Capstone Project

November 6, 2021

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 [86]: import tensorflow as tf
         from scipy.io import loadmat
         import matplotlib.pyplot as plt
         import numpy as np

         from sklearn.model_selection import train_test_split
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense, Activation, Conv2D, MaxPooling2D, Flatten,I
         from tensorflow.keras.utils import to_categorical
         from tensorflow.keras.callbacks import EarlyStopping,ModelCheckpoint,ReduceLROnPlateau
         from tensorflow.keras import initializers
         import random
```

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 [87]:
```
# 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 [88]:
```
# Extract the training and testing images and labels separately from the train and te
x_train = train['X']
y_train = train['y']
```

```
print(x_train.shape)
print(y_train.shape)
```

```
(32, 32, 3, 73257)
(73257, 1)
```

```
In [89]: # Extract the testing images and labels separately from the train and test dictionari
         x_test = test['X']
         y_test = test['y']

         print(x_test.shape)
         print(y_test.shape)
```

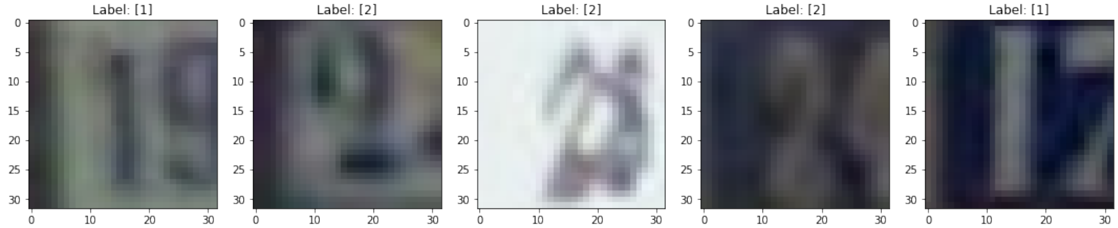
```
(32, 32, 3, 26032)
(26032, 1)
```

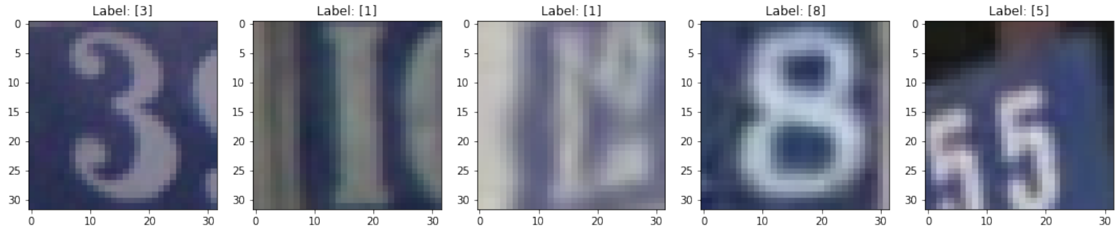
```
In [90]: # rehape x-train and x_test
         x_train = x_train.transpose(3,0,1,2)
         x_test = x_test.transpose(3,0,1,2)

         print(x_train.shape)
         print(x_test.shape)
```

```
(73257, 32, 32, 3)
(26032, 32, 32, 3)
```

```
In [91]: y_train[y_train == 10] = 0
         y_test[y_test == 10] = 0
```

```
In [92]: # Select a random sample of images and corresponding labels from the dataset (at leas
         num = 10
         num_row = 2

         rand_indices = np.random.randint(0,x_train.shape[0],num)

         num_col = 5# plot images
         fig, axes = plt.subplots(num_row, num_col, figsize=(15,15))
         for i in range(num):
             ax = axes[i//num_col, i%num_col]
             ax.imshow(x_train[rand_indices[i]], )
             ax.set_title('Label: {}'.format(y_train[rand_indices[i]]))
         plt.tight_layout()
         plt.show()
```





In [ ]:

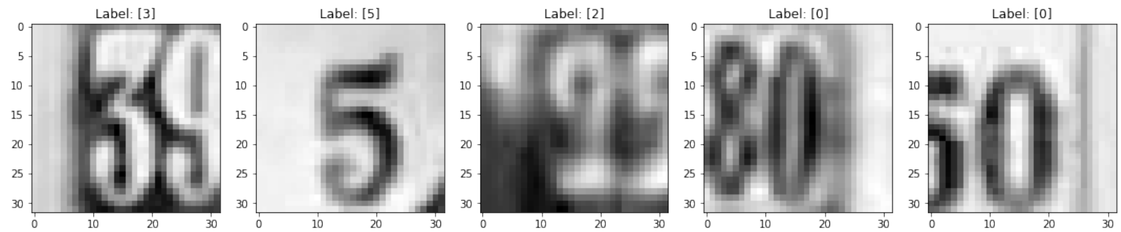
In [ ]:
```
# normalise X_train and X_test

x_train=x_train/255.
x_test=x_test/255.
```

