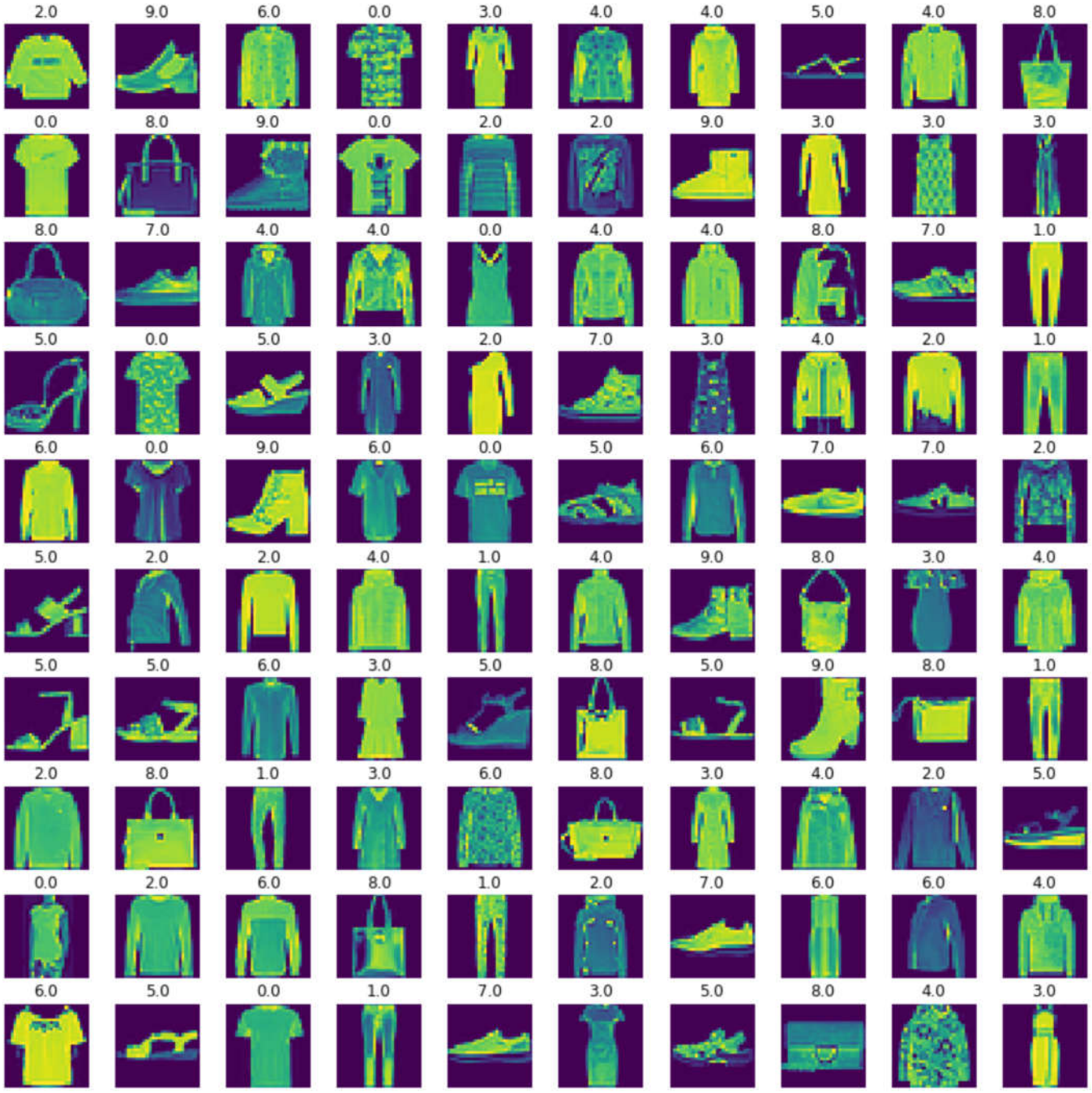
Case Study: Classification of Fashion Class

1. Problem Statement & Business Case

- Fashion-MNIST is a dataset of Zalando's article images consisting of a training set of 60,000 examples and a test set of 10,000 examples.
- Each example is a 28x28 grayscale image, associated with a label from 10 classes. We intend Fashion-MNIST to serve as a direct drop-in replacement for the original MNIST dataset for benchmarking machine learning algorithms. It shares the same image size and structure of training and testing splits.
- Here is an example how the data look like along with its Class Numbers
- Source: Data Set (https://github.com/zalandoresearch/fashion-mnist)

