = 'sparse_categorical_crossentropy', optimizer = Adam(lr=0.001), me
```

In [29]:
```
cnn.fit(X_train, y_train, epochs = 50, batch_size = 512, verbose = 1, validation_dat
```

```
Epoch 1/50
94/94 [==============================] - 41s 431ms/step - loss: 0.8849 - accuracy:
0.6748 - val_loss: 0.4992 - val_accuracy: 0.8219
Epoch 2/50
94/94 [==============================] - 34s 364ms/step - loss: 0.4484 - accuracy:
0.8426 - val_loss: 0.4152 - val_accuracy: 0.8547
Epoch 3/50
94/94 [==============================] - 34s 361ms/step - loss: 0.3906 - accuracy:
0.8638 - val_loss: 0.3742 - val_accuracy: 0.8714
Epoch 4/50
94/94 [==============================] - 35s 376ms/step - loss: 0.3556 - accuracy:
0.8764 - val_loss: 0.3692 - val_accuracy: 0.8717
Epoch 5/50
```

```
94/94 [==============================] - 34s 361ms/step - loss: 0.3331 - accuracy:
0.8849 - val_loss: 0.3280 - val_accuracy: 0.8832
Epoch 6/50
94/94 [==============================] - 34s 363ms/step - loss: 0.3139 - accuracy:
0.8901 - val_loss: 0.3213 - val_accuracy: 0.8885
Epoch 7/50
94/94 [==============================] - 35s 371ms/step - loss: 0.3022 - accuracy:
0.8943 - val_loss: 0.3119 - val_accuracy: 0.8907
Epoch 8/50
94/94 [==============================] - 34s 358ms/step - loss: 0.2880 - accuracy:
0.8996 - val_loss: 0.3050 - val_accuracy: 0.8939
Epoch 9/50
94/94 [==============================] - 34s 366ms/step - loss: 0.2782 - accuracy:
0.9022 - val_loss: 0.2902 - val_accuracy: 0.8979
Epoch 10/50
94/94 [==============================] - 34s 363ms/step - loss: 0.2670 - accuracy:
0.9062 - val_loss: 0.2968 - val_accuracy: 0.8951
Epoch 11/50
94/94 [==============================] - 34s 364ms/step - loss: 0.2608 - accuracy:
0.9079 - val_loss: 0.2808 - val_accuracy: 0.9022
Epoch 12/50
94/94 [==============================] - 34s 364ms/step - loss: 0.2502 - accuracy:
0.9119 - val_loss: 0.2795 - val_accuracy: 0.9021
Epoch 13/50
94/94 [==============================] - 33s 348ms/step - loss: 0.2441 - accuracy:
0.9138 - val_loss: 0.2921 - val_accuracy: 0.8962
Epoch 14/50
94/94 [==============================] - 33s 356ms/step - loss: 0.2398 - accuracy:
0.9141 - val_loss: 0.2721 - val_accuracy: 0.9038
Epoch 15/50
94/94 [==============================] - 34s 356ms/step - loss: 0.2289 - accuracy:
0.9197 - val_loss: 0.2735 - val_accuracy: 0.9023
Epoch 16/50
94/94 [==============================] - 36s 385ms/step - loss: 0.2252 - accuracy:
0.9210 - val_loss: 0.2593 - val_accuracy: 0.9084
Epoch 17/50
94/94 [==============================] - 34s 362ms/step - loss: 0.2164 - accuracy:
0.9243 - val_loss: 0.2598 - val_accuracy: 0.9078
Epoch 18/50
94/94 [==============================] - 33s 356ms/step - loss: 0.2134 - accuracy:
0.9249 - val_loss: 0.2567 - val_accuracy: 0.9087
Epoch 19/50
94/94 [==============================] - 34s 357ms/step - loss: 0.2111 - accuracy:
0.9255 - val_loss: 0.2551 - val_accuracy: 0.9090
Epoch 20/50
94/94 [==============================] - 33s 356ms/step - loss: 0.2013 - accuracy:
0.9291 - val_loss: 0.2563 - val_accuracy: 0.9078
Epoch 21/50
94/94 [==============================] - 33s 355ms/step - loss: 0.2027 - accuracy:
0.9281 - val_loss: 0.2604 - val_accuracy: 0.9081
Epoch 22/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1920 - accuracy:
0.9321 - val_loss: 0.2521 - val_accuracy: 0.9093
Epoch 23/50
94/94 [==============================] - 34s 365ms/step - loss: 0.1875 - accuracy:
0.9339 - val_loss: 0.2531 - val_accuracy: 0.9084
Epoch 24/50
94/94 [==============================] - 33s 356ms/step - loss: 0.1832 - accuracy:
0.9364 - val_loss: 0.2563 - val_accuracy: 0.9094
Epoch 25/50
94/94 [==============================] - 33s 356ms/step - loss: 0.1789 - accuracy:
0.9383 - val_loss: 0.2498 - val_accuracy: 0.9115
Epoch 26/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1757 - accuracy:
0.9381 - val_loss: 0.2470 - val_accuracy: 0.9120
Epoch 27/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1675 - accuracy:
0.9421 - val_loss: 0.2486 - val_accuracy: 0.9128
Epoch 28/50
```