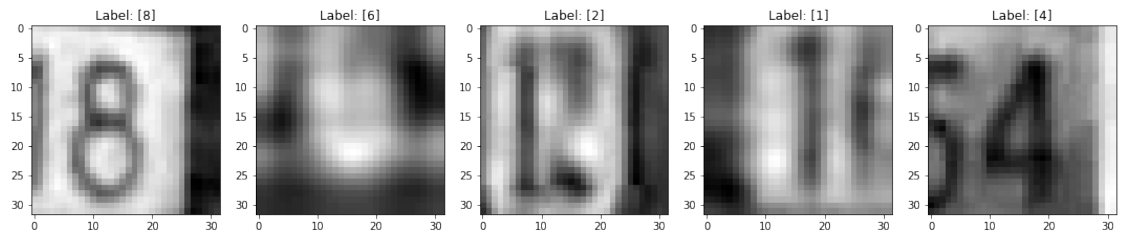
In [93]:
```
# Convert the training and test images to grayscale by taking the average across all c
# for each pixel.

x_train_grey = np.expand_dims (np.average(x_train, axis=-1), -1)
x_test_grey =  np.expand_dims (np.average(x_test, axis=-1), -1)
print(x_train_grey.shape)
print(x_test_grey.shape)
```

```
(73257, 32, 32, 1)
(26032, 32, 32, 1)
```

In [94]:
```
#* Select a random sample of the grayscale images and corresponding labels from the da
num = 10
num_row = 2

rand_indices = np.random.randint(0,x_train_grey.shape[0],num)
```

```
num_col = 5# plot images
fig, axes = plt.subplots(num_row, num_col, figsize=(15,15))
for i in range(num):
    ax = axes[i//num_col, i%num_col]
    ax.imshow(x_train_grey[rand_indices[i]].squeeze(axis=2), cmap='gray')
    ax.set_title('Label: {}'.format(y_train[rand_indices[i]]))
plt.tight_layout()
plt.show()
```





In [ ]:

In [95]:
```
y_train_binarised = to_categorical(y_train.astype('int64'), 10)

y_test_binarised = to_categorical(y_test.astype('int64'), 10)
```

In [96]:
```
y_train_binarised[0]
```

Out[96]:
```
array([0., 1., 0., 0., 0., 0., 0., 0., 0., 0.], dtype=float32)
```

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 [97]:
```
# Split train data to train and validation sets
X_train, X_val, y_train, y_val = train_test_split(x_train_grey, y_train_binarised
                                                  , train_size=0.85, ran
```

Build MLP Classifer

In [98]:
```
def MLPClassifer(input_shape):

    model = Sequential([
        Flatten(input_shape=input_shape),
        Dense(512, activation = 'relu', kernel_initializer = initializers.RandomNormal
        Dense(64, activation = 'relu', kernel_initializer = initializers.RandomNormal
        Dense(32, activation = 'relu', kernel_initializer = initializers.RandomNormal
        Dense(10, activation = 'softmax'),

    ])
    adam = tf.keras.optimizers.Adam(lr = 0.002)

    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accura
    return model
```

In [99]:
```
# create an instance of the MLP Classifer
model = MLPClassifer(x_train_grey[1].shape)
```

In [ ]:

In [100]:
```
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_5 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_16 (Dense)             (None, 512)               524800
_________________________________________________________________
dense_17 (Dense)             (None, 64)                32832
_________________________________________________________________
```

```
dense_18 (Dense)             (None, 32)               2080
_________________________________________________________________
dense_19 (Dense)             (None, 10)               330
=================================================================
Total params: 560,042
Trainable params: 560,042
Non-trainable params: 0
_________________________________________________________________
```

In [101]:
```
checkpoint_filepath = '/tmp/checkpoint'
save_model_checkpoint = ModelCheckpoint(checkpoint_filepath, monitor='val_accuracy',s
                                                         save_best_only=True, save_weights_on
reduce_lr = ReduceLROnPlateau(monitor='val_accuracy',
                              factor=0.5,
                              patience=3,
                              verbose=1)

early_stopping = EarlyStopping(monitor='val_accuracy', patience=3)
```

In [102]:
```
history = model.fit(x_train_grey, y_train_binarised,validation_data=(X_val, y_val),
                    epochs=25,callbacks=[save_model_checkpoint,reduce_lr ],verbose =
```