These are the 10 classes:

- 0 - T-shirt/top
- 1 - Trouser
- 2 - Pullover
- 3 - Dress
- 4 - Coat
- 5 - Sandal
- 6 - Shirt
- 7 - Sneaker
- 8 - Bag
- 9 - Ankle boot



2. Importing Libraries & Data Set

In [1]:

```
# import libraries
import pandas as pd # Import Pandas for data manipulation using dataframes
import numpy as np # Import Numpy for data statistical analysis
import matplotlib.pyplot as plt # Import matplotlib for data visualisation
import seaborn as sns
import warnings
warnings.filterwarnings('ignore') # To Ignore warnings given by Jupyter Notebook about
import random
```

- Reading the Data files using Pandas read_csv command

In [2]:

```
# dataframes creation for both training and testing datasets
fashion_train_df = pd.read_csv('fashion-mnist_train.csv')
fashion_test_df = pd.read_csv('fashion-mnist_test.csv')
```

3. Data Visualization

In [3]:

```
# The head of the training dataset
# 785 columns indicates 784 cols of - 28x28 pixels and 1 coloumn for the label
# After you check the tail, 60,000 training dataset are present
fashion_train_df.head()
```

Out[3]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel
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	
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 rows × 785 columns

In [4]:

```
#The last elements in the training dataset
fashion_train_df.tail()
```

Out[4]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775
59995	9	0	0	0	0	0	0	0	0	0	...	0
59996	1	0	0	0	0	0	0	0	0	0	...	73
59997	8	0	0	0	0	0	0	0	0	0	...	160
59998	8	0	0	0	0	0	0	0	0	0	...	0
59999	7	0	0	0	0	0	0	0	0	0	...	0

5 rows × 785 columns

In [5]:

```
# Similarly for the Test Dataset
fashion_test_df.head()
```

Out[5]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel
0	0	0	0	0	0	0	0	0	9	8	...	103	
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	
4	3	0	0	0	0	0	0	0	0	0	...	0	

5 rows × 785 columns

In [6]:

```
fashion_test_df.tail()
```

Out[6]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	p
9995	0	0	0	0	0	0	0	0	0	0	...	32	
9996	6	0	0	0	0	0	0	0	0	0	...	0	
9997	8	0	0	0	0	0	0	0	0	0	...	175	
9998	8	0	1	3	0	0	0	0	0	0	...	0	
9999	1	0	0	0	0	0	0	0	140	119	...	111	

5 rows × 785 columns

In [7]:

```
# The Shape of training set & testing set
fashion_train_df.shape, fashion_test_df.shape
```

Out[7]:

```
((60000, 785), (10000, 785))
```

In [8]:

```
# Create training and testing arrays to ease our operation of visualization
# Arrays can be created using np.array command and convert the data type to float32 bit
training = np.array(fashion_train_df, dtype = 'float32')
testing = np.array(fashion_test_df, dtype='float32')
```

In [9]:

```
# The shapes of training & testing arrays
training.shape, testing.shape
```

Out[9]:

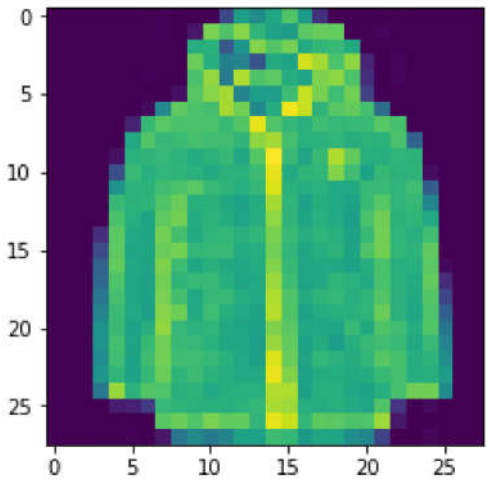
```
((60000, 785), (10000, 785))
```

In [10]:

```
# Remember the 10 classes decoding is 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

# Let's view some images!
i = random.randint(1,60000) # select any random index from 1 to 60,000
plt.imshow(training[i,1:].reshape((28,28)) ) # reshape and plot the image
training[i,0]
```

