Capstone_Project

October 26, 2020

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 (you could download the notebook with File -> Download .ipynb, open the notebook locally, and then File -> Download as -> PDF via LaTeX), and 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 [2]: import tensorflow as tf
        from scipy.io import loadmat

        import numpy as np
        import matplotlib.pyplot as plt
```

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.

The train and test datasets required for this project can be downloaded from here and here. Once unzipped, you will have two files: `train_32x32.mat` and `test_32x32.mat`. You should store these files in Drive for use in this Colab notebook.

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 [3]:
```
# Run this cell to connect to your Drive folder

from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

In [4]:
```
# Load the dataset from Drive folder

train = loadmat("gdrive/My Drive/Colab Notebooks/TensorFlow2/course 1/week 5/data/trai
test = loadmat("gdrive/My Drive/Colab Notebooks/TensorFlow2/course 1/week 5/data/test_
```

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

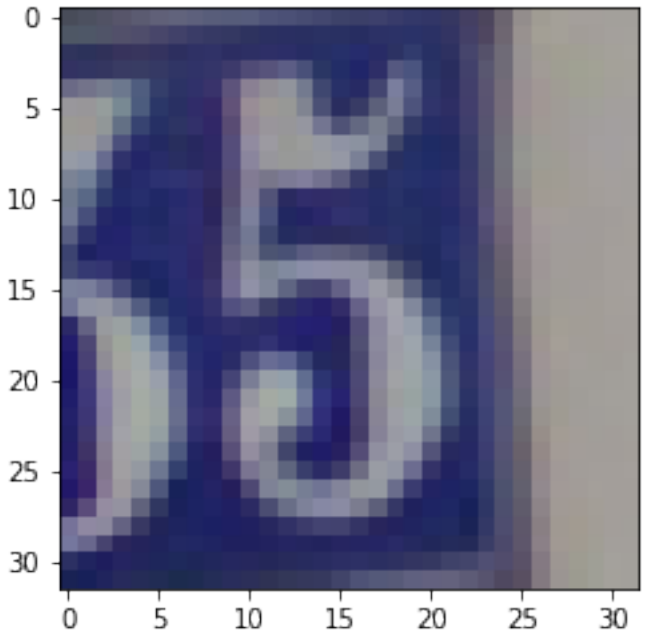
- Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.
- Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.
- Convert the training and test images to grayscale by taking 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 [5]:
```
#extract training and testing data + normalizing:

x_train = train['X']
x_train = np.moveaxis(x_train, -1, 0) / 255
y_train = train['y']

x_test = test['X']
x_test = np.moveaxis(x_test, -1, 0) / 255
y_test = test['y']

#correcting labels: 10 -> 0
y_train = np.where(y_train == 10, 0, y_train)
```

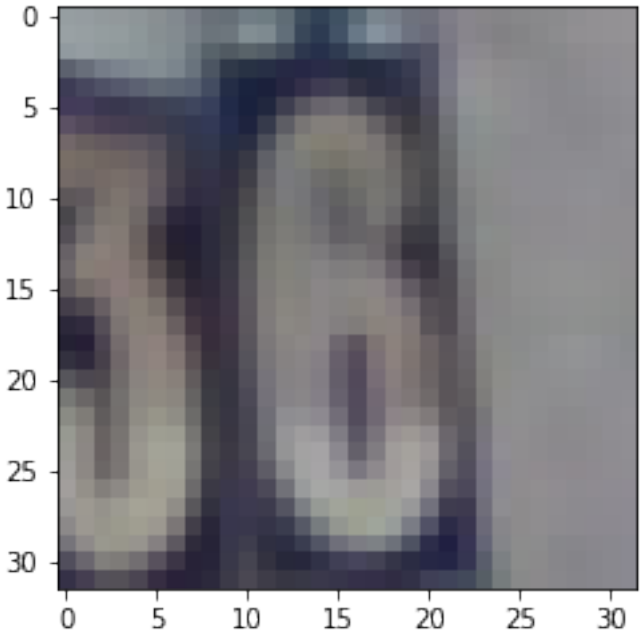
```
        y_test = np.where(y_test == 10, 0, y_test)

        print(f"x_train shape: {x_train.shape}")
        print(f"y_train shape: {y_train.shape}")
        print(f"x_test shape: {x_test.shape}")
        print(f"y_test shape: {y_test.shape}")
```

```
x_train shape: (73257, 32, 32, 3)
y_train shape: (73257, 1)
x_test shape: (26032, 32, 32, 3)
y_test shape: (26032, 1)
```

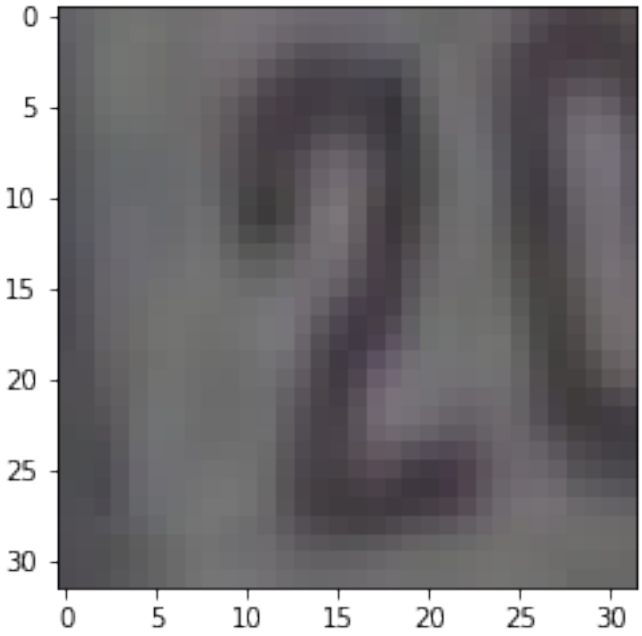
In [6]:
```
#display 10 random images and their labels from the dataset

        for i in range(10):
          rand_idx = np.random.choice(x_train.shape[0])
          img = x_train[rand_idx]
          plt.imshow(img)
          plt.show()
          print(f"Label: {y_train [rand_idx]}")
```