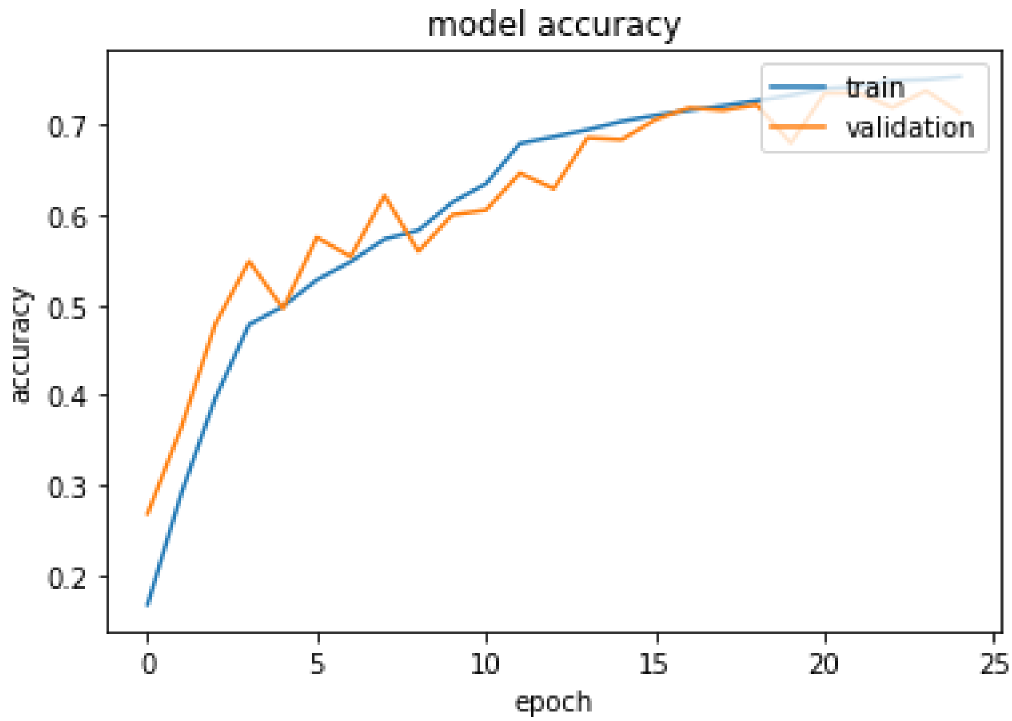
```
Train on 62268 samples, validate on 10989 samples
Epoch 1/25
62208/62268 [============================>.] - ETA: 0s - loss: 9.2184 - accuracy: 0.1671
Epoch 00001: val_accuracy improved from -inf to 0.26809, saving model to /tmp/checkpoint
62268/62268 [==============================] - 42s 673us/sample - loss: 9.2124 - accuracy: 0.16
Epoch 2/25
62080/62268 [============================>.] - ETA: 0s - loss: 2.2404 - accuracy: 0.2908
Epoch 00002: val_accuracy improved from 0.26809 to 0.36418, saving model to /tmp/checkpoint
62268/62268 [==============================] - 37s 597us/sample - loss: 2.2396 - accuracy: 0.29
Epoch 3/25
62080/62268 [============================>.] - ETA: 0s - loss: 1.7971 - accuracy: 0.3959
Epoch 00003: val_accuracy improved from 0.36418 to 0.47857, saving model to /tmp/checkpoint
62268/62268 [==============================] - 37s 588us/sample - loss: 1.7968 - accuracy: 0.39
Epoch 4/25
62144/62268 [============================>.] - ETA: 0s - loss: 1.5587 - accuracy: 0.4781
Epoch 00004: val_accuracy improved from 0.47857 to 0.54846, saving model to /tmp/checkpoint
62268/62268 [==============================] - 37s 591us/sample - loss: 1.5585 - accuracy: 0.47
Epoch 5/25
62208/62268 [============================>.] - ETA: 0s - loss: 1.5003 - accuracy: 0.4983
Epoch 00005: val_accuracy did not improve from 0.54846
62268/62268 [==============================] - 37s 593us/sample - loss: 1.5003 - accuracy: 0.49
Epoch 6/25
62208/62268 [============================>.] - ETA: 0s - loss: 1.4230 - accuracy: 0.5279
Epoch 00006: val_accuracy improved from 0.54846 to 0.57503, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 605us/sample - loss: 1.4231 - accuracy: 0.52
```

```
Epoch 7/25
62144/62268 [============================>.] - ETA: 0s - loss: 1.3675 - accuracy: 0.5480
Epoch 00007: val_accuracy did not improve from 0.57503
62268/62268 [==============================] - 37s 602us/sample - loss: 1.3674 - accuracy: 0.54
Epoch 8/25
62080/62268 [============================>.] - ETA: 0s - loss: 1.3021 - accuracy: 0.5730
Epoch 00008: val_accuracy improved from 0.57503 to 0.62153, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 604us/sample - loss: 1.3019 - accuracy: 0.57
Epoch 9/25
62080/62268 [============================>.] - ETA: 0s - loss: 1.2788 - accuracy: 0.5826
Epoch 00009: val_accuracy did not improve from 0.62153
62268/62268 [==============================] - 37s 589us/sample - loss: 1.2783 - accuracy: 0.58
Epoch 10/25
62144/62268 [============================>.] - ETA: 0s - loss: 1.2028 - accuracy: 0.6138
Epoch 00010: val_accuracy did not improve from 0.62153
62268/62268 [==============================] - 37s 599us/sample - loss: 1.2023 - accuracy: 0.61
Epoch 11/25
62144/62268 [============================>.] - ETA: 0s - loss: 1.1523 - accuracy: 0.6348
Epoch 00011: val_accuracy did not improve from 0.62153

Epoch 00011: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
62268/62268 [==============================] - 38s 618us/sample - loss: 1.1525 - accuracy: 0.63
Epoch 12/25
62208/62268 [============================>.] - ETA: 0s - loss: 1.0299 - accuracy: 0.6792
Epoch 00012: val_accuracy improved from 0.62153 to 0.64628, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 615us/sample - loss: 1.0300 - accuracy: 0.67
Epoch 13/25
62144/62268 [============================>.] - ETA: 0s - loss: 1.0076 - accuracy: 0.6869
Epoch 00013: val_accuracy did not improve from 0.64628
62268/62268 [==============================] - 38s 617us/sample - loss: 1.0081 - accuracy: 0.68
Epoch 14/25
62144/62268 [============================>.] - ETA: 0s - loss: 0.9796 - accuracy: 0.6946
Epoch 00014: val_accuracy improved from 0.64628 to 0.68559, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 610us/sample - loss: 0.9794 - accuracy: 0.69
Epoch 15/25
62208/62268 [============================>.] - ETA: 0s - loss: 0.9560 - accuracy: 0.7037
Epoch 00015: val_accuracy did not improve from 0.68559
62268/62268 [==============================] - 38s 609us/sample - loss: 0.9558 - accuracy: 0.70
Epoch 16/25
62080/62268 [============================>.] - ETA: 0s - loss: 0.9360 - accuracy: 0.7103
Epoch 00016: val_accuracy improved from 0.68559 to 0.70571, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 612us/sample - loss: 0.9356 - accuracy: 0.71
Epoch 17/25
62208/62268 [============================>.] - ETA: 0s - loss: 0.9222 - accuracy: 0.7160
Epoch 00017: val_accuracy improved from 0.70571 to 0.71899, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 609us/sample - loss: 0.9222 - accuracy: 0.71
Epoch 18/25
62208/62268 [============================>.] - ETA: 0s - loss: 0.9048 - accuracy: 0.7210
```