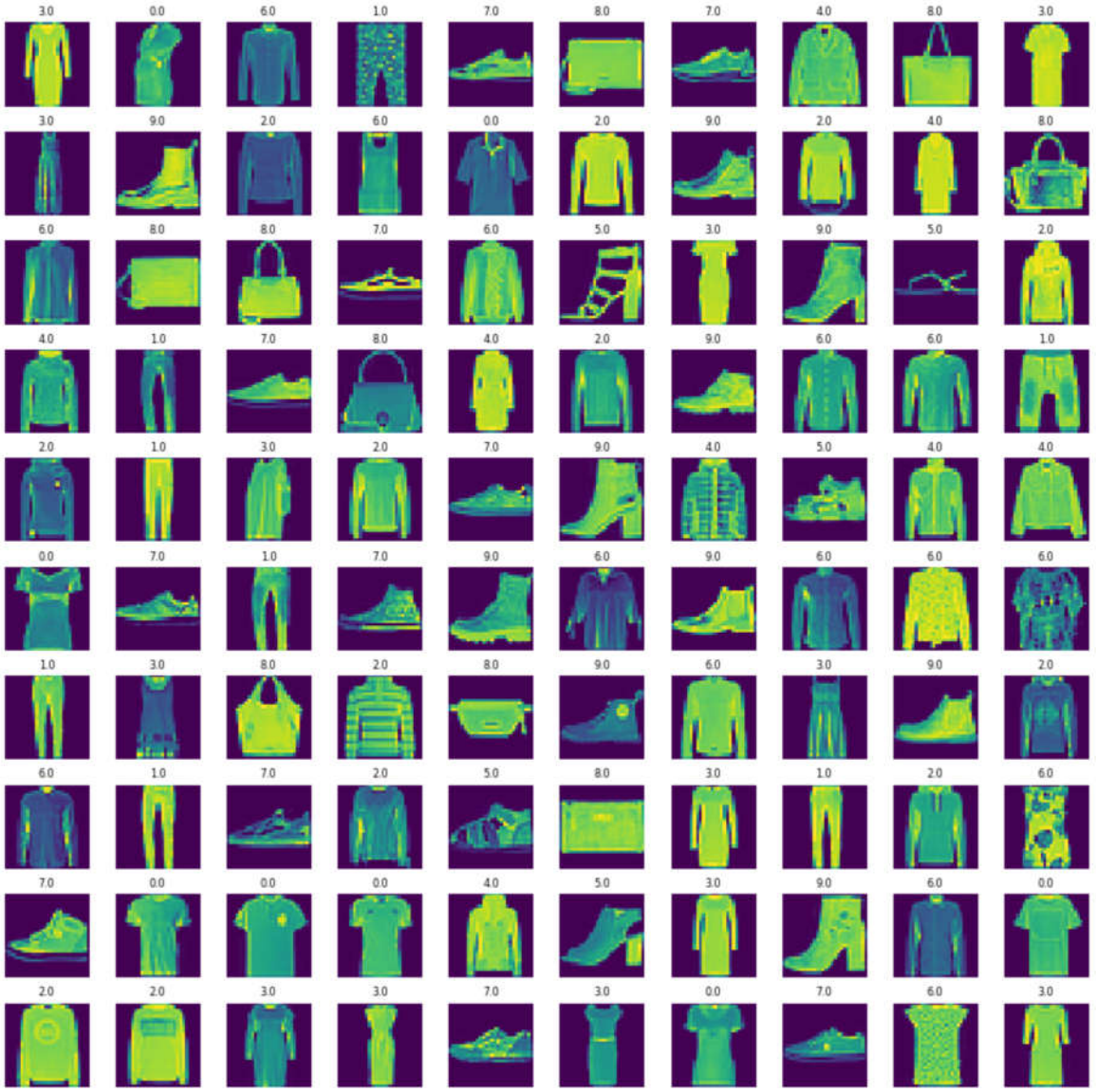
Out[10]:

```
4.0
```



In [11]:

```
# Let's view some images in a grid format
# Define the dimensions of the plot grid
rows = 10
cols = 10

# subplot return the figure object and axes object
# we can use the axes object to plot specific figures at various locations

fig, axes = plt.subplots(nrows=rows, ncols=cols, figsize = (15,15))

axes = axes.ravel() # to flaten the 15 x 15 matrix into 225 array


for i in np.arange(0, rows*cols): # create evenly spaces variables
    # Select a random number from 0 to len(training)
    num = np.random.randint(0, len(training))
    # read and display an image with the selected index
    axes[i].imshow(training[num,1:].reshape((28,28)) )
    axes[i].set_title(training[num,0], fontsize = 8)
    axes[i].axis('off')

plt.subplots_adjust(hspace=0.3)

# 0 => T-shirt/top
# 1 => Trouser
# 2 => Pullover
# 3 => Dress
# 4 => Coat
# 5 => Sandal
# 6 => Shirt
# 7 => Sneaker
# 8 => Bag
# 9 => Ankle boot
```



