Capstone Project

May 27, 2022

1 Capstone Project

1.1 Image classifier for the SVHN dataset

1.1.1 Instructions

In this notebook, you will create a neural network that classifies real-world images digits. You will use concepts from throughout this course in building, training, testing, validating and saving your Tensorflow classifier model.

This project is peer-assessed. Within this notebook you will find instructions in each section for how to complete the project. Pay close attention to the instructions as the peer review will be carried out according to a grading rubric that checks key parts of the project instructions. Feel free to add extra cells into the notebook as required.

1.1.2 How to submit

When you have completed the Capstone project notebook, you will submit a pdf of the notebook for peer review. First ensure that the notebook has been fully executed from beginning to end, and all of the cell outputs are visible. This is important, as the grading rubric depends on the reviewer being able to view the outputs of your notebook. Save the notebook as a pdf (File -> Download as -> PDF via LaTeX). You should then submit this pdf for review.

1.1.3 Let's get started!

We'll start by running some imports, and loading the dataset. For this project you are free to make further imports throughout the notebook as you wish.

```
In [1]: import random
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        %matplotlib inline
        import tensorflow as tf
        from scipy.io import loadmat
        from sklearn.model_selection import train_test_split
        from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, BatchNormaliz
        from tensorflow.keras.models import load_model, Sequential
        from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, CSVLogger
        from tensorflow.keras import regularizers
```

 For the capstone project, you will use the SVHN dataset. This is an image dataset of over 600,000 digit images in all, and is a harder dataset than MNIST as the numbers appear in the context of natural scene images. SVHN is obtained from house numbers in Google Street View images.

- Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu and A. Y. Ng. "Reading Digits in Natural Images with Unsupervised Feature Learning". NIPS Workshop on Deep Learning and Unsupervised Feature Learning, 2011.

Your goal is to develop an end-to-end workflow for building, training, validating, evaluating and saving a neural network that classifies a real-world image into one of ten classes.

```
In [2]: # Run this cell to load the dataset

        train = loadmat('data/train_32x32.mat')
        test = loadmat('data/test_32x32.mat')
```

Both `train` and `test` are dictionaries with keys `X` and `y` for the input images and labels respectively.

1.2 1. Inspect and preprocess the dataset

- Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.
- Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.
- Convert the training and test images to grayscale by taking the average across all colour channels for each pixel. *Hint: retain the channel dimension, which will now have size 1.*
- Select a random sample of the grayscale images and corresponding labels from the dataset (at least 10), and display them in a figure.

```
In [3]: # Extract data and labels
        train_images, train_labels = train['X'], train['y']
        test_images, test_labels = test['X'], test['y']
        train_images.shape, train_labels.shape, test_images.shape, test_labels.shape
```

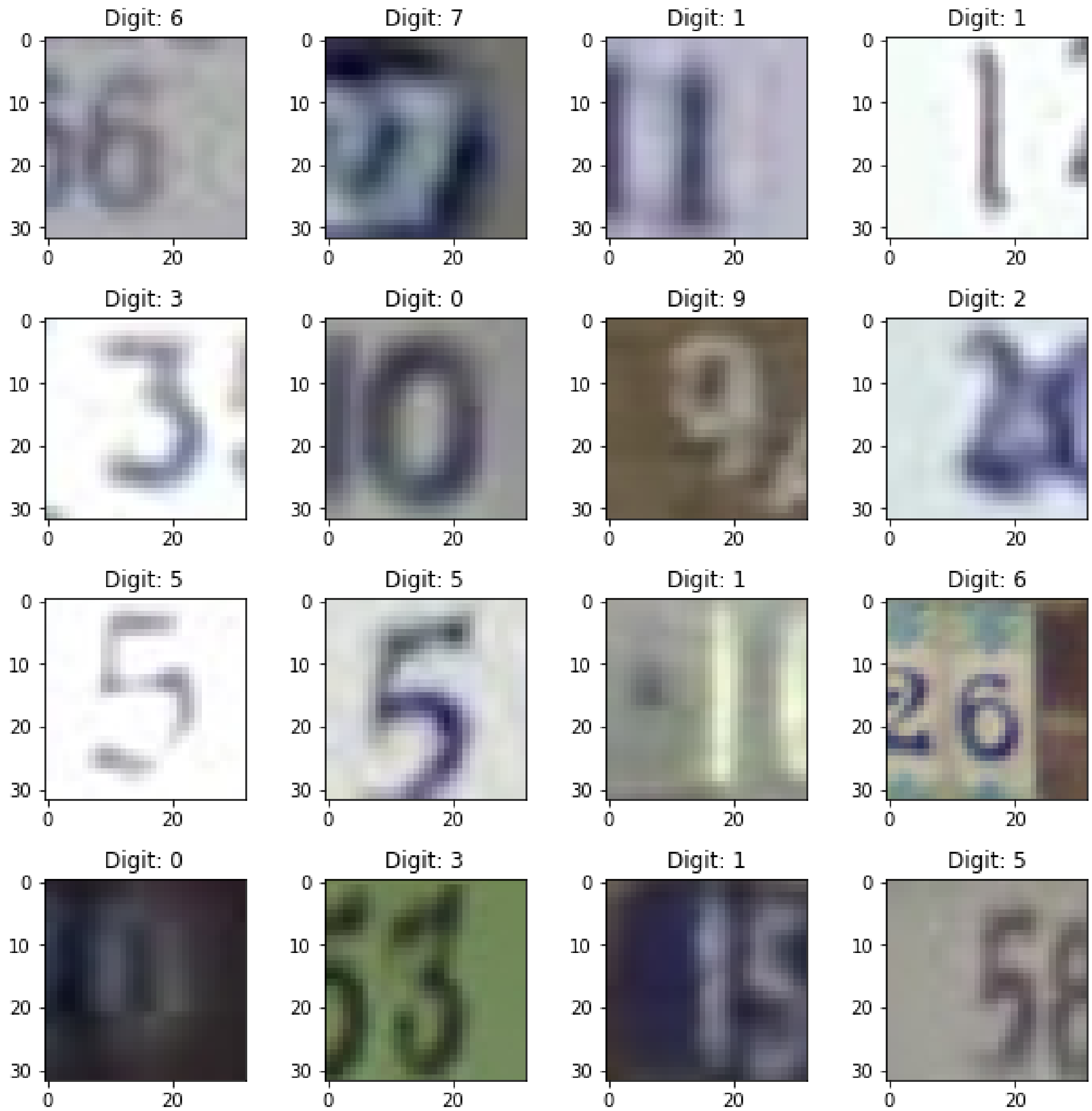
Out[3]: ((32, 32, 3, 73257), (73257, 1), (32, 32, 3, 26032), (26032, 1))

In [4]:
```
# Convert the 10th label to 0th label, for using sparse categorical crossentropy
train_labels[:,0][train_labels[:,0]==10]= 0
test_labels[:,0][test_labels[:,0]==10]= 0
```