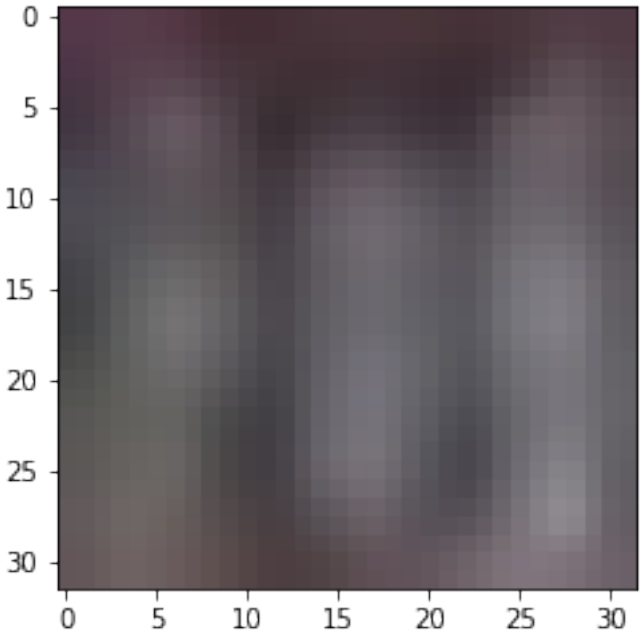

```
Label: [5]
```



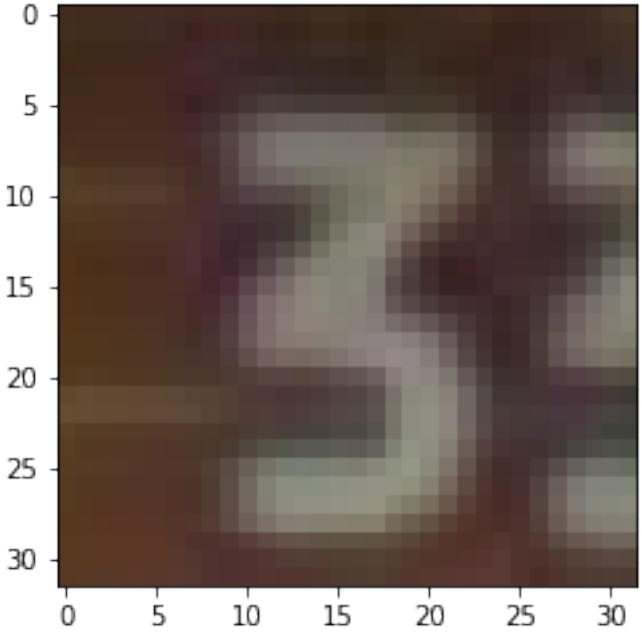

```
Label: [6]
```



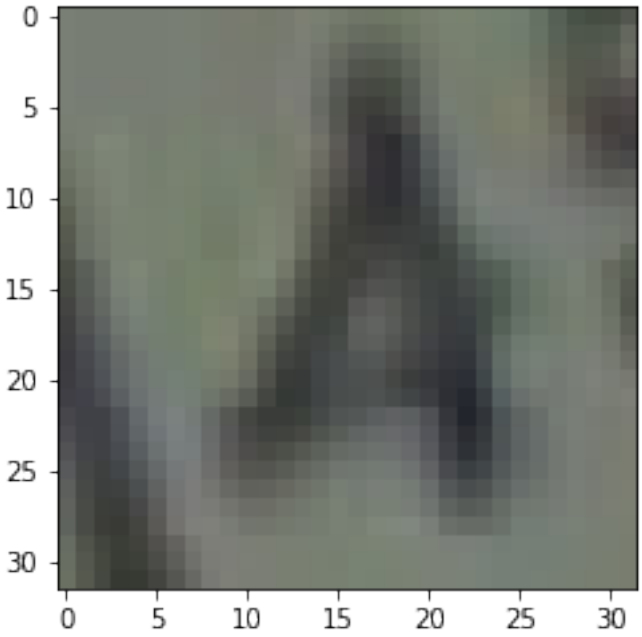

```
Label: [2]
```



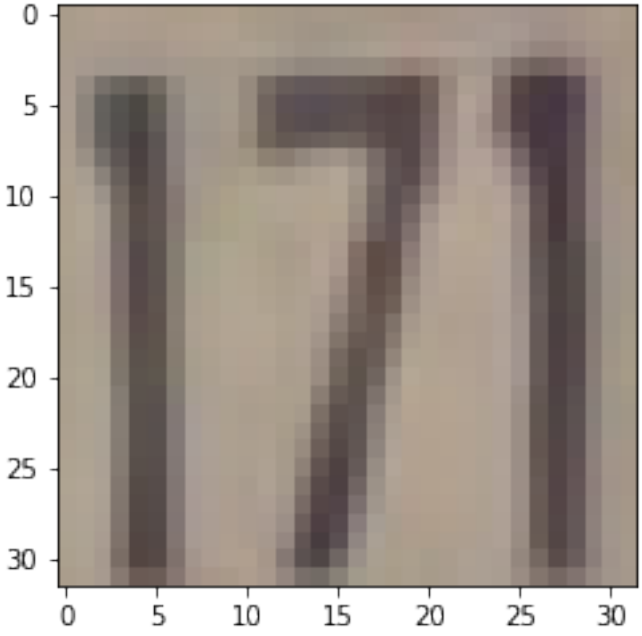

```
Label: [0]
```



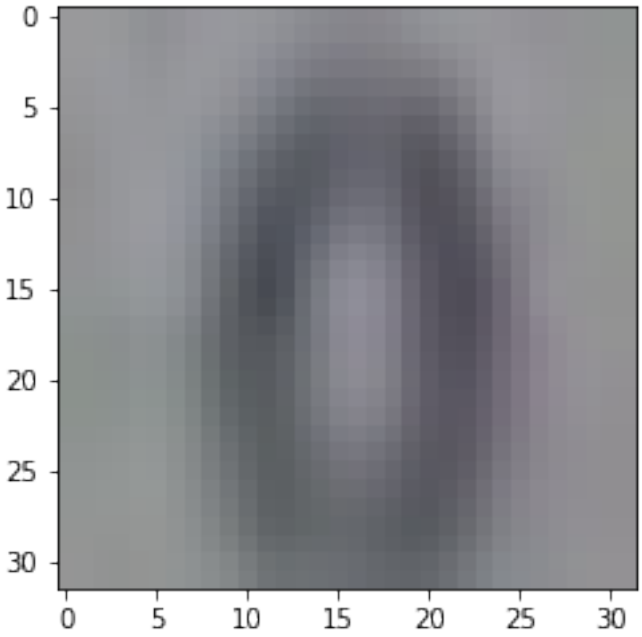

```
Label: [3]
```



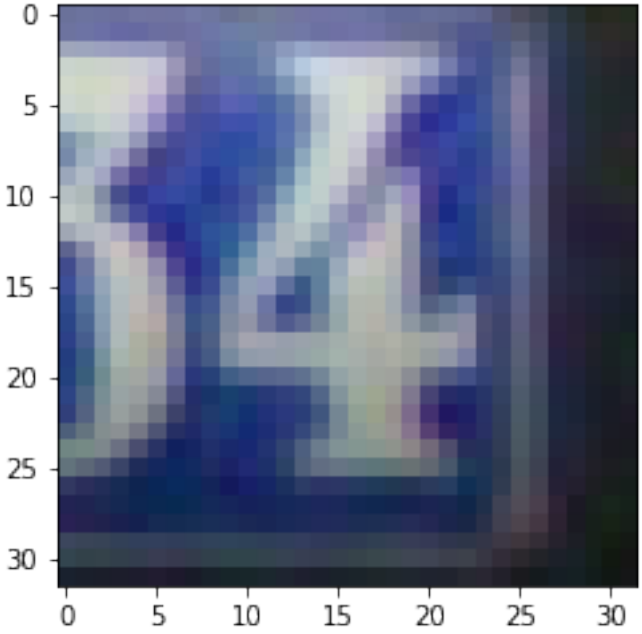

```
Label: [4]
```



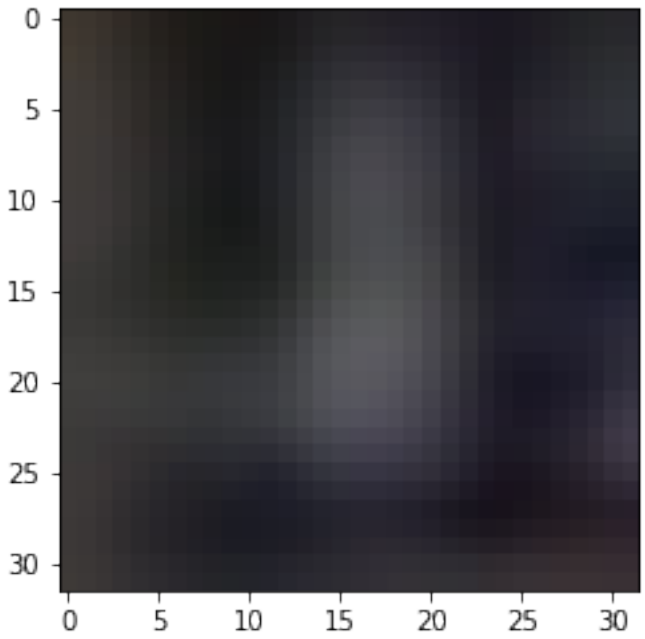

```
Label: [7]
```




```
Label: [0]
```




```
Label: [4]
```