```
94/94 [==============================] - 33s 356ms/step - loss: 0.1674 - accuracy: 0.9408 - val_loss: 0.2552 - val_accuracy: 0.9125
Epoch 29/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1638 - accuracy: 0.9422 - val_loss: 0.2497 - val_accuracy: 0.9114
Epoch 30/50
94/94 [==============================] - 33s 356ms/step - loss: 0.1580 - accuracy: 0.9440 - val_loss: 0.2635 - val_accuracy: 0.9093
Epoch 31/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1543 - accuracy: 0.9458 - val_loss: 0.2558 - val_accuracy: 0.9081
Epoch 32/50
94/94 [==============================] - 34s 365ms/step - loss: 0.1506 - accuracy: 0.9477 - val_loss: 0.2515 - val_accuracy: 0.9103
Epoch 33/50
94/94 [==============================] - 33s 349ms/step - loss: 0.1479 - accuracy: 0.9483 - val_loss: 0.2482 - val_accuracy: 0.9139
Epoch 34/50
94/94 [==============================] - 33s 354ms/step - loss: 0.1466 - accuracy: 0.9490 - val_loss: 0.2708 - val_accuracy: 0.9063
Epoch 35/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1404 - accuracy: 0.9508 - val_loss: 0.2637 - val_accuracy: 0.9089
Epoch 36/50
94/94 [==============================] - 33s 352ms/step - loss: 0.1365 - accuracy: 0.9532 - val_loss: 0.2634 - val_accuracy: 0.9093
Epoch 37/50
94/94 [==============================] - 33s 347ms/step - loss: 0.1343 - accuracy: 0.9532 - val_loss: 0.2572 - val_accuracy: 0.9103
Epoch 38/50
94/94 [==============================] - 34s 364ms/step - loss: 0.1294 - accuracy: 0.9551 - val_loss: 0.2561 - val_accuracy: 0.9128
Epoch 39/50
94/94 [==============================] - 33s 355ms/step - loss: 0.1292 - accuracy: 0.9543 - val_loss: 0.2584 - val_accuracy: 0.9133
Epoch 40/50
94/94 [==============================] - 34s 358ms/step - loss: 0.1240 - accuracy: 0.9568 - val_loss: 0.2574 - val_accuracy: 0.9138
Epoch 41/50
94/94 [==============================] - 34s 359ms/step - loss: 0.1203 - accuracy: 0.9590 - val_loss: 0.2619 - val_accuracy: 0.9113
Epoch 42/50
94/94 [==============================] - 34s 362ms/step - loss: 0.1166 - accuracy: 0.9602 - val_loss: 0.2631 - val_accuracy: 0.9118
Epoch 43/50
94/94 [==============================] - 34s 360ms/step - loss: 0.1146 - accuracy: 0.9604 - val_loss: 0.2787 - val_accuracy: 0.9084
Epoch 44/50
94/94 [==============================] - 33s 352ms/step - loss: 0.1123 - accuracy: 0.9617 - val_loss: 0.2659 - val_accuracy: 0.9139
Epoch 45/50
94/94 [==============================] - 36s 381ms/step - loss: 0.1059 - accuracy: 0.9648 - val_loss: 0.2669 - val_accuracy: 0.9127
Epoch 46/50
94/94 [==============================] - 34s 362ms/step - loss: 0.1077 - accuracy: 0.9640 - val_loss: 0.2693 - val_accuracy: 0.9121
Epoch 47/50
94/94 [==============================] - 33s 351ms/step - loss: 0.1034 - accuracy: 0.9648 - val_loss: 0.2665 - val_accuracy: 0.9135
Epoch 48/50
94/94 [==============================] - 33s 356ms/step - loss: 0.1005 - accuracy: 0.9659 - val_loss: 0.3021 - val_accuracy: 0.9014
Epoch 49/50
94/94 [==============================] - 33s 352ms/step - loss: 0.1001 - accuracy: 0.9656 - val_loss: 0.2731 - val_accuracy: 0.9146
Epoch 50/50
94/94 [==============================] - 33s 352ms/step - loss: 0.0950 - accuracy: 0.9679 - val_loss: 0.2716 - val_accuracy: 0.9162
```

Out[29]:
```
<tensorflow.python.keras.callbacks.History at 0x1b2f6313ee0>
```

In [30]:
```
evaluation = cnn.evaluate(X_test, y_test)
print('Test Accuracy : {:.3f}'.format(evaluation[1]))
```