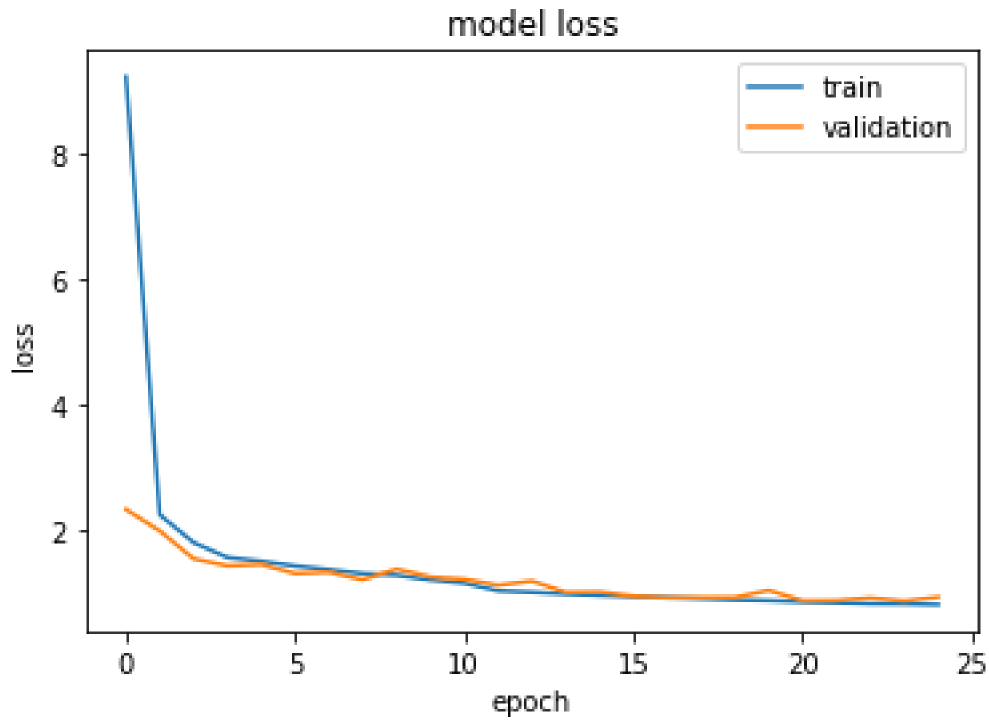
```
Epoch 00018: val_accuracy did not improve from 0.71899
62268/62268 [==============================] - 38s 604us/sample - loss: 0.9050 - accuracy: 0.72
Epoch 19/25
62144/62268 [============================>.] - ETA: 0s - loss: 0.8865 - accuracy: 0.7268
Epoch 00019: val_accuracy improved from 0.71899 to 0.72236, saving model to /tmp/checkpoint
62268/62268 [==============================] - 39s 625us/sample - loss: 0.8866 - accuracy: 0.72
Epoch 20/25
62080/62268 [============================>.] - ETA: 0s - loss: 0.8737 - accuracy: 0.7330
Epoch 00020: val_accuracy did not improve from 0.72236
62268/62268 [==============================] - 39s 629us/sample - loss: 0.8740 - accuracy: 0.73
Epoch 21/25
62144/62268 [============================>.] - ETA: 0s - loss: 0.8541 - accuracy: 0.7400
Epoch 00021: val_accuracy improved from 0.72236 to 0.73501, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 612us/sample - loss: 0.8539 - accuracy: 0.74
Epoch 22/25
62144/62268 [============================>.] - ETA: 0s - loss: 0.8415 - accuracy: 0.7426
Epoch 00022: val_accuracy improved from 0.73501 to 0.73519, saving model to /tmp/checkpoint
62268/62268 [==============================] - 38s 605us/sample - loss: 0.8415 - accuracy: 0.74
Epoch 23/25
62208/62268 [============================>.] - ETA: 0s - loss: 0.8255 - accuracy: 0.7490
Epoch 00023: val_accuracy did not improve from 0.73519
62268/62268 [==============================] - 39s 620us/sample - loss: 0.8257 - accuracy: 0.74
Epoch 24/25
62144/62268 [============================>.] - ETA: 0s - loss: 0.8218 - accuracy: 0.7502
Epoch 00024: val_accuracy improved from 0.73519 to 0.73783, saving model to /tmp/checkpoint
62268/62268 [==============================] - 39s 633us/sample - loss: 0.8220 - accuracy: 0.75
Epoch 25/25
62144/62268 [============================>.] - ETA: 0s - loss: 0.8098 - accuracy: 0.7535 ETA:
Epoch 00025: val_accuracy did not improve from 0.73783
62268/62268 [==============================] - 40s 642us/sample - loss: 0.8101 - accuracy: 0.75
```