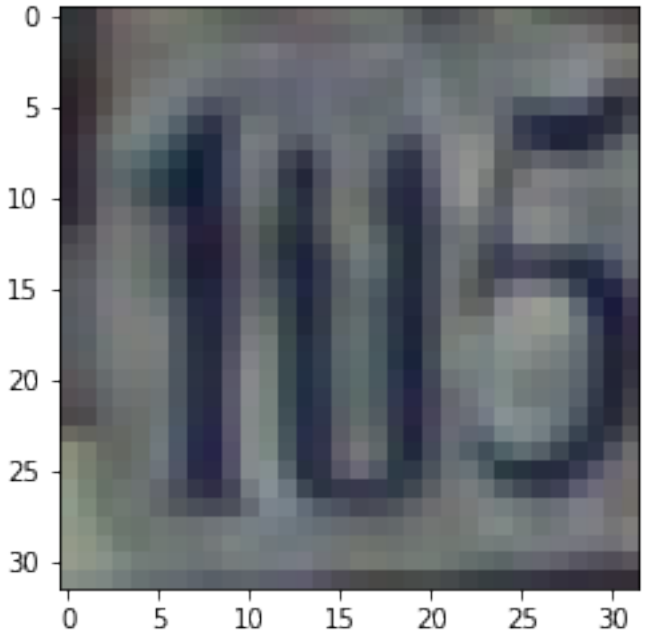



```
Label: [1]
```

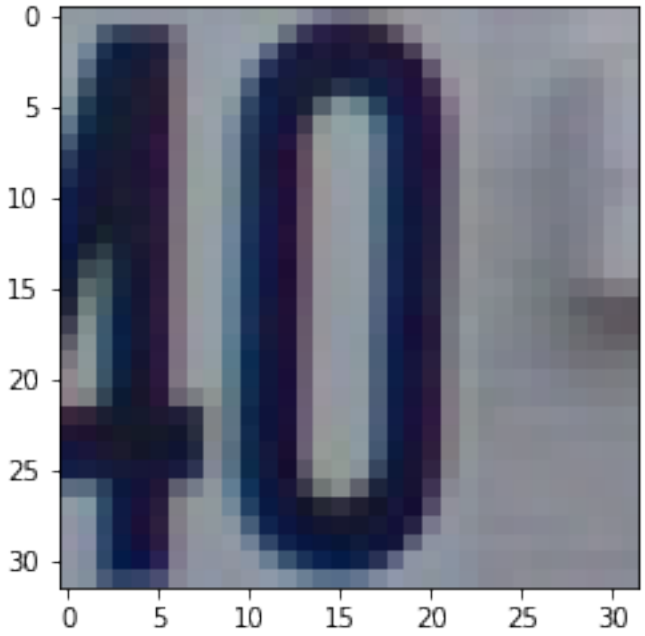
In [7]:
```
#convert to gray scale:

        x_train_gscaled = np.average(x_train,axis = -1)
        x_test_gscaled = np.average(x_test,axis = -1)

        #adding a dummy dimention:
        x_train_gscaled = x_train_gscaled[..., np.newaxis]
        x_test_gscaled = x_test_gscaled[..., np.newaxis]

        print(f"x_train_gscaled shape: {x_train_gscaled.shape}")
        print(f"x_test_gscaled shape: {x_test_gscaled.shape}")
```

```
x_train_gscaled shape: (73257, 32, 32, 1)
x_test_gscaled shape: (26032, 32, 32, 1)
```

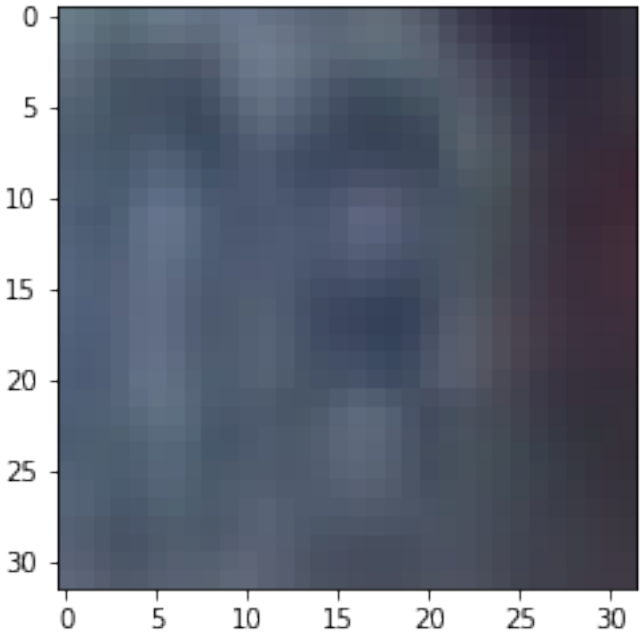
In [8]:
```
#display 10 random images and their labels from the gscaled dataset

        for i in range(10):
          rand_idx = np.random.choice(x_train_gscaled.shape[0])
          img = x_train[rand_idx]
          plt.imshow(img, cmap="gray", vmin=0, vmax= 1)
          plt.show()
          print(f"Label: {y_train[rand_idx]}")
```