In [5]:
```
# Plot random samples from train/test dataset
def visualize_data(images, labels, mode = 'color'):
    """
    Plots 16 random samples of the train/test data
    """
    # Take 16 random samples
    random_idx = random.sample(range(images.shape[-1]), 16)
    fig = plt.figure(figsize=(10, 10))
    for i in range(16):
        idx = random_idx[i]
        plt.subplot(4, 4, i+1)
        plt.subplots_adjust(left=0.1,
                            bottom=0.1,
                            top=0.9,
                            wspace=0.4,
                            hspace=0.4)
        # Plot the images
        if mode!='color':
            plt.imshow(images[..., idx], cmap = 'gray')
        else:
            plt.imshow(images[..., idx])
        # Title is kept as the digit label
        plt.title('Digit: {}'.format(labels[idx][0]))
    plt.show()
```

In [6]:
```
visualize_data(train_images, train_labels, mode = 'color')
```

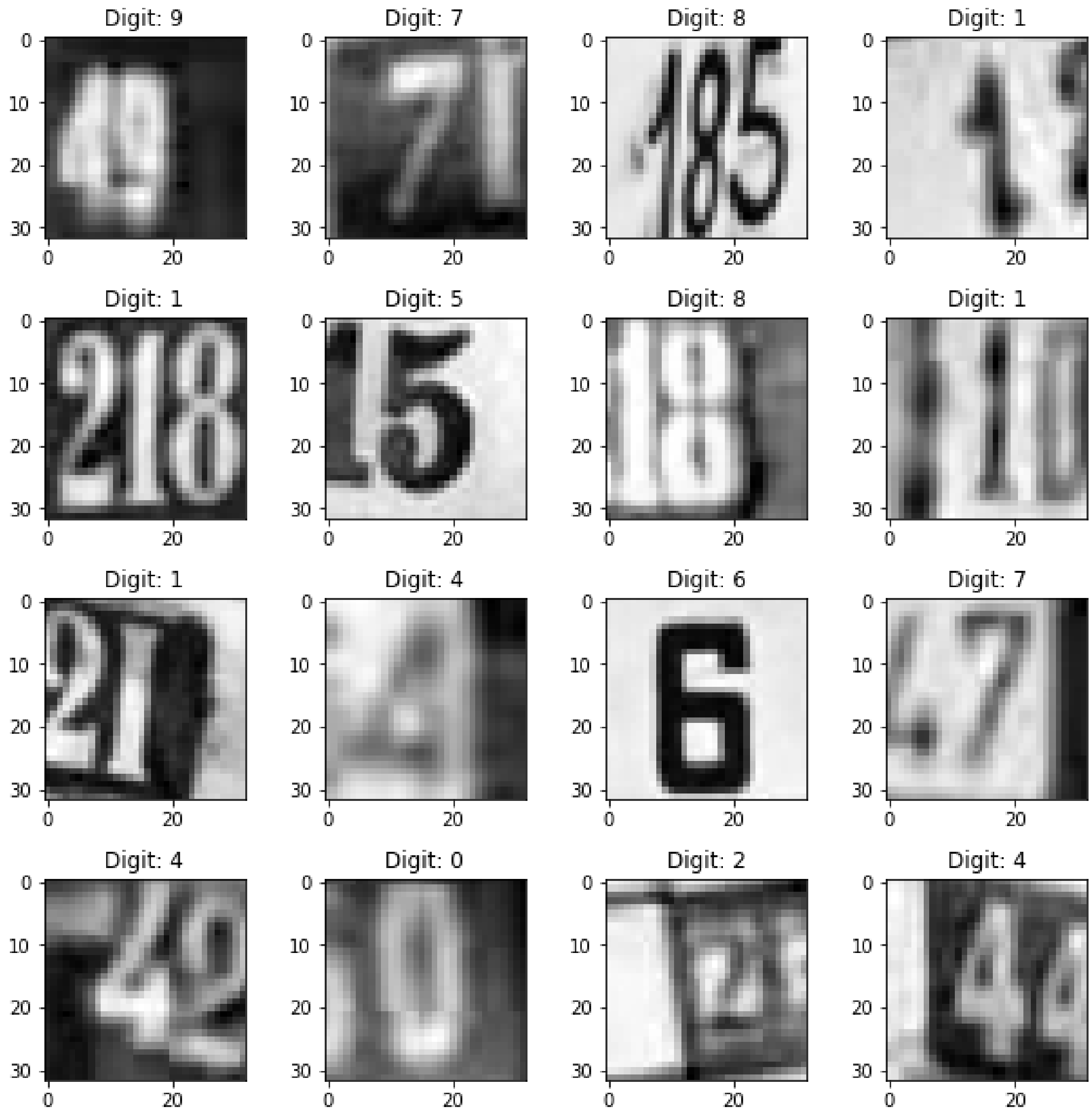

```
In [7]: visualize_data(test_images, test_labels, mode = 'color')
```