In [103]:

```python
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()
```



In [104]:
```
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()
```




```
In [105]: # * Compute and display the loss and accuracy of the trained model on the test set.
          scores = model.evaluate(x_test_grey, y_test_binarised, verbose=0)
          print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
          print("loss: " ,  ( scores[0]))
```

```
accuracy: 69.39%
loss:  1.0285637338394464
```

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 [125]:
```
def cnn_classifer(input_shape):

    model = Sequential()
    model.add(Conv2D(filters=16, kernel_size=3, activation='relu', input_shape=input_
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(filters=16, kernel_size=3, activation='relu'))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Flatten())
    model.add(Dropout(0.3))
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(10, activation='softmax'))
    #adam = optimizers.Adam(lr = 0.001)

    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accura

    return model
```

In [126]:
```
# create an instance of the CNN Classifer
model = cnn_classifer(x_train_grey[1].shape)
```

In [130]:
```
model.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_9 (Conv2D)            (None, 30, 30, 16)        160
_________________________________________________________________
batch_normalization_4 (Batch (None, 30, 30, 16)        64
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 15, 15, 16)        0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 13, 13, 16)        2320
_________________________________________________________________
batch_normalization_5 (Batch (None, 13, 13, 16)        64
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 6, 6, 16)          0
_________________________________________________________________
flatten_10 (Flatten)         (None, 576)               0
_________________________________________________________________
```

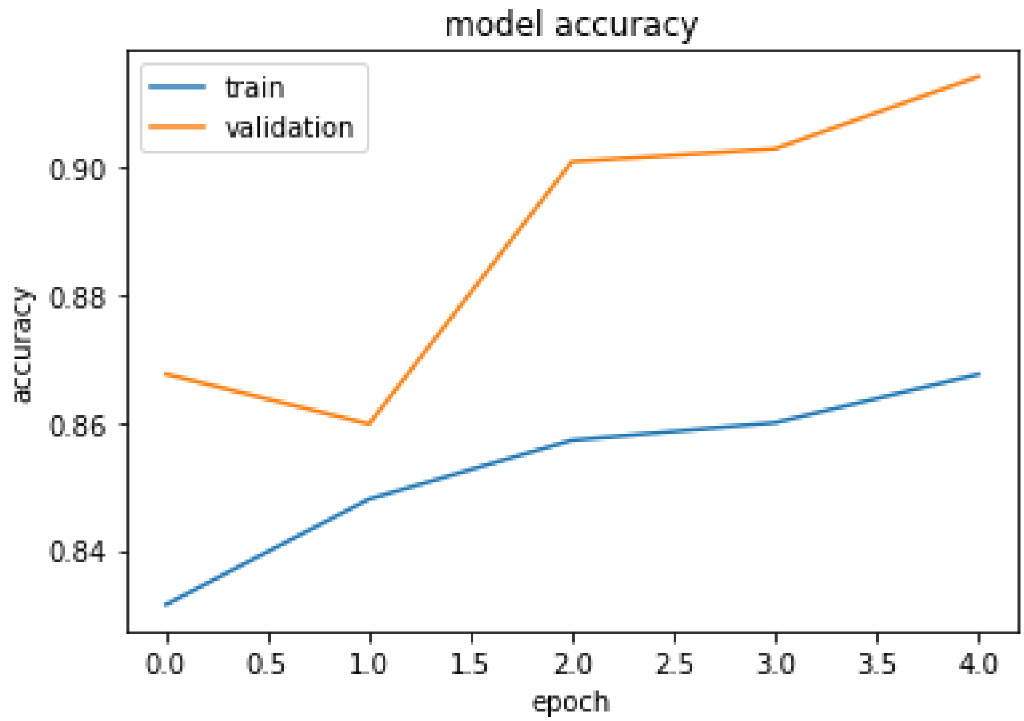
```
dropout_8 (Dropout)          (None, 576)              0
_________________________________________________________________
dense_28 (Dense)             (None, 128)              73856
_________________________________________________________________
dropout_9 (Dropout)          (None, 128)              0
_________________________________________________________________
dense_29 (Dense)             (None, 10)               1290
=================================================================
Total params: 77,754
Trainable params: 77,690
Non-trainable params: 64
_________________________________________________________________
```