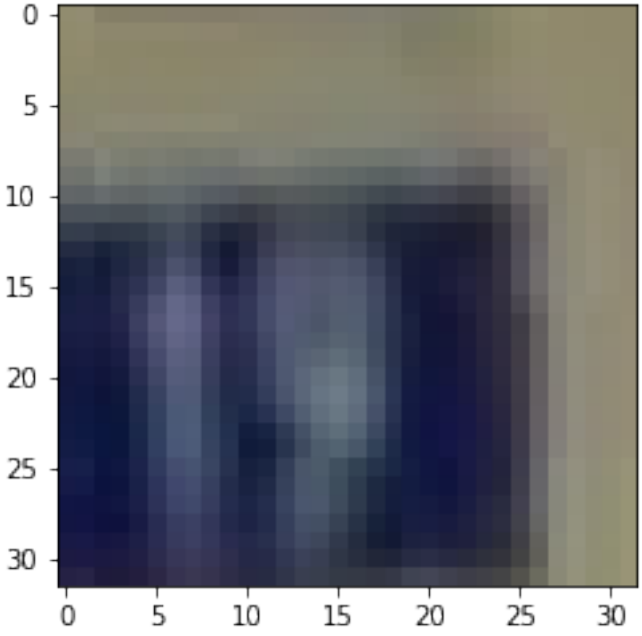

```
Label: [0]
```



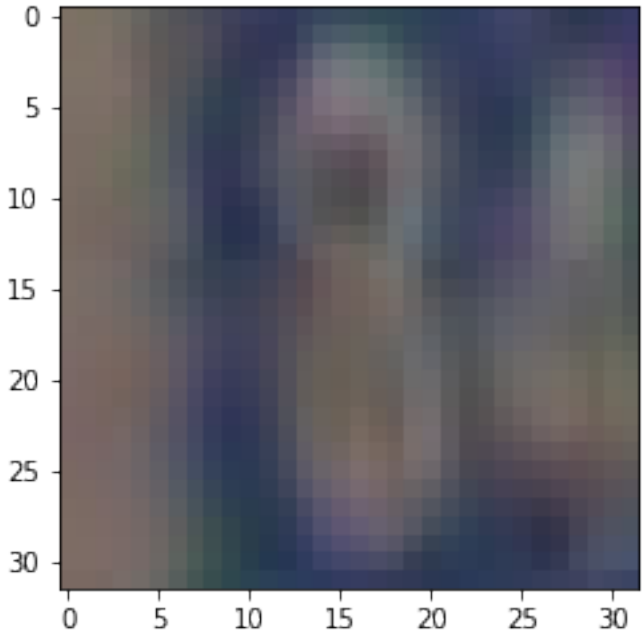

```
Label: [0]
```



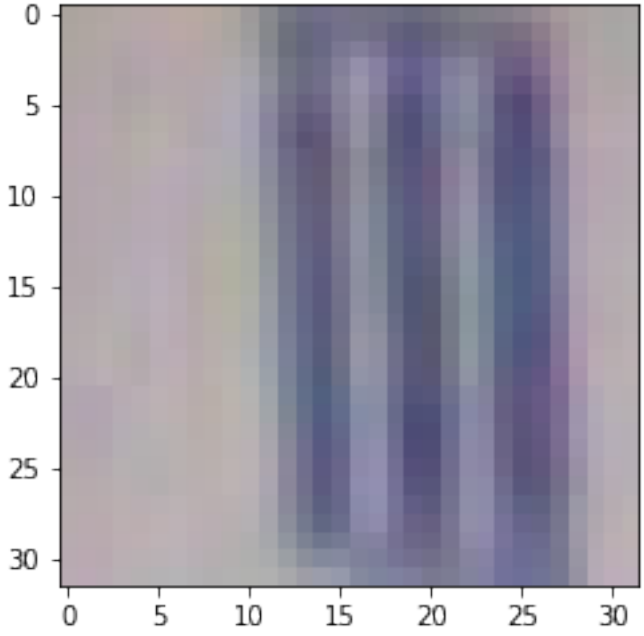

```
Label: [8]
```



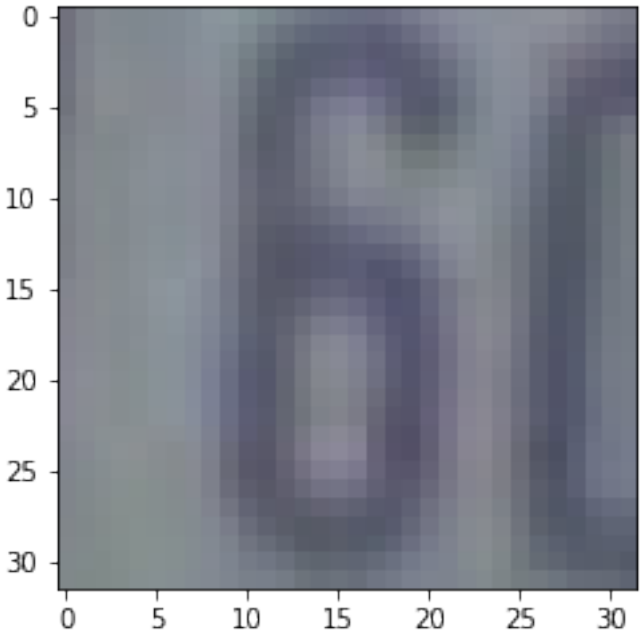

```
Label: [9]
```



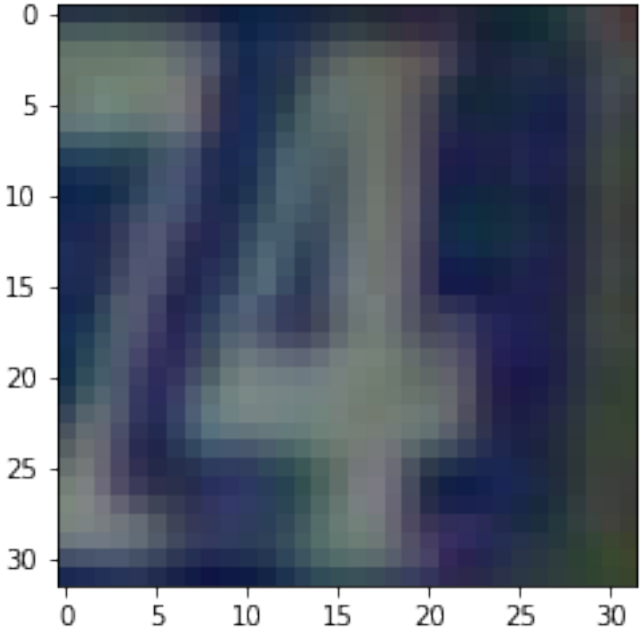

```
Label: [8]
```



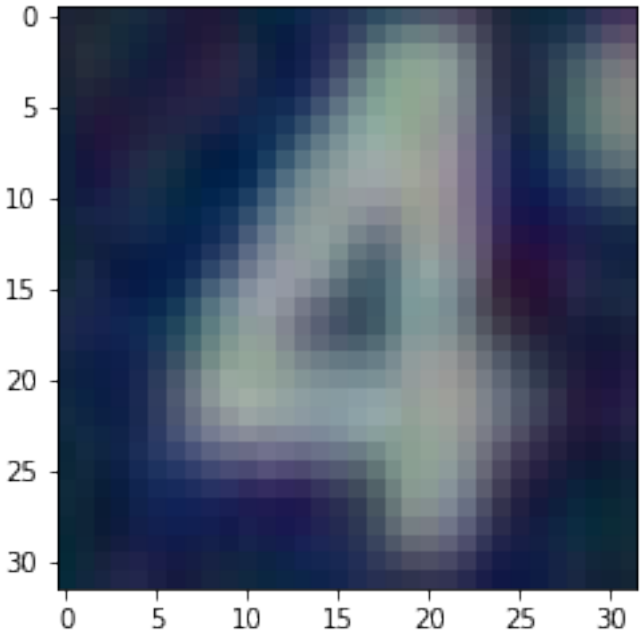

```
Label: [1]
```



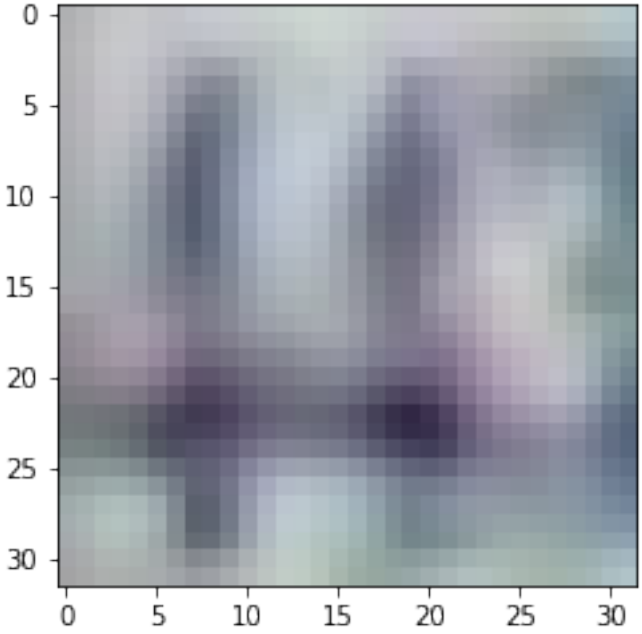

```
Label: [6]
```




```
Label: [4]
```




```
Label: [4]
```




```
Label: [4]
```

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 [9]: #imports for model:
        from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, BatchNormali
        from tensorflow.keras.models import Sequential
        from tensorflow.keras import regularizers

In [10]: #building the MLP model function:

         def get_model(input_shape, wd):
           #input_shape - the shape of our img
           #wd - weight decay parameter for l2 regularization

           model = Sequential([
                               Flatten(input_shape = input_shape), #flattening the img
                               Dense(1024, kernel_regularizer= regularizers.l2(wd),
                                     activation='relu'),
                               Dense(512, kernel_regularizer= regularizers.l2(wd),
                                     activation='relu'),
                               Dense(512, kernel_regularizer= regularizers.l2(wd),
                                     activation='relu'),
                               Dense(10, activation='softmax')
           ])

           return model

In [11]: #defining the input shape:
         input_shape = x_train_gscaled[0].shape

In [12]: #create the model & print summary:
         model = get_model(input_shape,1e-5)
         model.summary()

Model: "sequential"
_________________________________________________________________
```