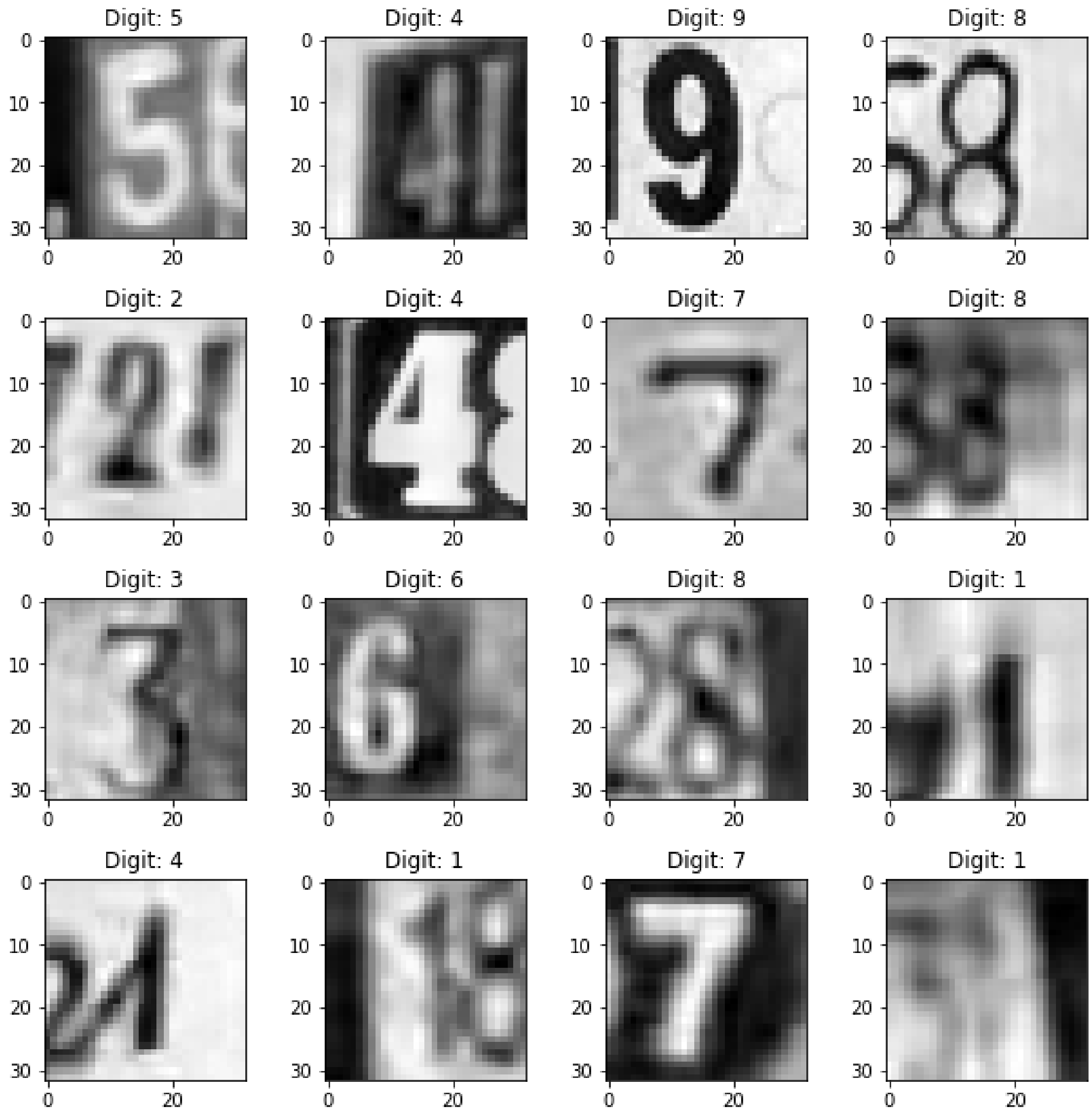
In [8]:
```
## Averaging across all channels
train_images = np.mean(train_images, axis = 2)
test_images = np.mean(test_images, axis = 2)
```

In [9]:
```
# Compute overall mean and standard deviation images of the dataset
mean_img = np.mean(np.concatenate([train_images, test_images], axis = 2), axis = 2)
stddev_img = np.std(np.concatenate([train_images, test_images], axis = 2), axis = 2)
train_images_norm = (train_images - mean_img[:,:,np.newaxis])/stddev_img[:,:,np.newaxis
test_images_norm = (test_images - mean_img[:,:,np.newaxis])/stddev_img[:,:,np.newaxis]
```

In [10]:
```
# Visualize After Averaging Channels
visualize_data(train_images, train_labels, mode = 'gray')
```



In [11]:
```
## Visualize Normalized Images after converting to Grayscale
visualize_data(train_images_norm, train_labels, mode = 'gray')
```



In [12]:
```
# Reshape such that the output dimension is (batch_size, num_features, num_features, 
train_images_norm = train_images_norm.transpose(2, 0, 1).reshape(-1, 32, 32, 1)
test_images_norm = test_images_norm.transpose(2, 0, 1).reshape(-1, 32, 32, 1)
```

In [13]:
```
# Split the dataset with validation split = 0.15, using stratify = train_labels will 
X_train, X_val, y_train, y_val = train_test_split(train_images_norm, train_labels, tes
X_test, y_test = test_images_norm, test_labels
```

In [14]:
```
# Delete unnecessary data which wont be used further
del train, test, train_images, test_images, train_images_norm, test_images_norm
```

1.3 2. MLP neural network classifier

- Build an MLP classifier model using the Sequential API. Your model should use only Flatten and Dense layers, with the final layer having a 10-way softmax output.
- You should design and build the model yourself. Feel free to experiment with different MLP architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 4 or 5 layers.*
- Print out the model summary (using the summary() method)
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.
- Your model should track at least one appropriate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback.
- As a guide, you should aim to achieve a final categorical cross entropy training loss of less than 1.0 (the validation loss might be higher).
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

In [15]:
```
# Define MLP Model
model = Sequential([Flatten(input_shape = (32, 32, 1), name = 'flatten'),
                    Dense(512, activation = 'relu', name = 'dense_1'),
                    Dense(128, activation= 'relu', name = 'dense_2'),
                    Dense(64, activation = 'relu', name = 'dense_3'),
                    Dense(32, activation = 'relu', name = 'dense_4'),
                    Dense(10, activation = 'softmax', name = 'output')])
print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
dense_2 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_4 (Dense)              (None, 32)                2080
_________________________________________________________________
output (Dense)               (None, 10)                330
=================================================================
Total params: 601,130
Trainable params: 601,130
Non-trainable params: 0
_________________________________________________________________
None
```

In [16]:
```
## Callbacks for MLP model

# Early stopping callback with a patience of 10, monitors val_loss
early_stopping_callback = EarlyStopping(monitor = 'val_loss', patience = 10, mode = 'r

# Saves only the best model according to val_loss
model_checkpoint_callback = ModelCheckpoint(filepath = 'checkpoint/model_{epoch:02d}'
                                            save_best_only = True, save_freq = 'epoch
                                            monitor = 'val_loss', mode = 'min', verbos

# CSVLogger saves the results as a csv file
csvlogger_checkpoint = CSVLogger('results.csv')
```