4. Training the Model

In [12]:

```
# Prepare the training and testing dataset into range of 0 and 1 to obtain better accur
X_train = training[:,1:]/255
y_train = training[:,0]

X_test = testing[:,1:]/255
y_test = testing[:,0]
```

In [13]:

```
# Split the train Data set into train & validate to validate the model accuracy indepen

from sklearn.model_selection import train_test_split

X_train, X_validate, y_train, y_validate = train_test_split(X_train, y_train, test_size
```

In [14]:

```
X_train.shape, y_train.shape, X_validate.shape, y_validate.shape
```

Out[14]:

```
((48000, 784), (48000,), (12000, 784), (12000,))
```

Creating a series of images to prepare for neural networks by reshaping the train & test values

In [15]:

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

In [16]:

```
X_train.shape, X_validate.shape, X_test.shape
# The below shaped indicates (48000,28,28,1)
# 48000 ---> No of Images or data rows
# 28 ------> Dimensions of image in pixels (28 Horizontal)
# 28 ------> Dimensions of image in pixels (28 Vertical)
# 1 -------> No of colored layers present on the image / thickness of color layer (in c
```

Out[16]:

```
((48000, 28, 28, 1), (12000, 28, 28, 1), (10000, 28, 28, 1))
```

---

5. Neural Networks

In [17]:

```
# Importing required libraries
import keras
from keras.models import Sequential # To read and load Model
from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout # For Network
from keras.optimizers import Adam
```

```
Using TensorFlow backend.
```

In [18]:

```
# Creating our model instance in a variable
cnn_model = Sequential()

# Trying with 32 Kernels
cnn_model.add(Conv2D(32,3, 3, input_shape = (28,28,1), activation='relu'))
cnn_model.add(MaxPooling2D(pool_size = (2, 2)))
cnn_model.add(Flatten())
cnn_model.add(Dense(output_dim = 32, activation = 'relu'))

# We have 10 nos of classes to be identified, lets take 10 Nos a output layer of networ
cnn_model.add(Dense(output_dim = 10, activation = 'sigmoid'))
```

```
WARNING:tensorflow:From c:\users\science\appdata\local\programs\python\pytho
n37\lib\site-packages\tensorflow\python\framework\op_def_library.py:263: col
ocate_with (from tensorflow.python.framework.ops) is deprecated and will be
removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
```

In [19]:

```
# The summary of our model
cnn_model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 5408)              0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                173088
_________________________________________________________________
dense_2 (Dense)              (None, 10)                330
=================================================================
Total params: 173,738
Trainable params: 173,738
Non-trainable params: 0
_________________________________________________________________
```

In [20]:

```
# Compile the neural networks using a loss and an optimizer
cnn_model.compile(loss ='sparse_categorical_crossentropy', optimizer=Adam(lr=0.001),met
```