In [131]:
```
checkpoint_filepath = 'checkpoint_cnn)'
save_model_checkpoint_CNN = ModelCheckpoint(checkpoint_filepath, monitor='val_accurac
                                            save_best_only=True, save_weights_on


early_stopping_CNN = EarlyStopping(monitor='val_accuracy', patience=3)
```

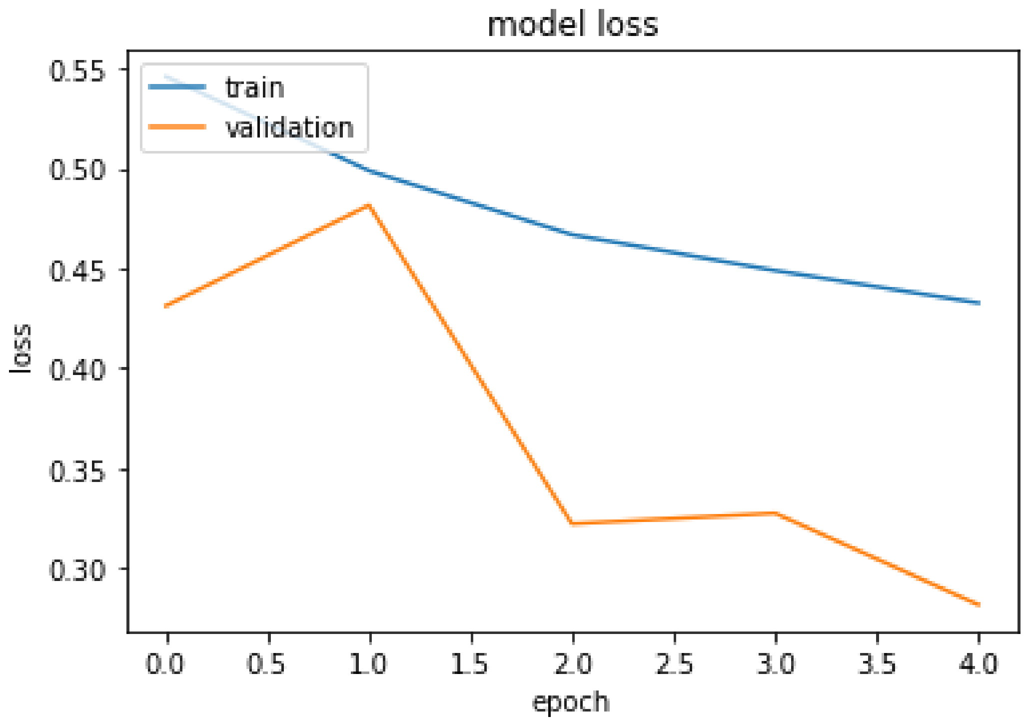
In [132]:
```
history = model.fit(x_train_grey, y_train_binarised,validation_data=(X_val, y_val),
                    epochs=5,callbacks=[save_model_checkpoint_CNN,early_stopping_CNN]
                    verbose = 1, batch_size=64, validation_freq=1)
```

```
Train on 73257 samples, validate on 10989 samples
Epoch 1/5
73257/73257 [==============================] - 311s 4ms/sample - loss: 0.5459 - accuracy: 0.83
Epoch 2/5
73257/73257 [==============================] - 298s 4ms/sample - loss: 0.4988 - accuracy: 0.84
Epoch 3/5
73257/73257 [==============================] - 299s 4ms/sample - loss: 0.4667 - accuracy: 0.85
Epoch 4/5
73257/73257 [==============================] - 299s 4ms/sample - loss: 0.4488 - accuracy: 0.86
Epoch 5/5
73257/73257 [==============================] - 299s 4ms/sample - loss: 0.4326 - accuracy: 0.86
```

In [135]:
```
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```




```
In [136]: # summarize history for loss
          plt.plot(history.history['loss'])
          plt.plot(history.history['val_loss'])
          plt.title('model loss')
          plt.ylabel('loss')
          plt.xlabel('epoch')
          plt.legend(['train', 'validation'], loc='upper left')
          plt.show()
```