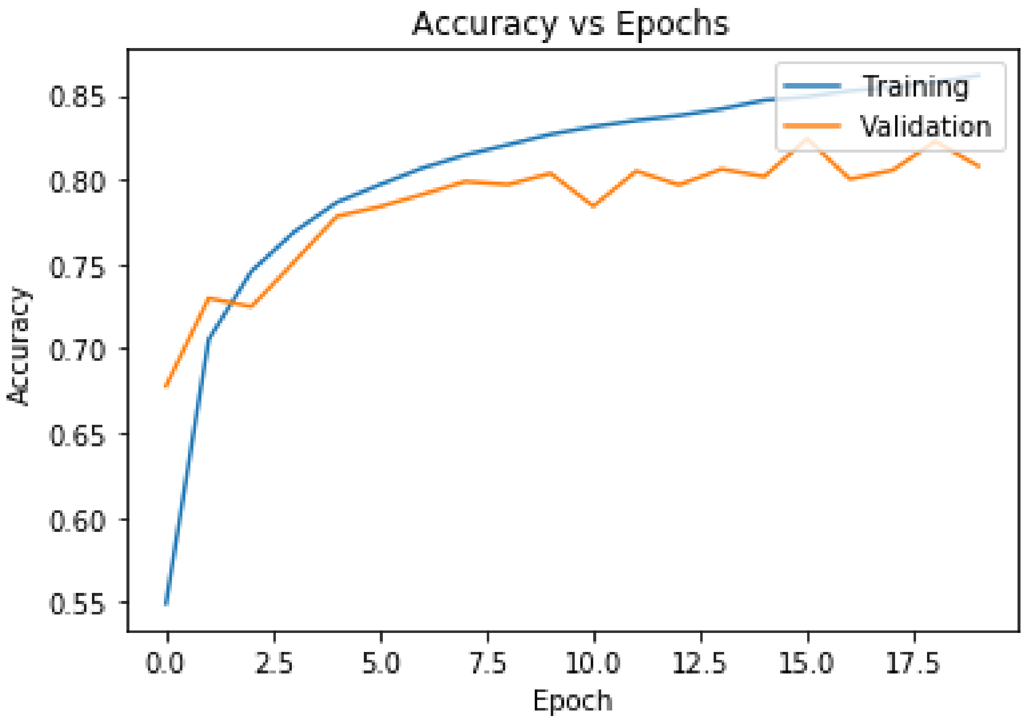
In [17]:
```
# Compile and Fit the model, store the history of MLP later for getting checkpoint
model.compile(optmizer = 'adam', loss = 'sparse_categorical_crossentropy', metrics =
history = model.fit(X_train, y_train, batch_size = 64,
                    epochs = 20, callbacks = [early_stopping_callback, model_checkpoi
                    validation_data = (X_val, y_val), verbose = 1)
```

```
Train on 62268 samples, validate on 10989 samples
Epoch 1/20
62208/62268 [============================>.] - ETA: 0s - loss: 1.3830 - accuracy: 0.5491
Epoch 00001: val_loss improved from inf to 1.00603, saving model to checkpoint/model_01
62268/62268 [==============================] - 71s 1ms/sample - loss: 1.3826 - accuracy: 0.549
Epoch 2/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.9478 - accuracy: 0.7054
Epoch 00002: val_loss improved from 1.00603 to 0.86031, saving model to checkpoint/model_02
62268/62268 [==============================] - 54s 869us/sample - loss: 0.9478 - accuracy: 0.70
Epoch 3/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.8279 - accuracy: 0.7458
Epoch 00003: val_loss did not improve from 0.86031
62268/62268 [==============================] - 54s 875us/sample - loss: 0.8281 - accuracy: 0.74
Epoch 4/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.7532 - accuracy: 0.7690
Epoch 00004: val_loss improved from 0.86031 to 0.84022, saving model to checkpoint/model_04
62268/62268 [==============================] - 54s 869us/sample - loss: 0.7531 - accuracy: 0.76
Epoch 5/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.7006 - accuracy: 0.7866
Epoch 00005: val_loss improved from 0.84022 to 0.74313, saving model to checkpoint/model_05
62268/62268 [==============================] - 54s 866us/sample - loss: 0.7007 - accuracy: 0.78
Epoch 6/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.6667 - accuracy: 0.7970
Epoch 00006: val_loss improved from 0.74313 to 0.73364, saving model to checkpoint/model_06
62268/62268 [==============================] - 54s 875us/sample - loss: 0.6666 - accuracy: 0.79
Epoch 7/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.6356 - accuracy: 0.8069
Epoch 00007: val_loss improved from 0.73364 to 0.70959, saving model to checkpoint/model_07
62268/62268 [==============================] - 55s 886us/sample - loss: 0.6354 - accuracy: 0.80
```

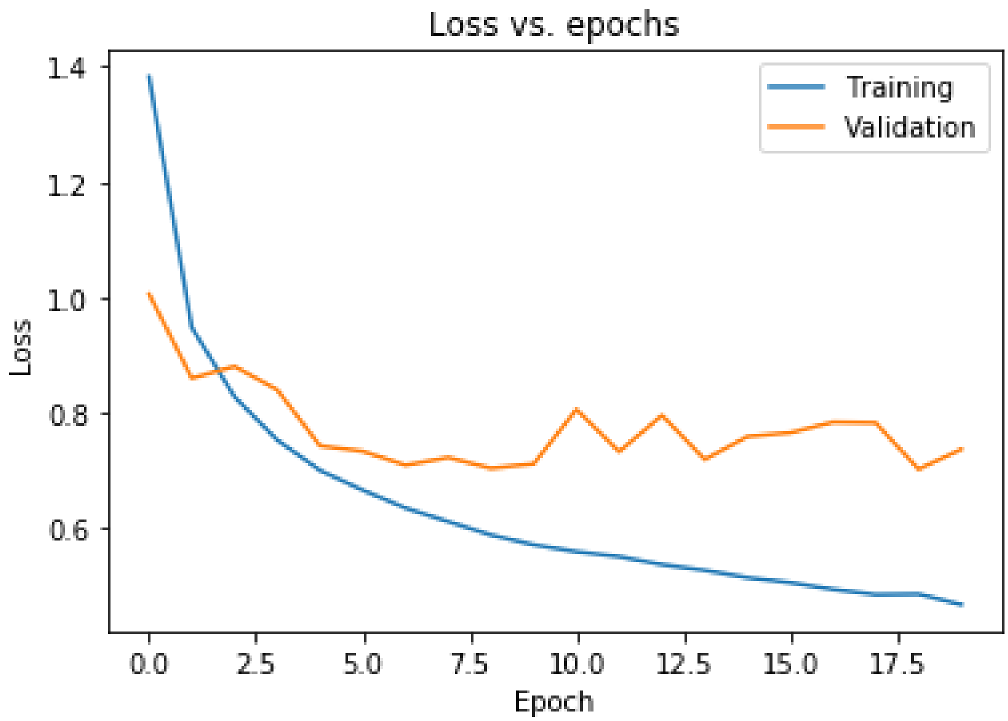
```
Epoch 8/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.6119 - accuracy: 0.8146
Epoch 00008: val_loss did not improve from 0.70959
62268/62268 [==============================] - 55s 883us/sample - loss: 0.6119 - accuracy: 0.81
Epoch 9/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.5886 - accuracy: 0.8207
Epoch 00009: val_loss improved from 0.70959 to 0.70419, saving model to checkpoint/model_09
62268/62268 [==============================] - 54s 868us/sample - loss: 0.5887 - accuracy: 0.82
Epoch 10/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.5714 - accuracy: 0.8269
Epoch 00010: val_loss did not improve from 0.70419
62268/62268 [==============================] - 54s 860us/sample - loss: 0.5717 - accuracy: 0.82
Epoch 11/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5595 - accuracy: 0.8314
Epoch 00011: val_loss did not improve from 0.70419
62268/62268 [==============================] - 55s 880us/sample - loss: 0.5597 - accuracy: 0.83
Epoch 12/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5512 - accuracy: 0.8350
Epoch 00012: val_loss did not improve from 0.70419
62268/62268 [==============================] - 55s 882us/sample - loss: 0.5512 - accuracy: 0.83
Epoch 13/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.5373 - accuracy: 0.8379
Epoch 00013: val_loss did not improve from 0.70419
62268/62268 [==============================] - 54s 874us/sample - loss: 0.5373 - accuracy: 0.83
Epoch 14/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5273 - accuracy: 0.8420
Epoch 00014: val_loss did not improve from 0.70419
62268/62268 [==============================] - 55s 883us/sample - loss: 0.5274 - accuracy: 0.84
Epoch 15/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.5149 - accuracy: 0.8470
Epoch 00015: val_loss did not improve from 0.70419
62268/62268 [==============================] - 54s 861us/sample - loss: 0.5150 - accuracy: 0.84
Epoch 16/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.5064 - accuracy: 0.8491
Epoch 00016: val_loss did not improve from 0.70419
62268/62268 [==============================] - 55s 880us/sample - loss: 0.5063 - accuracy: 0.84
Epoch 17/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.4947 - accuracy: 0.8526
Epoch 00017: val_loss did not improve from 0.70419
62268/62268 [==============================] - 55s 886us/sample - loss: 0.4946 - accuracy: 0.85
Epoch 18/20
62144/62268 [============================>.] - ETA: 0s - loss: 0.4857 - accuracy: 0.8547
Epoch 00018: val_loss did not improve from 0.70419
62268/62268 [==============================] - 54s 870us/sample - loss: 0.4858 - accuracy: 0.85
Epoch 19/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4866 - accuracy: 0.8574
Epoch 00019: val_loss improved from 0.70419 to 0.70266, saving model to checkpoint/model_19
62268/62268 [==============================] - 55s 877us/sample - loss: 0.4866 - accuracy: 0.85
```

```
Epoch 20/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4679 - accuracy: 0.8616
Epoch 00020: val_loss did not improve from 0.70266
62268/62268 [==============================] - 55s 883us/sample - loss: 0.4682 - accuracy: 0.86
```

```
In [18]: # Plot Train and Validation Accuracy for MLP Model
         plt.plot(history.history['accuracy'])
         plt.plot(history.history['val_accuracy'])
         plt.title('Accuracy vs Epochs')
         plt.xlabel('Epoch')
         plt.ylabel('Accuracy')
         plt.legend(['Training', 'Validation'], loc = 'upper right')
         plt.show()
```




```
In [19]: # Plot Train and Validation Loss for MLP Model
         plt.plot(history.history['loss'])
         plt.plot(history.history['val_loss'])
         plt.title('Loss vs. epochs')
         plt.ylabel('Loss')
         plt.xlabel('Epoch')
         plt.legend(['Training', 'Validation'], loc='upper right')
         plt.show()
```




```
In [20]: # Evaluate MLP Model on Test Data
         test_loss, test_acc = model.evaluate(X_test, y_test, verbose = 0)
         print("Test loss: {}, Test Accuracy: {}".format(test_loss, test_acc))
```

```
Test loss: 0.924770849060265, Test Accuracy: 0.7801551818847656
```