In [21]:

```
epochs = 50 # The no. of times the data enters through the created network
# FIt the data with our reshaped train values and validate with our splitted validation
history = cnn_model.fit(X_train,
                        y_train,
                        batch_size = 512,
                        nb_epoch = epochs,
                        verbose = 1,
                        validation_data = (X_validate, y_validate))
```

```
WARNING:tensorflow:From c:\users\science\appdata\local\programs\python\pytho
n37\lib\site-packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a futur
e version.
Instructions for updating:
Use tf.cast instead.
Train on 48000 samples, validate on 12000 samples
Epoch 1/50
48000/48000 [==============================] - 28s 577us/step - loss: 0.8819
- acc: 0.7207 - val_loss: 0.4749 - val_acc: 0.8406
Epoch 2/50
48000/48000 [==============================] - 23s 481us/step - loss: 0.4430
- acc: 0.8438 - val_loss: 0.4125 - val_acc: 0.8558
Epoch 3/50
48000/48000 [==============================] - 23s 479us/step - loss: 0.3802
- acc: 0.8663 - val_loss: 0.3705 - val_acc: 0.8731
Epoch 4/50
48000/48000 [==============================] - 23s 477us/step - loss: 0.3537
- acc: 0.8766 - val_loss: 0.3454 - val_acc: 0.8821
Epoch 5/50
48000/48000 [==============================] - 23s 478us/step - loss: 0.3340
- acc: 0.8817 - val_loss: 0.3403 - val_acc: 0.8837
Epoch 6/50
48000/48000 [==============================] - 24s 505us/step - loss: 0.3169
- acc: 0.8874 - val_loss: 0.3217 - val_acc: 0.8871
Epoch 7/50
48000/48000 [==============================] - 24s 492us/step - loss: 0.2976
- acc: 0.8962 - val_loss: 0.3140 - val_acc: 0.8928
Epoch 8/50
48000/48000 [==============================] - 24s 490us/step - loss: 0.2940
- acc: 0.8959 - val_loss: 0.3175 - val_acc: 0.8893
Epoch 9/50
48000/48000 [==============================] - 24s 491us/step - loss: 0.2807
- acc: 0.9012 - val_loss: 0.2988 - val_acc: 0.8974
Epoch 10/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.2706
- acc: 0.9040 - val_loss: 0.2901 - val_acc: 0.8987
Epoch 11/50
48000/48000 [==============================] - 24s 492us/step - loss: 0.2643
- acc: 0.9065 - val_loss: 0.2924 - val_acc: 0.8975
Epoch 12/50
48000/48000 [==============================] - 24s 497us/step - loss: 0.2551
- acc: 0.9102 - val_loss: 0.2829 - val_acc: 0.9016
Epoch 13/50
48000/48000 [==============================] - 24s 491us/step - loss: 0.2488
- acc: 0.9112 - val_loss: 0.2789 - val_acc: 0.9033
Epoch 14/50
48000/48000 [==============================] - 24s 493us/step - loss: 0.2414
- acc: 0.9156 - val_loss: 0.2735 - val_acc: 0.9048
Epoch 15/50
```

```
48000/48000 [==============================] - 24s 493us/step - loss: 0.2385
- acc: 0.9154 - val_loss: 0.2802 - val_acc: 0.9045
Epoch 16/50
48000/48000 [==============================] - 24s 495us/step - loss: 0.2304
- acc: 0.9176 - val_loss: 0.2791 - val_acc: 0.8993
Epoch 17/50
48000/48000 [==============================] - 24s 494us/step - loss: 0.2259
- acc: 0.9192 - val_loss: 0.2666 - val_acc: 0.9089
Epoch 18/50
48000/48000 [==============================] - 24s 497us/step - loss: 0.2185
- acc: 0.9221 - val_loss: 0.2651 - val_acc: 0.9071
Epoch 19/50
48000/48000 [==============================] - 24s 493us/step - loss: 0.2145
- acc: 0.9245 - val_loss: 0.2636 - val_acc: 0.9088
Epoch 20/50
48000/48000 [==============================] - 23s 490us/step - loss: 0.2110
- acc: 0.9242 - val_loss: 0.2675 - val_acc: 0.9058
Epoch 21/50
48000/48000 [==============================] - 24s 493us/step - loss: 0.2071
- acc: 0.9256 - val_loss: 0.2614 - val_acc: 0.9093
Epoch 22/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.2015
- acc: 0.9287 - val_loss: 0.2580 - val_acc: 0.9102
Epoch 23/50
48000/48000 [==============================] - 24s 493us/step - loss: 0.1980