```
In [137]: # * Compute and display the loss and accuracy of the trained model on the test set.
          scores = model.evaluate(x_test_grey, y_test_binarised, verbose=0)
          print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
          print("loss: " ,  ( scores[0]))
```

```
accuracy: 88.61%
loss:  0.37976543343389557
```

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 [196]: # inialize the MLP Classifer
          mlp_model = MLPClassifer(x_train_grey[1].shape)
          mlp_model.load_weights('/tmp/checkpoint')
```

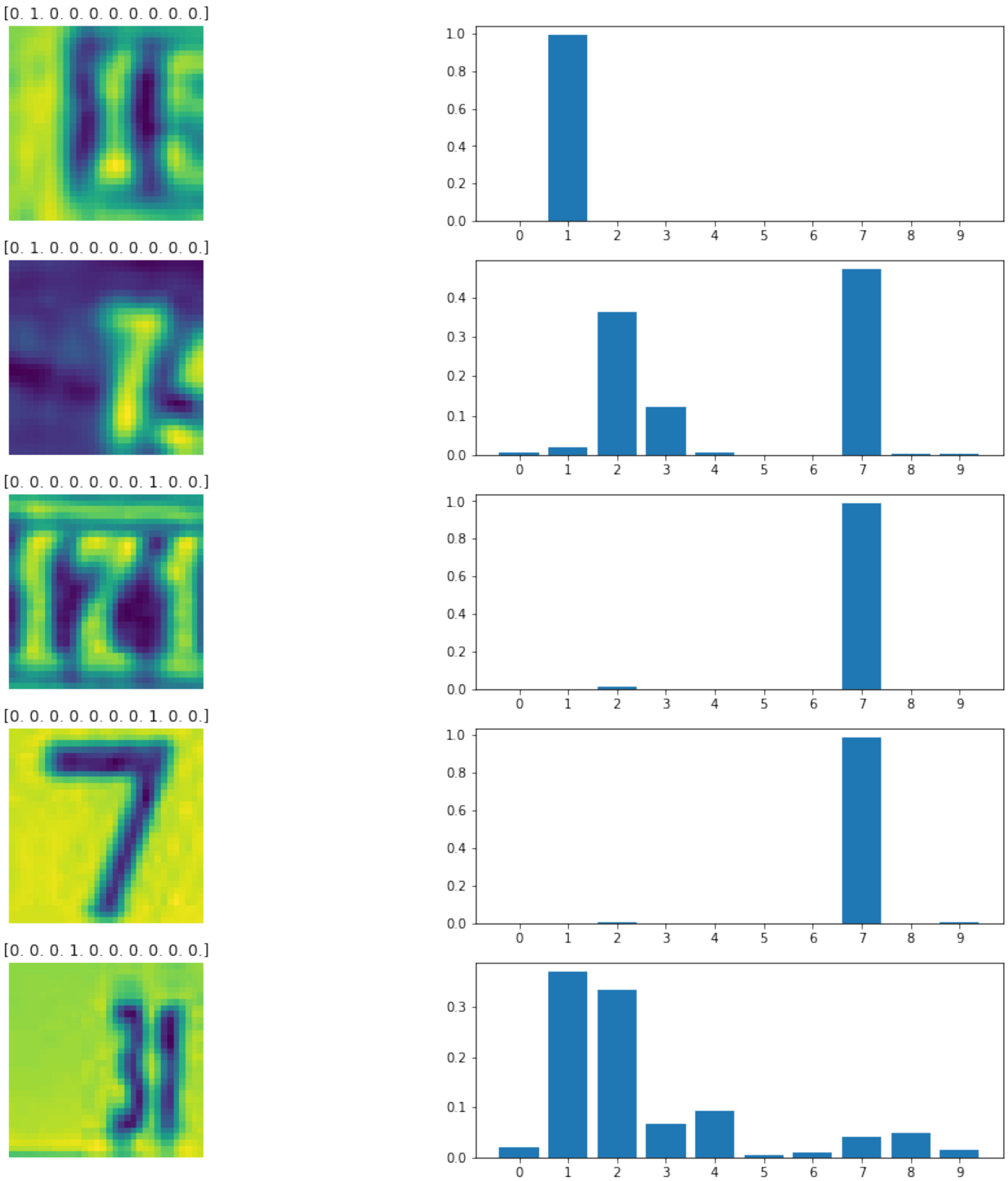
```
Out[196]: <tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7fc20c7a3a20>
```

```
In [197]: # inialize the CNN Classifer
          cnn_model = cnn_classifer(x_train_grey[1].shape)
          cnn_model.load_weights('checkpoint_cnn)')
```