1.4 3. CNN neural network classifier

- Build a CNN classifier model using the Sequential API. Your model should use the Conv2D, MaxPool2D, BatchNormalization, Flatten, Dense and Dropout layers. The final layer should again have a 10-way softmax output.
- You should design and build the model yourself. Feel free to experiment with different CNN architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 2 or 3 convolutional layers and 2 fully connected layers.)*
- The CNN model should use fewer trainable parameters than your MLP model.
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.
- Your model should track at least one appropriate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback.
- You should aim to beat the MLP model performance with fewer parameters!
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

```
In [21]: # Instantiate CNN Model
         cnn_model = Sequential([
             Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu', padding = 'same',
                    input_shape = (32, 32, 1), name = 'conv_1'),
             MaxPooling2D((3, 3), name = 'pool_1'),
             Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu', padding = 'same',
                    name = 'conv_2'),
             MaxPooling2D((3, 3), name = 'pool_2'),
             Flatten(name = 'flatten'),
             Dense(units = 128, activation = 'relu', name = 'dense_1'),
             Dense(units = 64, activation = 'relu', name = 'dense_2'),
             Dense(units = 10, activation = 'softmax', name = 'dense_3')
         ])
         print(cnn_model.summary())
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv_1 (Conv2D)              (None, 32, 32, 64)        640
_________________________________________________________________
pool_1 (MaxPooling2D)        (None, 10, 10, 64)        0
_________________________________________________________________
conv_2 (Conv2D)              (None, 10, 10, 64)        36928
_________________________________________________________________
pool_2 (MaxPooling2D)        (None, 3, 3, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 576)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               73856
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 120,330
Trainable params: 120,330
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [22]: # Callbacks for CNN Model
         cnn_early_stopping_callback = EarlyStopping(monitor = 'val_loss', patience = 5, mode =
         cnn_model_checkpoint_callback = ModelCheckpoint(filepath = 'cnn_model_checkpoint/model
                                                         save_freq = 'epoch', save_best_only = True
                                                         monitor = 'val_loss', mode = 'min', verbos
```

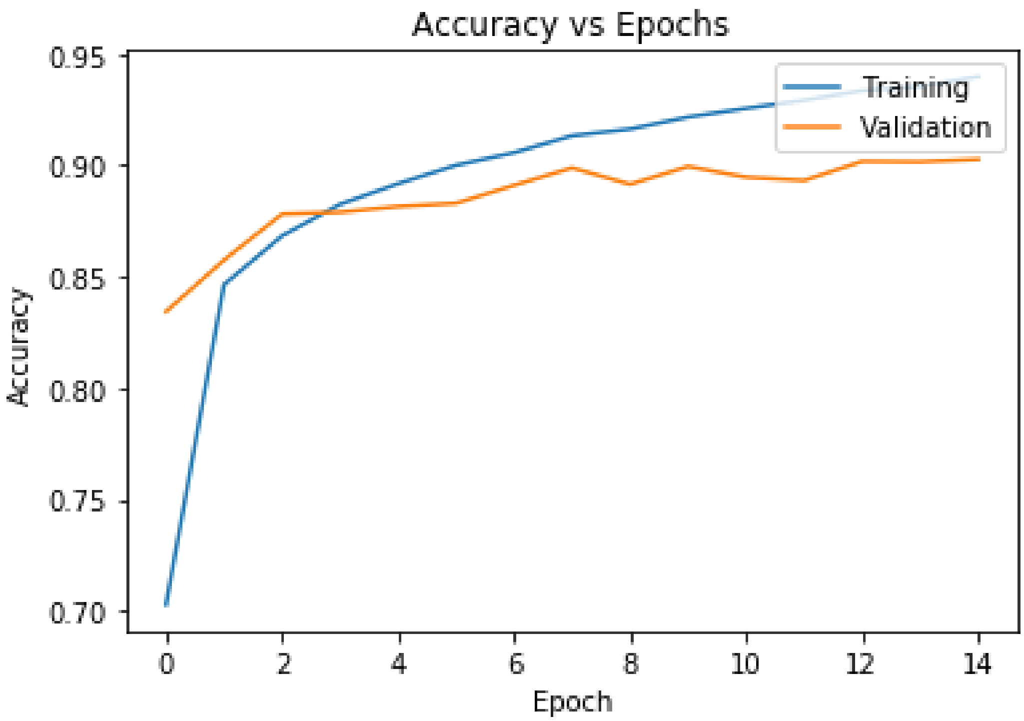
```
In [23]: # Compile and Fit the CNN Model, store history for accessing checkpoints later
```

```
cnn_model.compile(optimizer = 'adam', loss = 'sparse_categorical_crossentropy', metric
cnn_history = cnn_model.fit(X_train, y_train, batch_size = 64,
                            epochs = 20, callbacks = [cnn_early_stopping_callback, cnn_model_c
                            validation_data = (X_val, y_val), verbose = 1)
```