```
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 1024)              1049600
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
dense_2 (Dense)              (None, 512)               262656
_________________________________________________________________
dense_3 (Dense)              (None, 10)                5130
=================================================================
Total params: 1,842,186
Trainable params: 1,842,186
Non-trainable params: 0
_________________________________________________________________
```

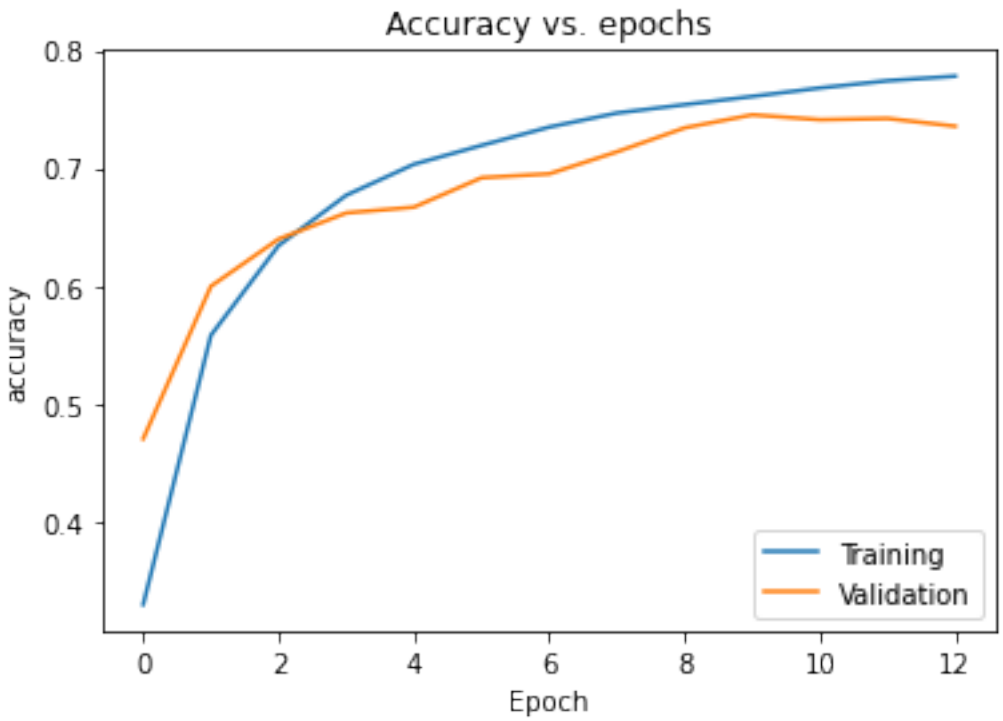
```
In [13]: #compiling the model:
         model.compile(optimizer= 'adam', loss= 'sparse_categorical_crossentropy',
                       metrics=['accuracy'])

In [14]: #imports for callbacks
         from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping

In [1]: #creating callbacks for training:

        def get_checkpoint_best_only(path):
          #path - the path for where to save model weightss
          checkpoint = ModelCheckpoint(filepath = path, save_weights_only = True,
                                       save_best_only = True, save_freq = 'epoch',
                                          monitor = 'val_accuracy', verbose = 1)
          return checkpoint

        def get_earlystop():
          #monitoring the validation set accuracy
          early_stop = EarlyStopping(monitor = 'val_accuracy', patience = 3, mode = 'max')
          return early_stop

In [16]: #getting the callbacks:
         checkpoint = get_checkpoint_best_only("gdrive/My Drive/Colab Notebooks/TensorFlow2/cou
         early_stop = get_earlystop()

In [17]: #training:
         history = model.fit(x = x_train_gscaled, y = y_train, batch_size=64 ,
                             epochs= 30, validation_data=(x_test_gscaled, y_test),
                             callbacks= [checkpoint, early_stop])
```

```
Epoch 1/30
1145/1145 [==============================] - ETA: 0s - loss: 1.8973 - accuracy: 0.3293
```

```
Epoch 00001: val_accuracy improved from -inf to 0.47008, saving model to gdrive/My Drive/Colab
1145/1145 [==============================] - 38s 33ms/step - loss: 1.8973 - accuracy: 0.3293 -
Epoch 2/30
1144/1145 [============================>.] - ETA: 0s - loss: 1.3471 - accuracy: 0.5579
Epoch 00002: val_accuracy improved from 0.47008 to 0.59965, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 37s 32ms/step - loss: 1.3470 - accuracy: 0.5580 -
Epoch 3/30
1145/1145 [==============================] - ETA: 0s - loss: 1.1494 - accuracy: 0.6342
Epoch 00003: val_accuracy improved from 0.59965 to 0.63975, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 37s 32ms/step - loss: 1.1494 - accuracy: 0.6342 -
Epoch 4/30
1144/1145 [============================>.] - ETA: 0s - loss: 1.0309 - accuracy: 0.6770
Epoch 00004: val_accuracy improved from 0.63975 to 0.66195, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 37s 33ms/step - loss: 1.0309 - accuracy: 0.6770 -
Epoch 5/30
1145/1145 [==============================] - ETA: 0s - loss: 0.9507 - accuracy: 0.7033
Epoch 00005: val_accuracy improved from 0.66195 to 0.66683, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 39s 34ms/step - loss: 0.9507 - accuracy: 0.7033 -
Epoch 6/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.8996 - accuracy: 0.7194
Epoch 00006: val_accuracy improved from 0.66683 to 0.69188, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 38s 33ms/step - loss: 0.8997 - accuracy: 0.7194 -
Epoch 7/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.8489 - accuracy: 0.7349
Epoch 00007: val_accuracy improved from 0.69188 to 0.69518, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 39s 34ms/step - loss: 0.8489 - accuracy: 0.7349 -
Epoch 8/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.8133 - accuracy: 0.7468
Epoch 00008: val_accuracy improved from 0.69518 to 0.71389, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 38s 33ms/step - loss: 0.8132 - accuracy: 0.7469 -
Epoch 9/30
1145/1145 [==============================] - ETA: 0s - loss: 0.7901 - accuracy: 0.7540
Epoch 00009: val_accuracy improved from 0.71389 to 0.73425, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 38s 33ms/step - loss: 0.7901 - accuracy: 0.7540 -
Epoch 10/30
1145/1145 [==============================] - ETA: 0s - loss: 0.7683 - accuracy: 0.7609
Epoch 00010: val_accuracy improved from 0.73425 to 0.74531, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 38s 33ms/step - loss: 0.7683 - accuracy: 0.7609 -
Epoch 11/30
1145/1145 [==============================] - ETA: 0s - loss: 0.7460 - accuracy: 0.7681
Epoch 00011: val_accuracy did not improve from 0.74531
1145/1145 [==============================] - 38s 33ms/step - loss: 0.7460 - accuracy: 0.7681 -
Epoch 12/30
1145/1145 [==============================] - ETA: 0s - loss: 0.7278 - accuracy: 0.7743
Epoch 00012: val_accuracy did not improve from 0.74531
1145/1145 [==============================] - 38s 33ms/step - loss: 0.7278 - accuracy: 0.7743 -
Epoch 13/30
1145/1145 [==============================] - ETA: 0s - loss: 0.7173 - accuracy: 0.7782
```

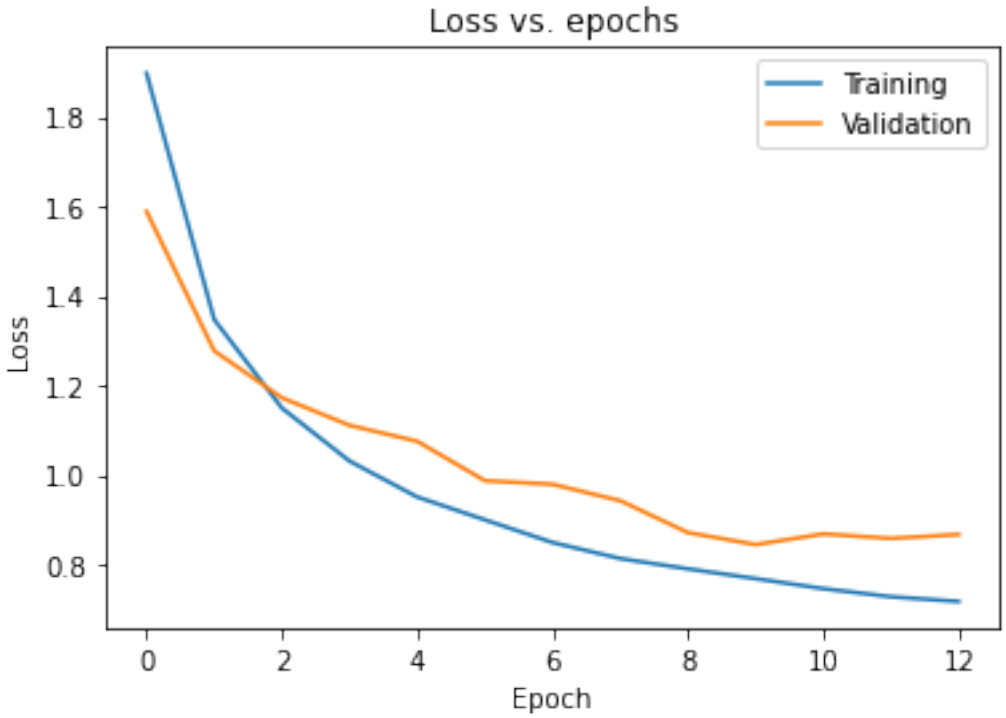
```
Epoch 00013: val_accuracy did not improve from 0.74531
1145/1145 [==============================] - 39s 34ms/step - loss: 0.7173 - accuracy: 0.7782 -
```

In [18]:
```
#plot accuracy vs epoch:

