Capstone Project

November 18, 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 tensorflow as tf
        from tensorflow.keras.layers import Flatten, Dense, Conv2D, MaxPooling2D, BatchNormaliz
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.callbacks import ModelCheckpoint, Callback
        from tensorflow.keras.preprocessing.image import load_img, img_to_array
        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.

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('D:\\GitHub\\Coursera\\Tensorflow2forDeepLearning\\GettingStartedWithT
test = loadmat('D:\\GitHub\\Coursera\\Tensorflow2forDeepLearning\\GettingStartedWithTe
```

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 training and testing images and labels
x_train = train['X'] / 255.
x_test = test['X'] /255.
```

```
y_train = train['y']
y_test = test['y']
```

In [4]:
```
for iTrain in range(len(y_train)):
    if y_train[iTrain] == 10:
        y_train[iTrain] = 0

for iTest in range(len(y_test)):
    if y_test[iTest] == 10:
        y_test[iTest] = 0
```

In [5]:
```
x_train = np.moveaxis(x_train,3,0)

x_test  = np.moveaxis(x_test,3,0)

x_train.shape
```

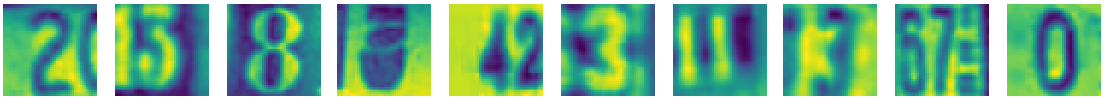
Out[5]:
```
(73257, 32, 32, 3)
```

In [6]:
```
# Display random sample of images and labels

fig, ax = plt.subplots(1, 10, figsize=(10, 1))
for i in range(10):
    random_inx = np.random.choice(x_train.shape[0])

    ax[i].set_axis_off()
    ax[i].imshow(x_train[random_inx])
```

In [7]:
```
x_train_gray = np.average(x_train, axis=3, keepdims = True)
x_test_gray = np.average(x_test, axis=3, keepdims = True)

x_train_gray.shape
```

Out[7]:
```
(73257, 32, 32, 1)
```

In [8]:
```
# Display random sample of images and labels

fig, ax = plt.subplots(1, 10, figsize=(10, 1))
for i in range(10):
    random_inx = np.random.choice(x_train_gray.shape[0])

    ax[i].set_axis_off()
    ax[i].imshow(x_train_gray[random_inx])
```



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]:
```
# Build the Sequential feedforward neural network model
model = Sequential([
    Flatten(input_shape=(32,32,1), name='flatten_1'),
    Dense(128, activation='relu',name='dense_layer_1'),
    Dense(64, activation='relu',name='dense_layer_2'),
    Dense(64, activation='relu', name='dense_layer_3'),
    Dense(10, activation='softmax', name='output_layer')
    ])

model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten_1 (Flatten)         (None, 1024)              0

 dense_layer_1 (Dense)       (None, 128)               131200

 dense_layer_2 (Dense)       (None, 64)                8256

 dense_layer_3 (Dense)       (None, 64)                4160

 output_layer (Dense)        (None, 10)                650
```

```
=================================================================
Total params: 144,266
Trainable params: 144,266
Non-trainable params: 0
_________________________________________________________________
```

In [10]:
```python
# Compile the model

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

In [11]:
```python
# Create Tensorflow checkpoint object

checkpoint_best_path = 'model_checkpoints_best\\checkpoint'
checkpoint_best = ModelCheckpoint(filepath=checkpoint_best_path, save_weights_only=Tru
                                    save_best_only=True, verbose=1)
```

In [12]:
```python
class TrainingCallback(Callback):

    def on_epoch_begin(self, epoch, logs=None):
        print(f"Starting epoch {epoch}")
```

In [13]:
```python
# Train the model, with some of the data reserved for validation