Out[197]: <tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7fc20c9ebfd0>

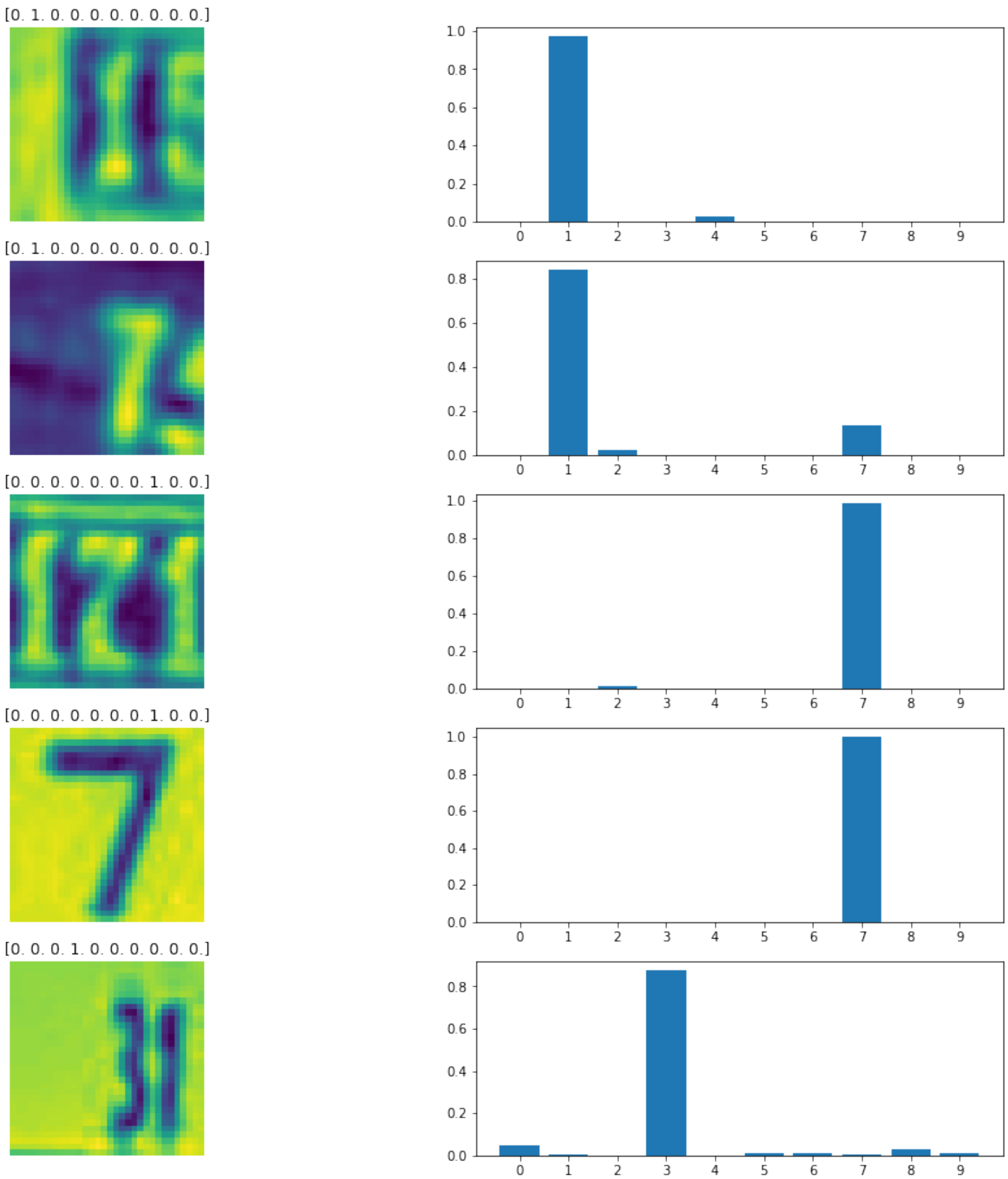
In [198]:
```
# selecting 5 random images from the test set and displaying them in a figure - MLP
index_images = list(np.random.randint(0, x_test_grey.shape[0], [5]))
```

In [199]:
```
#make prediction using the loaded models
predictions_mlp_model = mlp_model.predict(x_test_grey[index_images])
# showing MLP results
fig = plt.figure(figsize=(16, 16))
for i in range(5):
    fig.add_subplot(5, 2, 1+i*2)
    plt.axis('off')
    plt.imshow(x_test_grey[index_images[i],:,:,:].squeeze(axis=2))
    plt.title(y_test_binarised[index_images[i]]%10)
    fig.add_subplot(5, 2, (i+1)*2)
    pred = list(predictions_mlp_model[i])
    plt.bar(list(np.arange(10)), pred)
    plt.xticks(list(np.arange(10)))
plt.show()
```




```
In [200]: predictions_cnn_model = cnn_model.predict(x_test_grey[index_images])
          # showing CNN results
          fig = plt.figure(figsize=(16, 16))
          for i in range(5):
              fig.add_subplot(5, 2, 1+i*2)
              plt.axis('off')
              plt.imshow(x_test_grey[index_images[i],:,:,:].squeeze(axis=2))
              plt.title(y_test_binarised[index_images[i]]%10)
              fig.add_subplot(5, 2, (i+1)*2)
```

```
        pred = list(predictions_cnn_model[i])
        plt.bar(list(np.arange(10)), pred)
        plt.xticks(list(np.arange(10)))
    plt.show()
```




```
In [ ]:
```