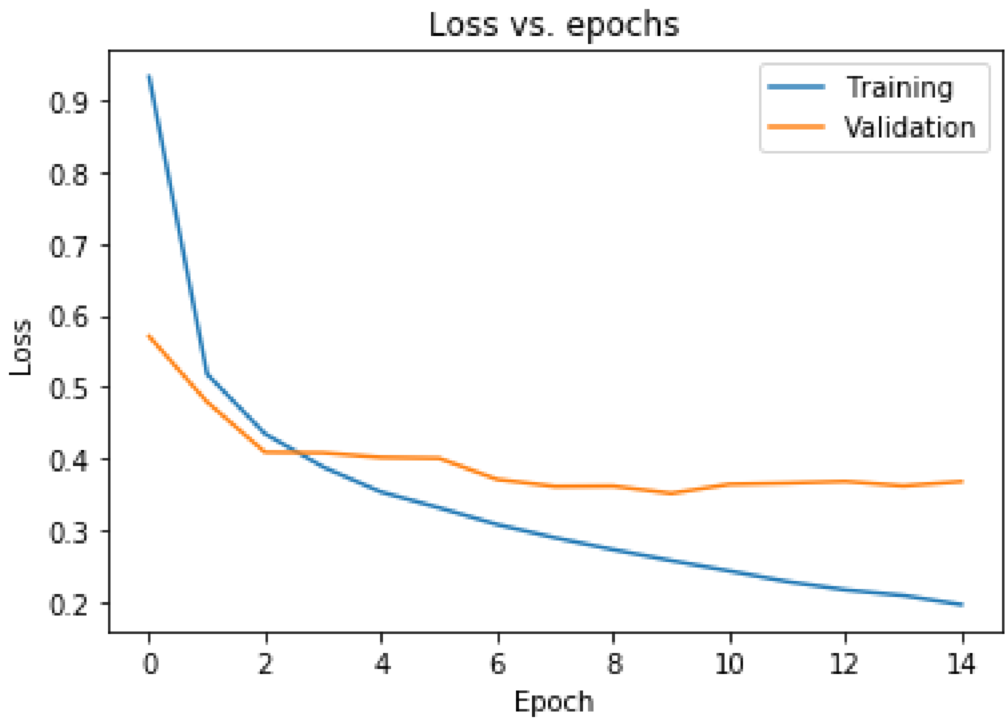
```
Train on 62268 samples, validate on 10989 samples
Epoch 1/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.9327 - accuracy: 0.7026
Epoch 00001: val_loss improved from inf to 0.57043, saving model to cnn_model_checkpoint/model_
62268/62268 [==============================] - 402s 6ms/sample - loss: 0.9324 - accuracy: 0.702
Epoch 2/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5176 - accuracy: 0.8465
Epoch 00002: val_loss improved from 0.57043 to 0.47909, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 393s 6ms/sample - loss: 0.5179 - accuracy: 0.846
Epoch 3/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4344 - accuracy: 0.8683
Epoch 00003: val_loss improved from 0.47909 to 0.40881, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 393s 6ms/sample - loss: 0.4346 - accuracy: 0.868
Epoch 4/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.3885 - accuracy: 0.8825
Epoch 00004: val_loss improved from 0.40881 to 0.40813, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 404s 6ms/sample - loss: 0.3885 - accuracy: 0.882
Epoch 5/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.3535 - accuracy: 0.8919
Epoch 00005: val_loss improved from 0.40813 to 0.40156, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 388s 6ms/sample - loss: 0.3536 - accuracy: 0.891
Epoch 6/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.3316 - accuracy: 0.9001
Epoch 00006: val_loss improved from 0.40156 to 0.40047, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 388s 6ms/sample - loss: 0.3315 - accuracy: 0.900
Epoch 7/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.3083 - accuracy: 0.9057
Epoch 00007: val_loss improved from 0.40047 to 0.37119, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 406s 7ms/sample - loss: 0.3082 - accuracy: 0.905
Epoch 8/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2897 - accuracy: 0.9133
Epoch 00008: val_loss improved from 0.37119 to 0.36135, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 414s 7ms/sample - loss: 0.2897 - accuracy: 0.913
Epoch 9/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2731 - accuracy: 0.9163
Epoch 00009: val_loss did not improve from 0.36135
62268/62268 [==============================] - 401s 6ms/sample - loss: 0.2732 - accuracy: 0.916
Epoch 10/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2579 - accuracy: 0.9216
Epoch 00010: val_loss improved from 0.36135 to 0.35167, saving model to cnn_model_checkpoint/mo
62268/62268 [==============================] - 401s 6ms/sample - loss: 0.2578 - accuracy: 0.921
Epoch 11/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2433 - accuracy: 0.9256
```

```
Epoch 00011: val_loss did not improve from 0.35167
62268/62268 [==============================] - 389s 6ms/sample - loss: 0.2434 - accuracy: 0.925
Epoch 12/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2287 - accuracy: 0.9292
Epoch 00012: val_loss did not improve from 0.35167
62268/62268 [==============================] - 386s 6ms/sample - loss: 0.2287 - accuracy: 0.929
Epoch 13/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2173 - accuracy: 0.9335
Epoch 00013: val_loss did not improve from 0.35167
62268/62268 [==============================] - 380s 6ms/sample - loss: 0.2173 - accuracy: 0.933
Epoch 14/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.2094 - accuracy: 0.9353
Epoch 00014: val_loss did not improve from 0.35167
62268/62268 [==============================] - 382s 6ms/sample - loss: 0.2093 - accuracy: 0.935
Epoch 15/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.1968 - accuracy: 0.9398
Epoch 00015: val_loss did not improve from 0.35167
62268/62268 [==============================] - 386s 6ms/sample - loss: 0.1966 - accuracy: 0.939
```