history = model.fit(x_train_gray, y_train, epochs=30, validation_split=0.15, batch_siz
```

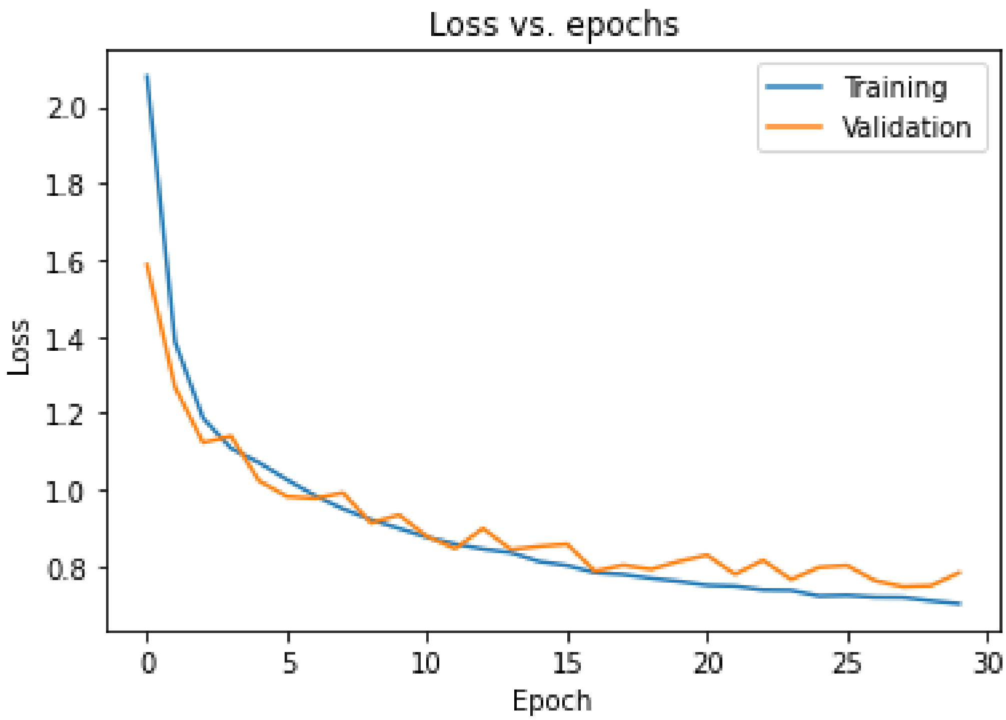
```
Starting epoch 0
Epoch 1/30
959/973 [============================>.] - ETA: 0s - loss: 2.0862 - accuracy: 0.2532
Epoch 1: loss improved from inf to 2.07951, saving model to model_checkpoints_best\checkpoint
973/973 [==============================] - 2s 2ms/step - loss: 2.0795 - accuracy: 0.2559 - val_
Starting epoch 1
Epoch 2/30
964/973 [============================>.] - ETA: 0s - loss: 1.3869 - accuracy: 0.5410
Epoch 2: loss improved from 2.07951 to 1.38615, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 1.3862 - accuracy: 0.5414 - val_
Starting epoch 2
Epoch 3/30
950/973 [============================>.] - ETA: 0s - loss: 1.1889 - accuracy: 0.6229
Epoch 3: loss improved from 1.38615 to 1.18634, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 1.1863 - accuracy: 0.6239 - val_
Starting epoch 3
Epoch 4/30
938/973 [===========================>..] - ETA: 0s - loss: 1.1077 - accuracy: 0.6534
Epoch 4: loss improved from 1.18634 to 1.10709, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 1.1071 - accuracy: 0.6533 - val_
Starting epoch 4
Epoch 5/30
```