```
313/313 [==============================] - 3s 8ms/step - loss: 0.2745 - accuracy: 0.
9172
Test Accuracy : 0.917
```

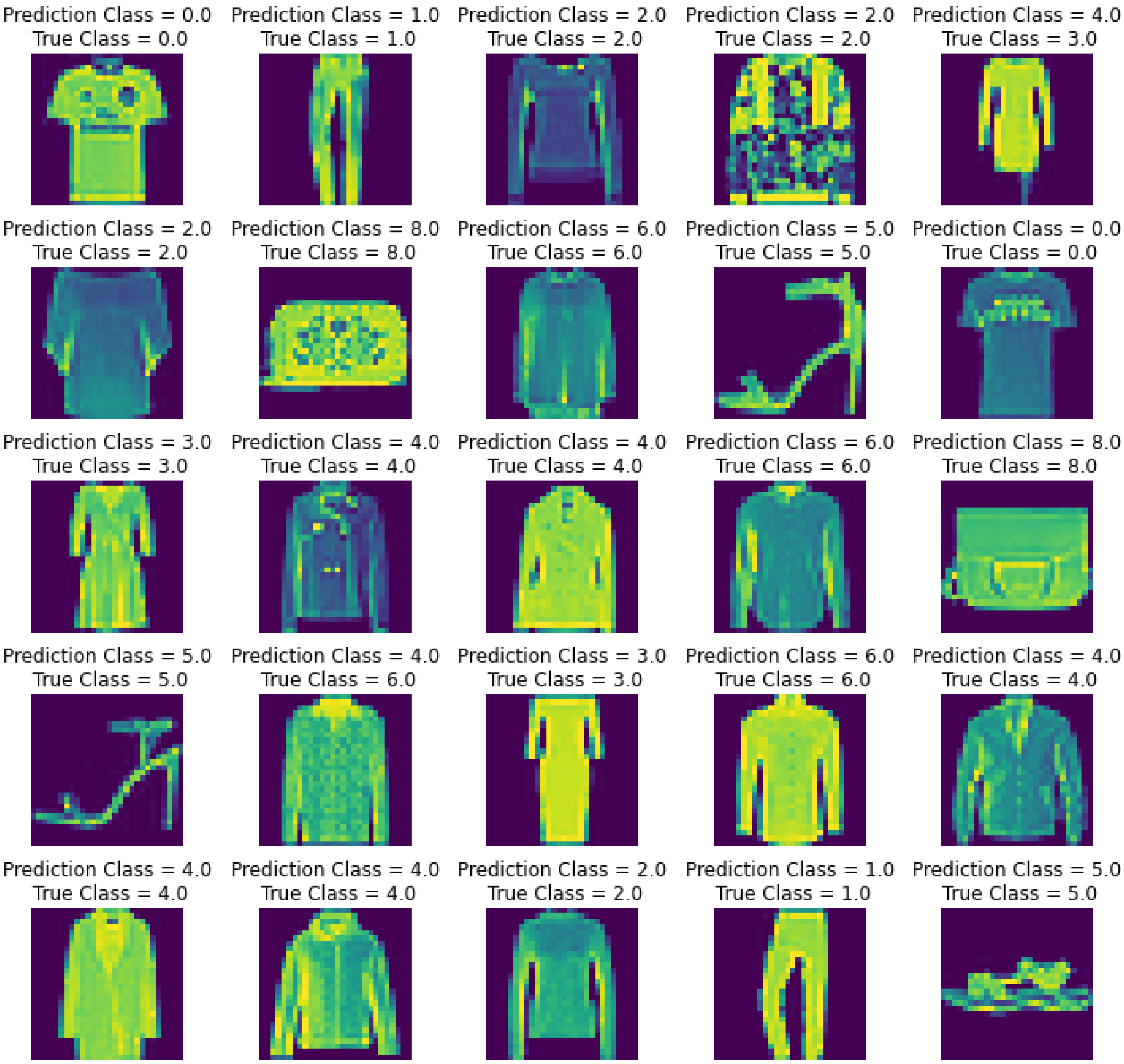
In [31]:
```
predicted_classes = cnn.predict_classes(X_test)
```