In [24]:
```python
# Plot Train and Validation Accuracy for CNN Model
plt.plot(cnn_history.history['accuracy'])
plt.plot(cnn_history.history['val_accuracy'])
plt.title('Accuracy vs Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Training', 'Validation'], loc = 'upper right')
plt.show()
```



In [25]:
```
# Plot Train and Validation Loss for CNN Model
plt.plot(cnn_history.history['loss'])
plt.plot(cnn_history.history['val_loss'])
plt.title('Loss vs. epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='upper right')
plt.show()
```




```
In [26]: # Test Loss of CNN Model
         test_loss, test_acc = cnn_model.evaluate(X_test, y_test, verbose = 2)
         print("Test Loss: {}, Test Accuracy: {}".format(test_loss, test_acc))
```

```
26032/1 - 47s - loss: 0.3610 - accuracy: 0.8978
Test Loss: 0.39057045084376807, Test Accuracy: 0.897779643535614
```

1.5 4. Get model predictions

- Load the best weights for the MLP and CNN models that you saved during the training run.
- Randomly select 5 images and corresponding labels from the test set and display the images with their labels.
- Alongside the image and label, show each model's predictive distribution as a bar chart, and the final model prediction given by the label with maximum probability.

```
In [27]: # Use the history of MLP and CNN Models to get a dataframe
         df_mlp = pd.DataFrame(history.history)
         df_cnn = pd.DataFrame(cnn_history.history)
```

```
In [28]: # Since we saved the best model (each epoch) only when the val_loss was min, we extra
         mlp_best_epoch = df_mlp.val_loss.idxmin() + 1
         cnn_best_epoch = df_cnn.val_loss.idxmin() + 1
```

In [29]:
```
# We use the epoch at which val_loss was minimum to get the model checkpoint path
mlp_best_checkpoint = '/home/jovyan/work/5/checkpoint/model_{}'.format(mlp_best_epoch
cnn_best_checkpoint = '/home/jovyan/work/5/cnn_model_checkpoint/model_{}'.format(cnn_
```

In [30]:
```
## Instantiate new models MLP and CNN to load the weights
mlp_model = Sequential([Flatten(input_shape = (32, 32, 1), name = 'flatten'),
                    Dense(512, activation = 'relu', name = 'dense_1'),
                    Dense(128, activation= 'relu', name = 'dense_2'),
                    Dense(64, activation = 'relu', name = 'dense_3'),
                    Dense(32, activation = 'relu', name = 'dense_4'),
                    Dense(10, activation = 'softmax', name = 'output')])
cnn_model = Sequential([
    Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu', padding = 'same',
           input_shape = (32, 32, 1), name = 'conv_1'),
    MaxPooling2D((3, 3), name = 'pool_1'),
    Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu', padding = 'same',
           name = 'conv_2'),
    MaxPooling2D((3, 3), name = 'pool_2'),
    Flatten(name = 'flatten'),
    Dense(units = 128, activation = 'relu', name = 'dense_1'),
    Dense(units = 64, activation = 'relu', name = 'dense_2'),
    Dense(units = 10, activation = 'softmax', name = 'dense_3')
])
```

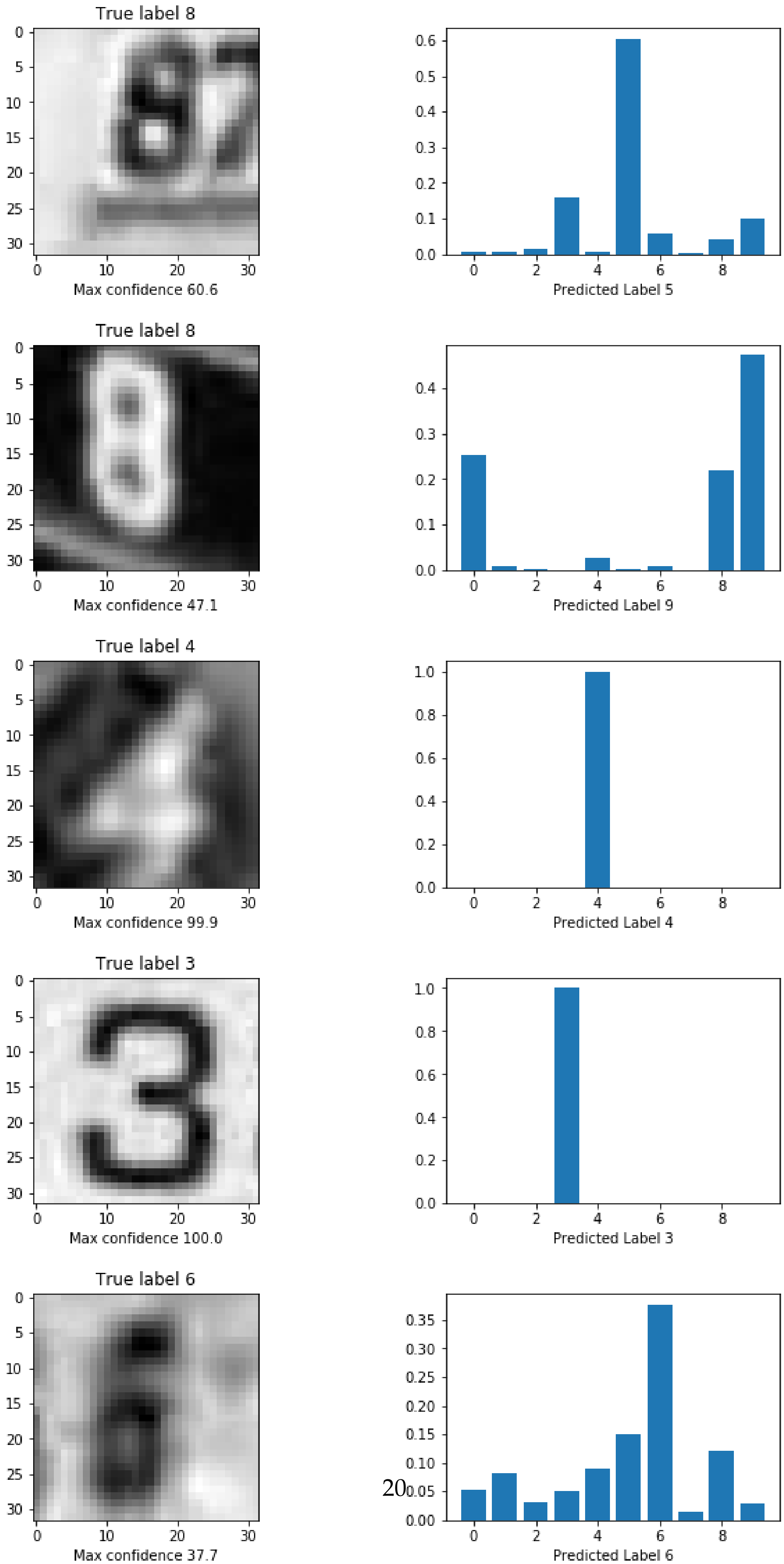
In [31]:
```
## Load weights using checkpoint and new model
mlp_model.load_weights(mlp_best_checkpoint)
cnn_model.load_weights(cnn_best_checkpoint)
```