- acc: 0.9290 - val_loss: 0.2573 - val_acc: 0.9103
Epoch 24/50
48000/48000 [==============================] - 24s 491us/step - loss: 0.1942
- acc: 0.9316 - val_loss: 0.2682 - val_acc: 0.9069
Epoch 25/50
48000/48000 [==============================] - 24s 492us/step - loss: 0.1900
- acc: 0.9330 - val_loss: 0.2584 - val_acc: 0.9118
Epoch 26/50
48000/48000 [==============================] - 24s 492us/step - loss: 0.1870
- acc: 0.9336 - val_loss: 0.2623 - val_acc: 0.9104
Epoch 27/50
48000/48000 [==============================] - 25s 519us/step - loss: 0.1840
- acc: 0.9343 - val_loss: 0.2676 - val_acc: 0.9051
Epoch 28/50
48000/48000 [==============================] - 24s 495us/step - loss: 0.1813
- acc: 0.9359 - val_loss: 0.2588 - val_acc: 0.9098
Epoch 29/50
48000/48000 [==============================] - 24s 491us/step - loss: 0.1740
- acc: 0.9387 - val_loss: 0.2562 - val_acc: 0.9144
Epoch 30/50
48000/48000 [==============================] - 24s 494us/step - loss: 0.1726
- acc: 0.9390 - val_loss: 0.2629 - val_acc: 0.9097
Epoch 31/50
48000/48000 [==============================] - 24s 491us/step - loss: 0.1698
- acc: 0.9403 - val_loss: 0.2570 - val_acc: 0.9131
Epoch 32/50
48000/48000 [==============================] - 24s 495us/step - loss: 0.1680
- acc: 0.9408 - val_loss: 0.2628 - val_acc: 0.9112
Epoch 33/50
48000/48000 [==============================] - 24s 493us/step - loss: 0.1632
- acc: 0.9429 - val_loss: 0.2708 - val_acc: 0.9083
Epoch 34/50
48000/48000 [==============================] - 24s 493us/step - loss: 0.1628
- acc: 0.9423 - val_loss: 0.2572 - val_acc: 0.9106
Epoch 35/50
48000/48000 [==============================] - 24s 494us/step - loss: 0.1602
```

```
- acc: 0.9435 - val_loss: 0.2676 - val_acc: 0.9091
Epoch 36/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.1568
- acc: 0.9449 - val_loss: 0.2682 - val_acc: 0.9073
Epoch 37/50
48000/48000 [==============================] - 24s 499us/step - loss: 0.1506
- acc: 0.9477 - val_loss: 0.2594 - val_acc: 0.9122
Epoch 38/50
48000/48000 [==============================] - 24s 498us/step - loss: 0.1503
- acc: 0.9479 - val_loss: 0.2595 - val_acc: 0.9122
Epoch 39/50
48000/48000 [==============================] - 24s 499us/step - loss: 0.1449
- acc: 0.9493 - val_loss: 0.2604 - val_acc: 0.9131
Epoch 40/50
48000/48000 [==============================] - 24s 501us/step - loss: 0.1419
- acc: 0.9499 - val_loss: 0.2632 - val_acc: 0.9133
Epoch 41/50
48000/48000 [==============================] - 24s 500us/step - loss: 0.1410
- acc: 0.9516 - val_loss: 0.2619 - val_acc: 0.9108
Epoch 42/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.1394
- acc: 0.9509 - val_loss: 0.2692 - val_acc: 0.9102
Epoch 43/50
48000/48000 [==============================] - 24s 494us/step - loss: 0.1371
- acc: 0.9527 - val_loss: 0.2703 - val_acc: 0.9101
Epoch 44/50
48000/48000 [==============================] - 24s 497us/step - loss: 0.1371
- acc: 0.9516 - val_loss: 0.2725 - val_acc: 0.9074
Epoch 45/50
48000/48000 [==============================] - 24s 495us/step - loss: 0.1328
- acc: 0.9531 - val_loss: 0.2676 - val_acc: 0.9121
Epoch 46/50
48000/48000 [==============================] - 24s 497us/step - loss: 0.1271
- acc: 0.9558 - val_loss: 0.2679 - val_acc: 0.9103
Epoch 47/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.1217
- acc: 0.9590 - val_loss: 0.2634 - val_acc: 0.9129
Epoch 48/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.1252
- acc: 0.9562 - val_loss: 0.2694 - val_acc: 0.9109
Epoch 49/50
48000/48000 [==============================] - 24s 498us/step - loss: 0.1191
- acc: 0.9594 - val_loss: 0.2714 - val_acc: 0.9119
Epoch 50/50
48000/48000 [==============================] - 24s 496us/step - loss: 0.1162
- acc: 0.9609 - val_loss: 0.2729 - val_acc: 0.9108
```