try:
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
except KeyError:
    plt.plot(history.history['acc'])
    plt.plot(history.history['val_acc'])
plt.title('Accuracy vs. epochs')
plt.ylabel('accuracy')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='lower right')
plt.show()
```



In [19]:
```
#plot loss vs epoch:

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]: #evaluating the trained model:
         def evaluate_model(model, scaled_test_images, test_labels):
             test_loss, test_accuracy = model.evaluate(scaled_test_images,test_labels, verbose=
             return (test_loss, test_accuracy)

In [21]: #displaying test loss and accuracy:

         test_loss, test_accuracy = evaluate_model(model, x_test_gscaled, y_test)
         print(f"Test loss: {test_loss}")
         print(f"Test accuracy: {test_accuracy}")

814/814 - 6s - loss: 0.8669 - accuracy: 0.7356
Test loss: 0.8669062256813049
Test accuracy: 0.735594630241394
```

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 [45]:
```
#build CNN model:

def get_cnn_model(input_shape, wd, rate):
  model = Sequential([
                      Conv2D(16, (3,3), activation= 'relu',
                             input_shape = input_shape, name = "conv_1"),
                      BatchNormalization(name= 'batch_norm_1'),
                      MaxPooling2D((2, 2), name = "max_pool_1"),
                      Conv2D(32, (3,3), activation= 'relu',
                             input_shape = input_shape, name = "conv_2"),
                      BatchNormalization(name= 'batch_norm_2'),
                      MaxPooling2D((2, 2), name = "max_pool_2"),
                      Flatten(name = "flatten"),
                      Dense(256, activation= 'relu',
                            kernel_regularizer= regularizers.l1(wd), name = "dense_1"),
                      Dropout(rate),
                      Dense(256, activation= 'relu',
                            kernel_regularizer= regularizers.l1(wd), name = "dense_2"),
                      Dropout(rate),
                      Dense(10, activation= 'softmax', name = "dense_3")
  ])

  return model
```

In [46]:
```
#create the model & print summary:
model = get_cnn_model(input_shape, 1e-3, 0.15)
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv_1 (Conv2D)              (None, 30, 30, 16)        160
_________________________________________________________________
batch_norm_1 (BatchNormaliza (None, 30, 30, 16)        64
```

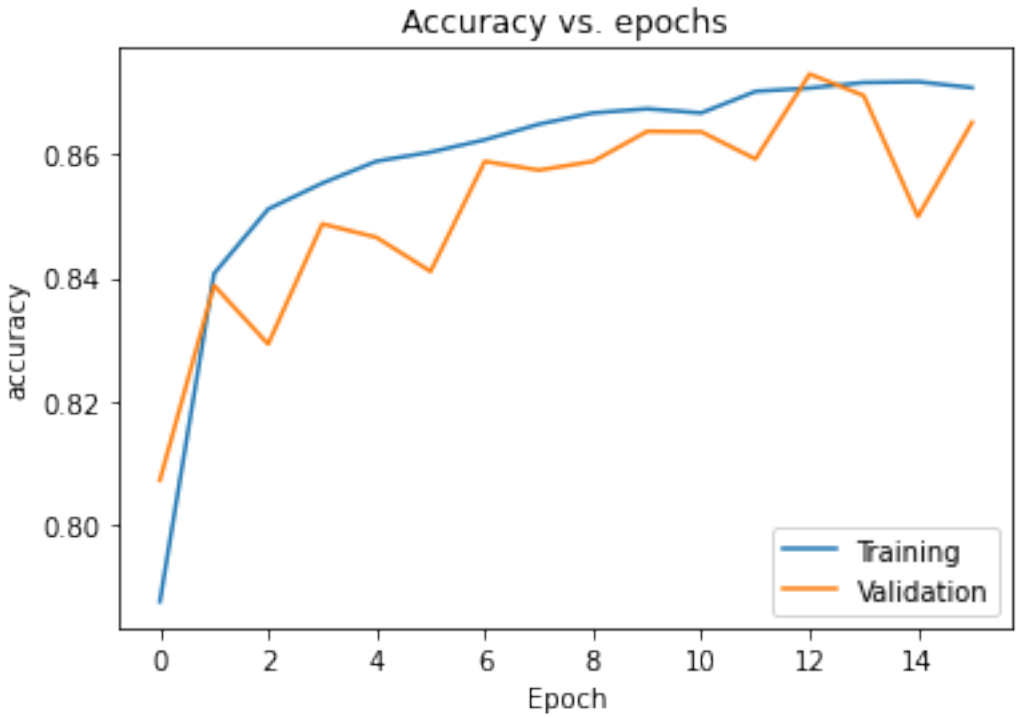
```
_________________________________________________________________
max_pool_1 (MaxPooling2D)    (None, 15, 15, 16)        0
_________________________________________________________________
conv_2 (Conv2D)              (None, 13, 13, 32)        4640
_________________________________________________________________
batch_norm_2 (BatchNormaliza (None, 13, 13, 32)        128
_________________________________________________________________
max_pool_2 (MaxPooling2D)    (None, 6, 6, 32)          0
_________________________________________________________________
flatten (Flatten)            (None, 1152)              0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               295168
_________________________________________________________________
dropout_10 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               65792
_________________________________________________________________
dropout_11 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 10)                2570
=================================================================
Total params: 368,522
Trainable params: 368,426
Non-trainable params: 96
_________________________________________________________________
```

```
In [47]: #compiling the model:
         model.compile(optimizer= 'adam', loss= 'sparse_categorical_crossentropy'
                       , metrics=['accuracy'])

In [25]: #imports for callbacks
         from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping

In [26]: #getting the callbacks: (same callbacks as before)
         checkpoint = get_checkpoint_best_only("gdrive/My Drive/Colab Notebooks/TensorFlow2/cou
         early_stop = get_earlystop()

In [48]: #training
         history = model.fit(x = x_train_gscaled, y = y_train, batch_size=64 ,
                             epochs= 30, validation_data=(x_test_gscaled, y_test),
                             callbacks= [checkpoint, early_stop])

Epoch 1/30
1144/1145 [============================>.] - ETA: 0s - loss: 3.0686 - accuracy: 0.7874
Epoch 00001: val_accuracy did not improve from 0.83985
1145/1145 [==============================] - 75s 66ms/step - loss: 3.0675 - accuracy: 0.7874 -
Epoch 2/30
1144/1145 [============================>.] - ETA: 0s - loss: 1.0539 - accuracy: 0.8406
```