Out[31]: <tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7f5b1808d6d8>

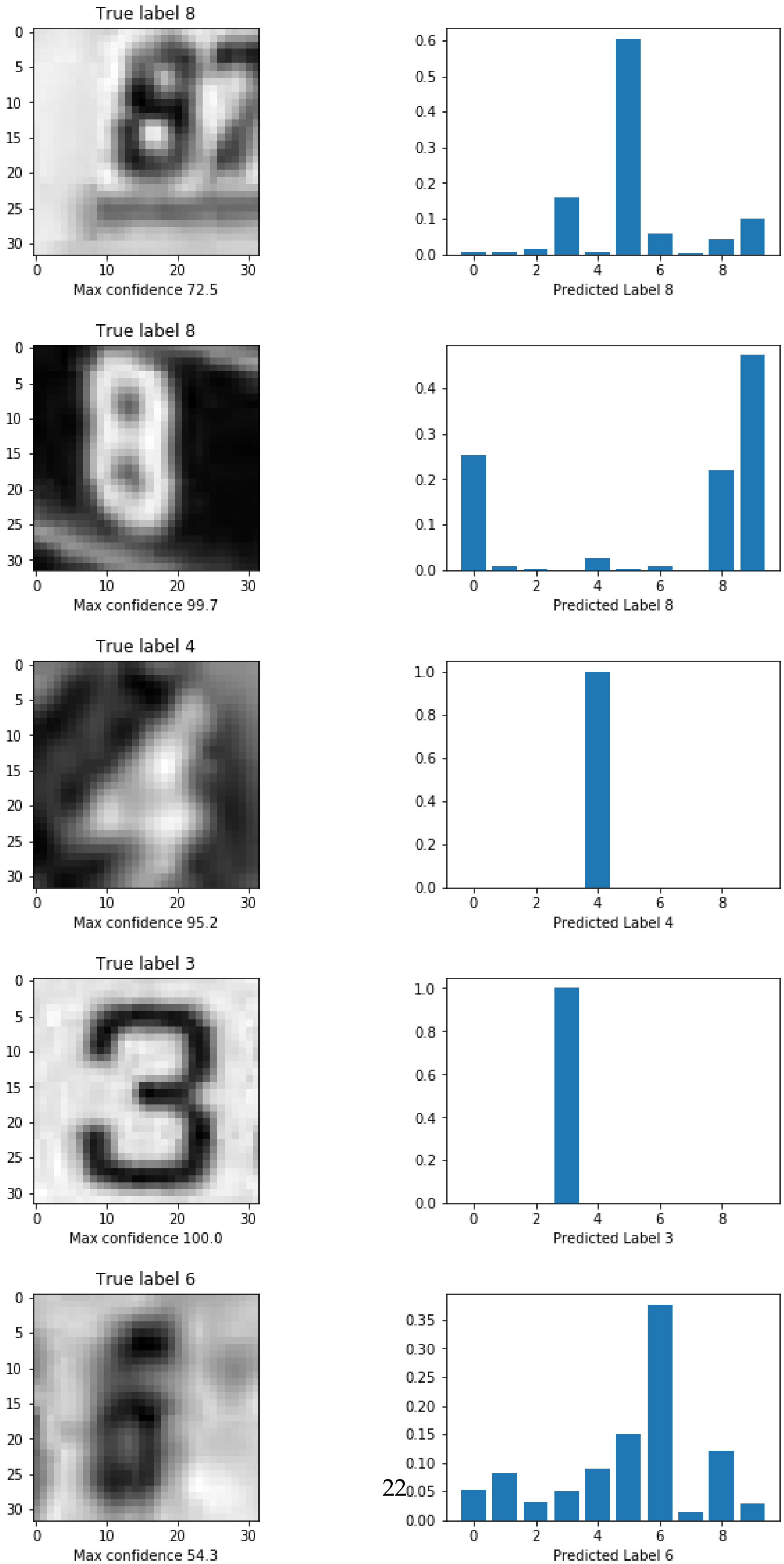
In [32]:
```
## Predict on test data
mlp_predictions = mlp_model.predict(X_test)
cnn_predictions = cnn_model.predict(X_test)
```

In [44]:
```
# Plot the predictions for MLP
#random_idx = random.sample(range(X_test.shape[0]), 5)
fig = plt.figure(figsize=(10, 10))
for i in range(5):
    idx = random_idx[i]
    predicted_label = np.argmax(mlp_predictions[idx])
    confidence = np.round(mlp_predictions[idx].max()*100, 1)
    true_label = y_test[idx][0]
    plt.subplot(5, 2, 2*i+1)
    plt.subplots_adjust(left=0.1,
                        bottom=0.01,
                        top=1.5,
                        wspace=0.4,
                        hspace=0.4)
    plt.imshow(X_test[idx].reshape(32, 32), cmap = 'gray')
```

```
    plt.title('True label {}'.format(true_label))
    plt.xlabel('Max confidence {}'.format(confidence))
    plt.subplot(5, 2, 2*i+2)
    plt.bar(range(10), mlp_predictions[idx])
    plt.xlabel('Predicted Label {}'.format(predicted_label))
plt.show()
```


True label 8
Max confidence 60.6
Predicted Label 5
True label 8
Max confidence 47.1
Predicted Label 9
True label 4
Max confidence 99.9
Predicted Label 4
True label 3
Max confidence 100.0
Predicted Label 3
True label 6
Max confidence 37.7
Predicted Label 6

In [45]:
```
# Plot the predictions for CNN
fig = plt.figure(figsize=(10, 10))
for i in range(5):
    idx = random_idx[i]
    predicted_label = np.argmax(cnn_predictions[idx])
    confidence = np.round(cnn_predictions[idx].max()*100, 1)
    true_label = y_test[idx][0]
    plt.subplot(5, 2, 2*i+1)
    plt.subplots_adjust(left=0.1,
                        bottom=0.01,
                        top=1.5,
                        wspace=0.4,
                        hspace=0.4)
    plt.imshow(X_test[idx].reshape(32, 32), cmap = 'gray')
    plt.title('True label {}'.format(true_label))
    plt.xlabel('Max confidence {}'.format(confidence))
    plt.subplot(5, 2, 2*i+2)
    plt.bar(range(10), mlp_predictions[idx])
    plt.xlabel('Predicted Label {}'.format(predicted_label))
plt.show()
```


True label 8
Max confidence 72.5
Predicted Label 8
True label 8
Max confidence 99.7
Predicted Label 8
True label 4
Max confidence 95.2
Predicted Label 4
True label 3
Max confidence 100.0
Predicted Label 3
True label 6
Max confidence 54.3
Predicted Label 6