---

6. Evaluating the Model

In [22]:

```
# Use inbuilt evaluate command to obtain the accuracy
evaluation = cnn_model.evaluate(X_test, y_test)
print('Test Accuracy : {:.3f}'.format(evaluation[1]))
```

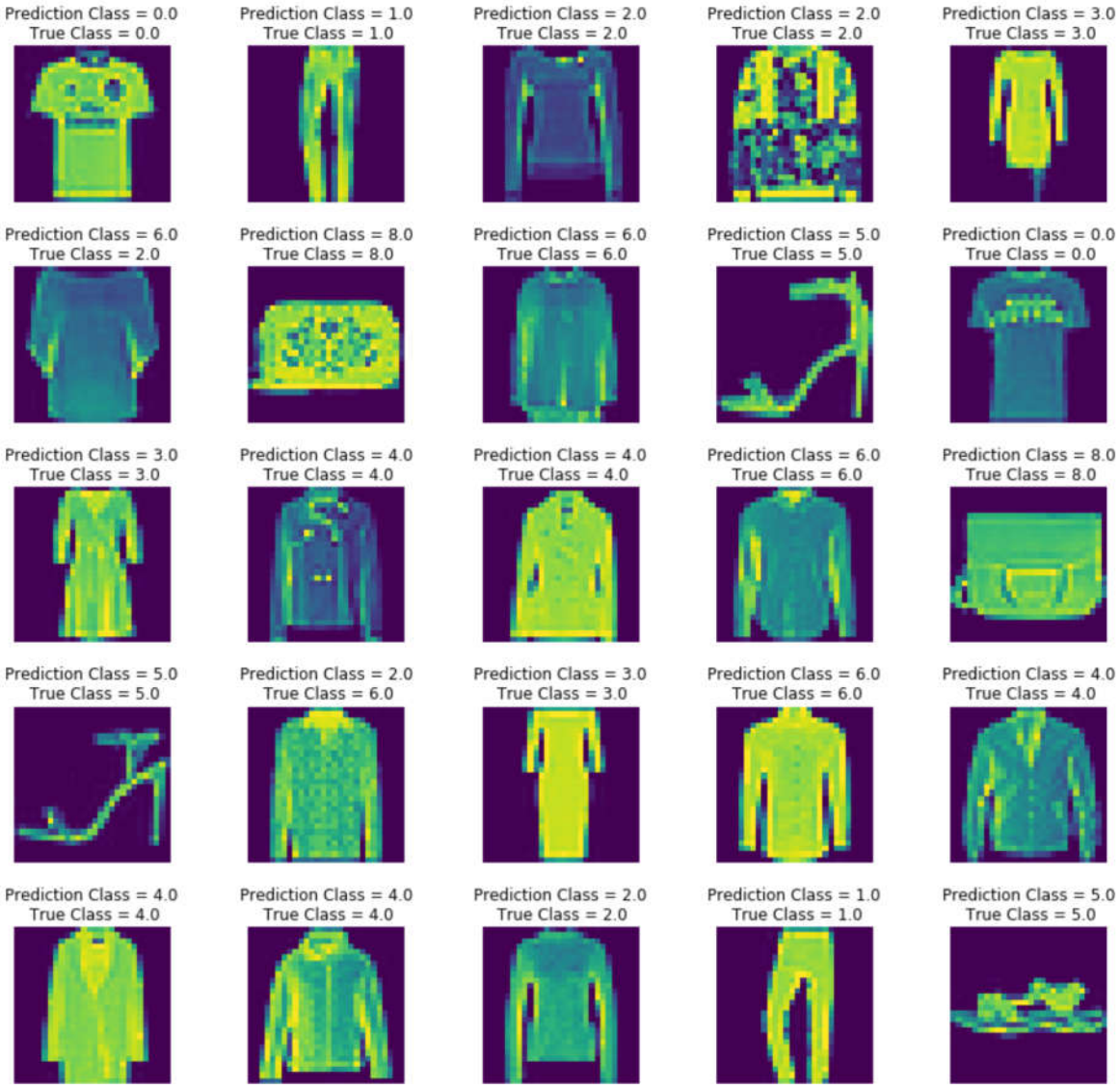
```
10000/10000 [==============================] - 2s 196us/step
Test Accuracy : 0.914
```

In [23]:

```
# Obtain the predictions for the test data using the model created
predicted_classes = cnn_model.predict_classes(X_test)
```

In [24]:

```
# The Visualization of Predicted Class & True class in a 5*5 Grid
rows = 5
cols = 5
fig, axes = plt.subplots(nrows=rows, ncols=cols, figsize = (15,15))
axes = axes.ravel()

for i in np.arange(0, rows * cols):
    axes[i].imshow(X_test[i].reshape(28,28))
    axes[i].set_title("Prediction Class = {:0.1f}\n True Class = {:0.1f}".format(predic
    axes[i].axis('off') # To make it cluster free
plt.subplots_adjust(wspace=0.5) # The amount of space provided between images
```