```
WARNING:tensorflow:From <ipython-input-31-ef5bdc73df9d>:1: Sequential.predict_classe
s (from tensorflow.python.keras.engine.sequential) is deprecated and will be removed
after 2021-01-01.
Instructions for updating:
Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does mu
lti-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(m
odel.predict(x) > 0.5).astype("int32")`,   if your model does binary classification
(e.g. if it uses a `sigmoid` last-layer activation).
```

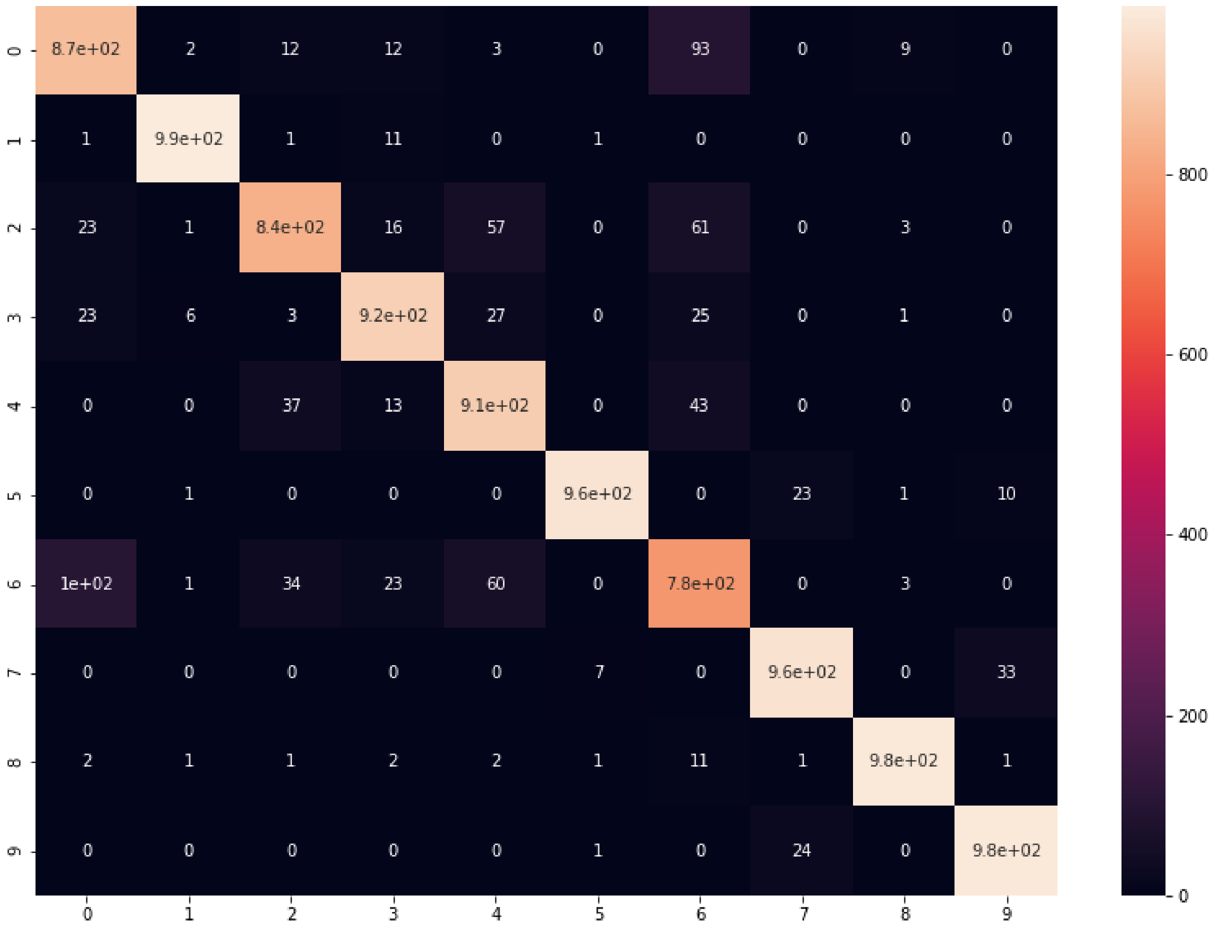
In [32]:
```
predicted_classes
```

Out[32]:
```
array([0, 1, 2, ..., 8, 8, 1], dtype=int64)
```

In [33]:
```
L = 5
W = 5
fig, axes = plt.subplots(L, W, figsize = (12,12))
axes = axes.ravel()
for i in np.arange(0, L * W):
    axes[i].imshow(X_test[i].reshape(28, 28))
    axes[i].set_title("Prediction Class = {:0.1f}\n True Class = {:0.1f}".format(pre
    axes[i].axis('off')
plt.subplots_adjust(wspace = 0.5)
#fig.savefig('Grid Image Showing Predicted Class vs True Class.png')
```



In [34]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predicted_classes)
plt.figure(figsize = (14, 10))
sns.heatmap(cm, annot = True)
#plt.savefig('Heatmap Showing Predicted class vs True Class.png')
```



In [35]:
```python
from sklearn.metrics import classification_report


target_names = ["Class {}".format(i) for i in range(1, 11)]
print(classification_report(y_test, predicted_classes, target_names = target_names))
```

```
              precision    recall  f1-score   support

     Class 1       0.85      0.87      0.86      1000
     Class 2       0.99      0.99      0.99      1000
     Class 3       0.91      0.84      0.87      1000
     Class 4       0.92      0.92      0.92      1000
     Class 5       0.86      0.91      0.88      1000
     Class 6       0.99      0.96      0.98      1000
     Class 7       0.77      0.78      0.77      1000
     Class 8       0.95      0.96      0.96      1000
     Class 9       0.98      0.98      0.98      1000
    Class 10       0.96      0.97      0.97      1000

    accuracy                           0.92     10000
   macro avg       0.92      0.92      0.92     10000
weighted avg       0.92      0.92      0.92     10000
```

Conclusion

As seen in output no. 29 & 30, our accuracies are as follows:

1. Training Data Accuracy - 96.79%
2. Validation Data Accuracy - 91.62%
3. Testing Data Accuracy - 91.7%

So when we print out our classification report we finally get an average accuracy of 92%.