```
Epoch 00002: val_accuracy did not improve from 0.83985
1145/1145 [==============================] - 74s 64ms/step - loss: 1.0538 - accuracy: 0.8406 -
Epoch 3/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9803 - accuracy: 0.8511
Epoch 00003: val_accuracy did not improve from 0.83985
1145/1145 [==============================] - 73s 64ms/step - loss: 0.9802 - accuracy: 0.8511 -
Epoch 4/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9640 - accuracy: 0.8553
Epoch 00004: val_accuracy improved from 0.83985 to 0.84872, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 74s 64ms/step - loss: 0.9640 - accuracy: 0.8553 -
Epoch 5/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9464 - accuracy: 0.8588
Epoch 00005: val_accuracy did not improve from 0.84872
1145/1145 [==============================] - 74s 65ms/step - loss: 0.9463 - accuracy: 0.8589 -
Epoch 6/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9356 - accuracy: 0.8604
Epoch 00006: val_accuracy did not improve from 0.84872
1145/1145 [==============================] - 74s 64ms/step - loss: 0.9356 - accuracy: 0.8604 -
Epoch 7/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9332 - accuracy: 0.8623
Epoch 00007: val_accuracy improved from 0.84872 to 0.85887, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 73s 64ms/step - loss: 0.9331 - accuracy: 0.8624 -
Epoch 8/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9266 - accuracy: 0.8650
Epoch 00008: val_accuracy did not improve from 0.85887
1145/1145 [==============================] - 73s 64ms/step - loss: 0.9268 - accuracy: 0.8649 -
Epoch 9/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9160 - accuracy: 0.8667
Epoch 00009: val_accuracy did not improve from 0.85887
1145/1145 [==============================] - 74s 64ms/step - loss: 0.9159 - accuracy: 0.8667 -
Epoch 10/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9081 - accuracy: 0.8674
Epoch 00010: val_accuracy improved from 0.85887 to 0.86374, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 74s 64ms/step - loss: 0.9082 - accuracy: 0.8674 -
Epoch 11/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9372 - accuracy: 0.8668
Epoch 00011: val_accuracy did not improve from 0.86374
1145/1145 [==============================] - 73s 64ms/step - loss: 0.9373 - accuracy: 0.8667 -
Epoch 12/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9235 - accuracy: 0.8703
Epoch 00012: val_accuracy did not improve from 0.86374
1145/1145 [==============================] - 74s 64ms/step - loss: 0.9236 - accuracy: 0.8702 -
Epoch 13/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.8968 - accuracy: 0.8708
Epoch 00013: val_accuracy improved from 0.86374 to 0.87304, saving model to gdrive/My Drive/Col
1145/1145 [==============================] - 74s 64ms/step - loss: 0.8967 - accuracy: 0.8708 -
Epoch 14/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9003 - accuracy: 0.8717
```

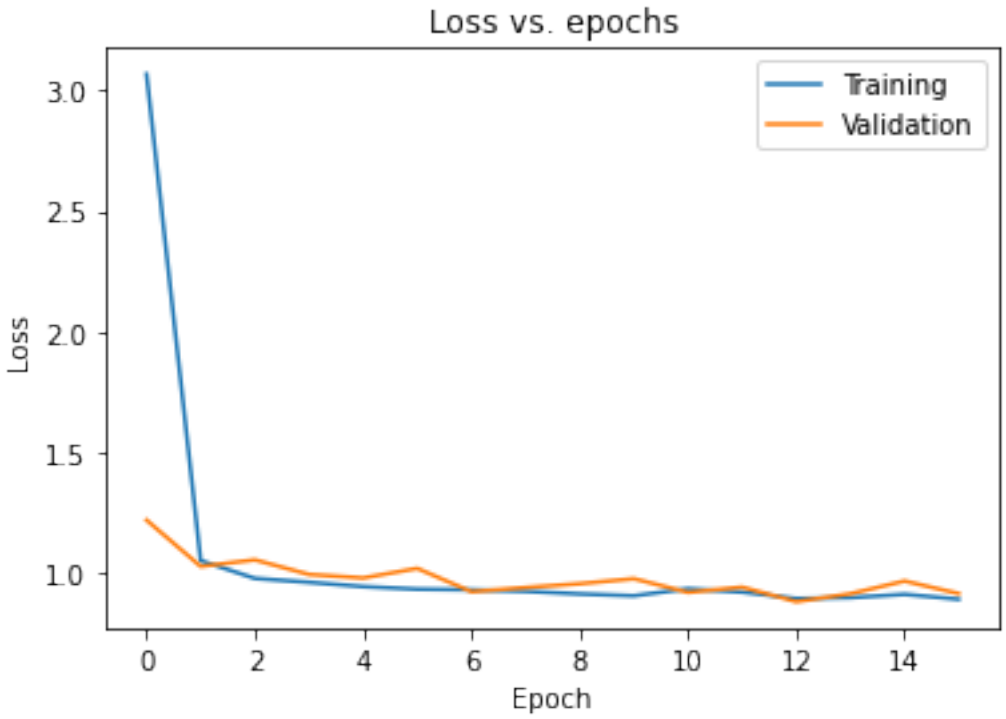
```
Epoch 00014: val_accuracy did not improve from 0.87304
1145/1145 [==============================] - 74s 65ms/step - loss: 0.9004 - accuracy: 0.8717 -
Epoch 15/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.9142 - accuracy: 0.8718
Epoch 00015: val_accuracy did not improve from 0.87304
1145/1145 [==============================] - 73s 64ms/step - loss: 0.9142 - accuracy: 0.8718 -
Epoch 16/30
1144/1145 [============================>.] - ETA: 0s - loss: 0.8940 - accuracy: 0.8708
Epoch 00016: val_accuracy did not improve from 0.87304
1145/1145 [==============================] - 73s 64ms/step - loss: 0.8940 - accuracy: 0.8708 -
```

In [49]:
```
#plot accuracy vs epoch:

try:
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
except KeyError:
    plt.plot(history.history['acc'])
    plt.plot(history.history['val_acc'])
plt.title('Accuracy vs. epochs')
plt.ylabel('accuracy')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='lower right')
plt.show()
```



In [50]: *#plot loss vs epoch:*

```
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 [51]: *#displaying test loss and accuracy: (using same function from mlp)*

```
test_loss, test_accuracy = evaluate_model(model, x_test_gscaled, y_test)
print(f"Test loss: {test_loss}")
print(f"Test accuracy: {test_accuracy}")
```

```
814/814 - 7s - loss: 0.9174 - accuracy: 0.8652
Test loss: 0.9173752665519714
Test accuracy: 0.8652043342590332
```

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 [52]:
```
#load weights function:

def load_model_weights(model, path):
  model.load_weights(path)
```