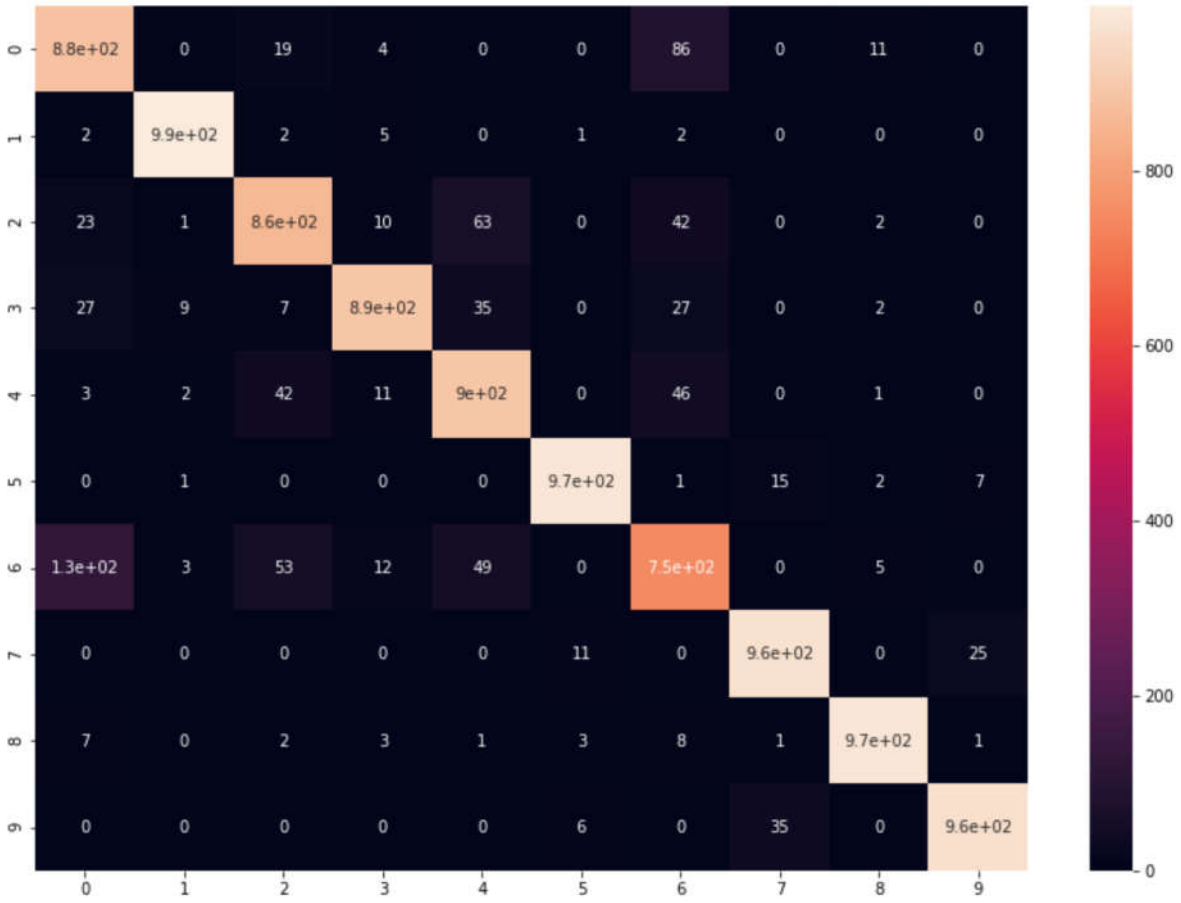


In [25]:

```
# The visualization of Properly predicted values using a heat map & confusion matrix fo
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predicted_classes)
plt.figure(figsize = (14,10))
sns.heatmap(cm, annot=True)
# Sum the diagonal element to get the total true correct values
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b67f56eda0>
```



In [26]:

```
from sklearn.metrics import classification_report

num_classes = 10
target_names = ["Class {}".format(i) for i in range(num_classes)]

print(classification_report(y_test, predicted_classes, target_names = target_names))
```

```
              precision    recall  f1-score   support

     Class 0       0.82      0.88      0.85      1000
     Class 1       0.98      0.99      0.99      1000
     Class 2       0.87      0.86      0.87      1000
     Class 3       0.95      0.89      0.92      1000
     Class 4       0.86      0.90      0.88      1000
     Class 5       0.98      0.97      0.98      1000
     Class 6       0.78      0.75      0.76      1000
     Class 7       0.95      0.96      0.96      1000
     Class 8       0.98      0.97      0.98      1000
     Class 9       0.97      0.96      0.96      1000

   micro avg       0.91      0.91      0.91     10000
   macro avg       0.91      0.91      0.91     10000
weighted avg       0.91      0.91      0.91     10000
```

Summary

- The model obtained is 94% accurate with the training dataset & 91% accurate with validation data set
- Model predicted 93% of accurate results with test data set taken
- This model can be further used for any 28*28 image class predictions.
- Maintaining a higher epochs gives us better test data predictions.

In [ ]:

```
```