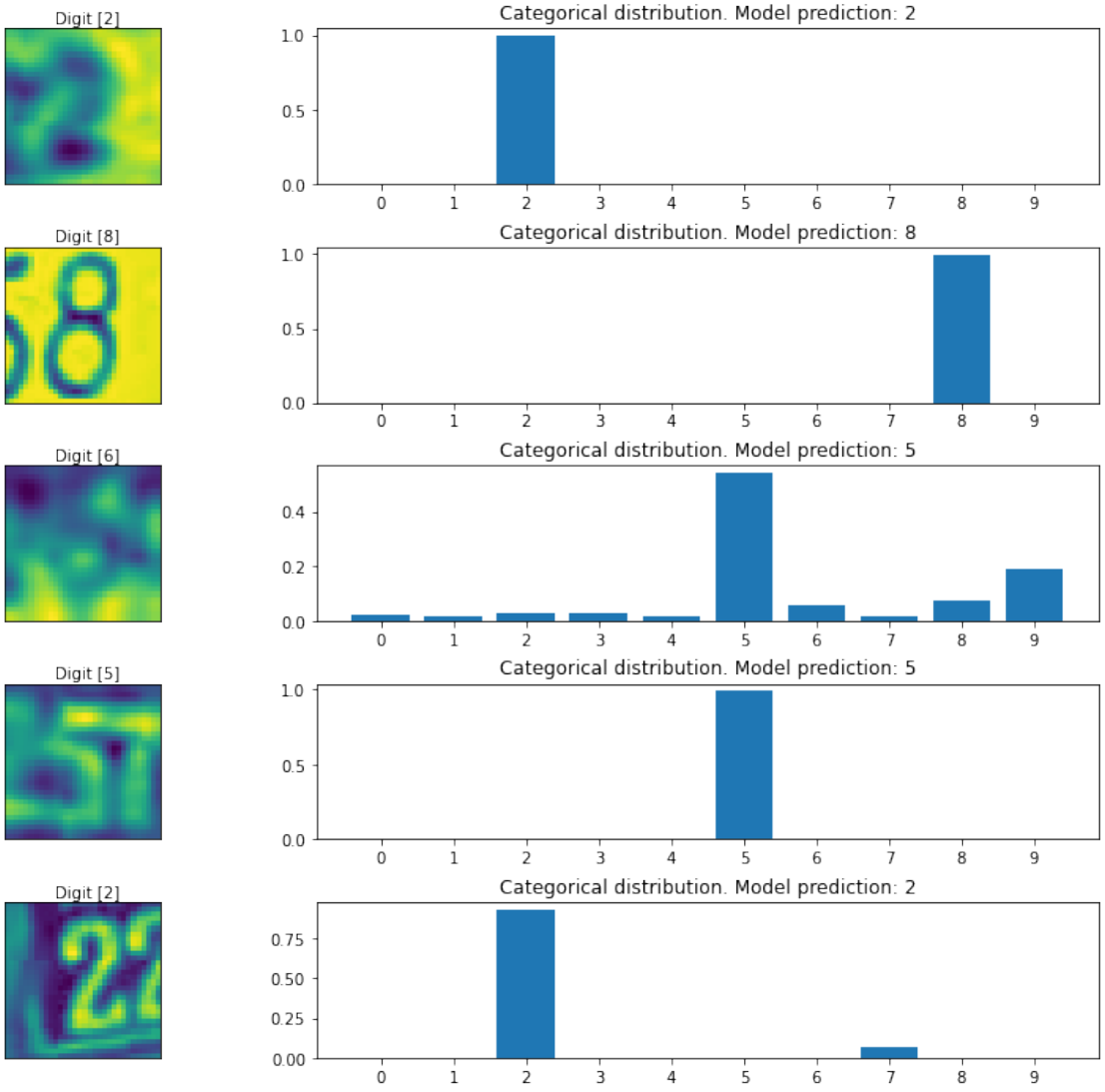
In [54]:
```
#initialize two new models
mlp_model = get_model(input_shape,1e-3)
cnn_model = get_cnn_model(input_shape,1e-3,0.15)
```

In [55]:
```
#load weights:
mlp_model.load_weights("gdrive/My Drive/Colab Notebooks/TensorFlow2/course 1/week 5/cl
cnn_model.load_weights("gdrive/My Drive/Colab Notebooks/TensorFlow2/course 1/week 5/cl
```

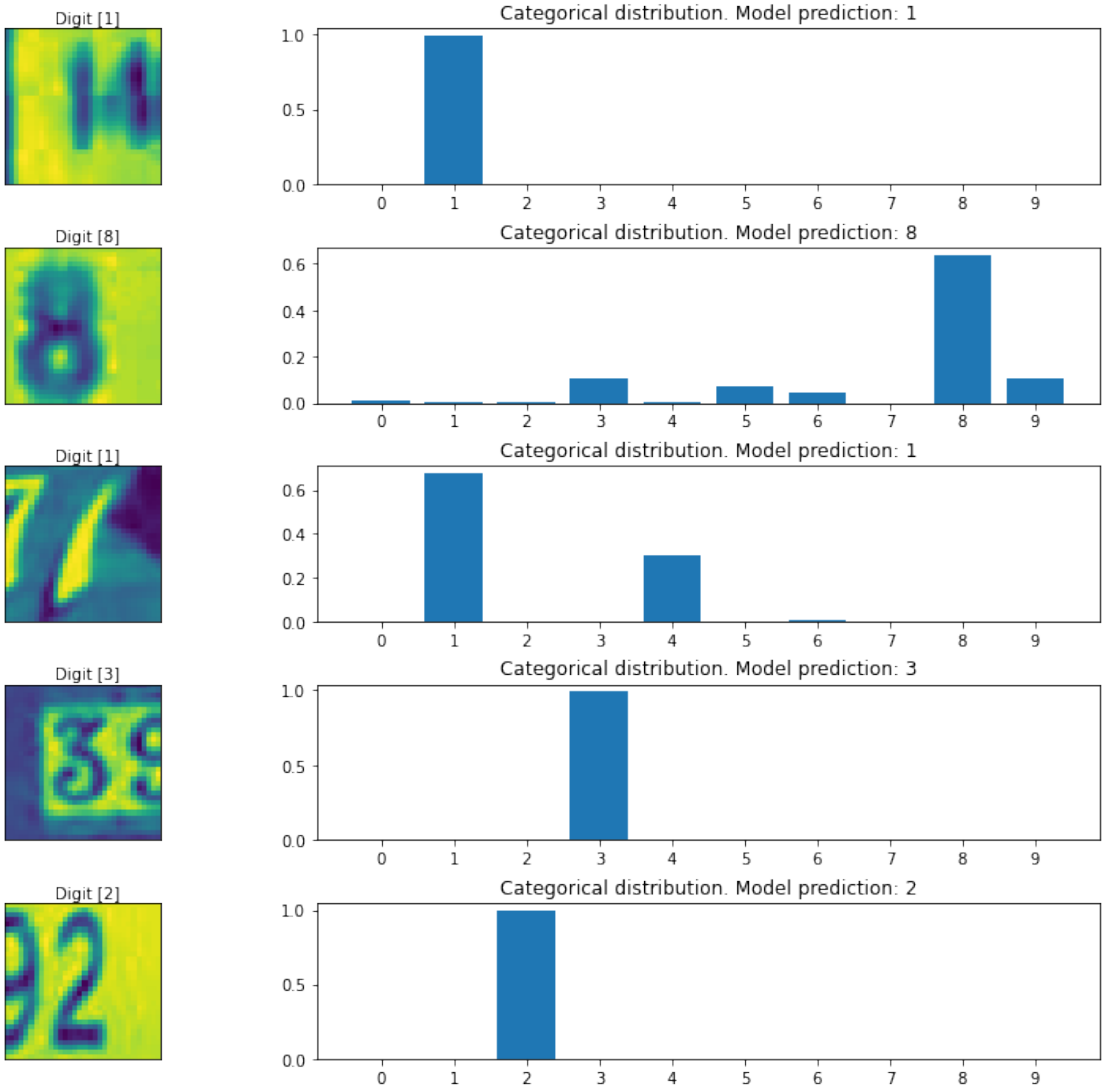
Out[55]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7fa2cfc59f60>
```

In [56]:
```
#predict and display function:

def predictions(model, scaled_test_images, test_labels):
  num_test_images = scaled_test_images.shape[0]

  rand_idx = np.random.choice(num_test_images, 5)
  random_test_images = scaled_test_images[rand_idx, ...]
  random_test_labels = test_labels[rand_idx, ...]

  predictions = model.predict(random_test_images)

  fig, axes = plt.subplots(5, 2, figsize=(16, 12))
  fig.subplots_adjust(hspace=0.4, wspace=-0.2)

  for i, (prediction, image, label) in
    enumerate(zip(predictions, random_test_images, random_test_labels)):
      axes[i, 0].imshow(np.squeeze(image))
      axes[i, 0].get_xaxis().set_visible(False)
      axes[i, 0].get_yaxis().set_visible(False)
      axes[i, 0].text(10., -1.5, f'Digit {label}')
      axes[i, 1].bar(np.arange(len(prediction)), prediction)
      axes[i, 1].set_xticks(np.arange(len(prediction)))
      axes[i, 1].set_title(f"Categorical distribution. Model prediction: {np.argmax(pr

  plt.show()
```

In [61]:
```
#predicting on mlp model:
predictions(mlp_model, x_test_gscaled, y_test)
```



In [59]:
```
#predicting on cnn model:
predictions(cnn_model, x_test_gscaled, y_test)
```


Digit [1]
Categorical distribution. Model prediction: 1
Digit [8]
Categorical distribution. Model prediction: 8
Digit [1]
Categorical distribution. Model prediction: 1
Digit [3]
Categorical distribution. Model prediction: 3
Digit [2]
Categorical distribution. Model prediction: 2