```
961/973 [============================>.] - ETA: 0s - loss: 1.0711 - accuracy: 0.6656
Epoch 5: loss improved from 1.10709 to 1.07025, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 1s 2ms/step - loss: 1.0702 - accuracy: 0.6658 - val_
Starting epoch 5
Epoch 6/30
965/973 [============================>.] - ETA: 0s - loss: 1.0261 - accuracy: 0.6806
Epoch 6: loss improved from 1.07025 to 1.02543, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 1.0254 - accuracy: 0.6809 - val_
Starting epoch 6
Epoch 7/30
934/973 [===========================>..] - ETA: 0s - loss: 0.9848 - accuracy: 0.6971
Epoch 7: loss improved from 1.02543 to 0.98382, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 0.9838 - accuracy: 0.6971 - val_
Starting epoch 7
Epoch 8/30
970/973 [============================>.] - ETA: 0s - loss: 0.9494 - accuracy: 0.7088
Epoch 8: loss improved from 0.98382 to 0.94922, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 0.9492 - accuracy: 0.7088 - val_
Starting epoch 8
Epoch 9/30
973/973 [==============================] - ETA: 0s - loss: 0.9210 - accuracy: 0.7154
Epoch 9: loss improved from 0.94922 to 0.92103, saving model to model_checkpoints_best\checkpoi
973/973 [==============================] - 2s 2ms/step - loss: 0.9210 - accuracy: 0.7154 - val_
Starting epoch 9
Epoch 10/30
932/973 [===========================>..] - ETA: 0s - loss: 0.8977 - accuracy: 0.7242
Epoch 10: loss improved from 0.92103 to 0.89814, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 1s 2ms/step - loss: 0.8981 - accuracy: 0.7244 - val_
Starting epoch 10
Epoch 11/30
942/973 [============================>.] - ETA: 0s - loss: 0.8740 - accuracy: 0.7307
Epoch 11: loss improved from 0.89814 to 0.87493, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.8749 - accuracy: 0.7307 - val_
Starting epoch 11
Epoch 12/30
971/973 [============================>.] - ETA: 0s - loss: 0.8578 - accuracy: 0.7366
Epoch 12: loss improved from 0.87493 to 0.85760, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 4s 4ms/step - loss: 0.8576 - accuracy: 0.7366 - val_
Starting epoch 12
Epoch 13/30
963/973 [============================>.] - ETA: 0s - loss: 0.8440 - accuracy: 0.7399
Epoch 13: loss improved from 0.85760 to 0.84399, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.8440 - accuracy: 0.7399 - val_
Starting epoch 13
Epoch 14/30
960/973 [============================>.] - ETA: 0s - loss: 0.8351 - accuracy: 0.7426
Epoch 14: loss improved from 0.84399 to 0.83473, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.8347 - accuracy: 0.7429 - val_
```

```
Starting epoch 14
Epoch 15/30
948/973 [============================>.] - ETA: 0s - loss: 0.8116 - accuracy: 0.7498
Epoch 15: loss improved from 0.83473 to 0.81151, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.8115 - accuracy: 0.7500 - val_
Starting epoch 15
Epoch 16/30
955/973 [============================>.] - ETA: 0s - loss: 0.8003 - accuracy: 0.7531
Epoch 16: loss improved from 0.81151 to 0.80099, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.8010 - accuracy: 0.7531 - val_
Starting epoch 16
Epoch 17/30
953/973 [============================>.] - ETA: 0s - loss: 0.7833 - accuracy: 0.7584
Epoch 17: loss improved from 0.80099 to 0.78239, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7824 - accuracy: 0.7586 - val_
Starting epoch 17
Epoch 18/30
973/973 [==============================] - ETA: 0s - loss: 0.7776 - accuracy: 0.7601
Epoch 18: loss improved from 0.78239 to 0.77765, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7776 - accuracy: 0.7601 - val_
Starting epoch 18
Epoch 19/30
948/973 [============================>.] - ETA: 0s - loss: 0.7684 - accuracy: 0.7616
Epoch 19: loss improved from 0.77765 to 0.76744, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7674 - accuracy: 0.7624 - val_
Starting epoch 19
Epoch 20/30
973/973 [==============================] - ETA: 0s - loss: 0.7594 - accuracy: 0.7645
Epoch 20: loss improved from 0.76744 to 0.75943, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 3s 3ms/step - loss: 0.7594 - accuracy: 0.7645 - val_
Starting epoch 20
Epoch 21/30
958/973 [============================>.] - ETA: 0s - loss: 0.7496 - accuracy: 0.7681
Epoch 21: loss improved from 0.75943 to 0.74939, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 3s 3ms/step - loss: 0.7494 - accuracy: 0.7682 - val_
Starting epoch 21
Epoch 22/30
955/973 [============================>.] - ETA: 0s - loss: 0.7463 - accuracy: 0.7692
Epoch 22: loss improved from 0.74939 to 0.74686, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 3s 3ms/step - loss: 0.7469 - accuracy: 0.7688 - val_
Starting epoch 22
Epoch 23/30
947/973 [============================>.] - ETA: 0s - loss: 0.7366 - accuracy: 0.7706
Epoch 23: loss improved from 0.74686 to 0.73707, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7371 - accuracy: 0.7704 - val_
Starting epoch 23
Epoch 24/30
969/973 [============================>.] - ETA: 0s - loss: 0.7362 - accuracy: 0.7716
```

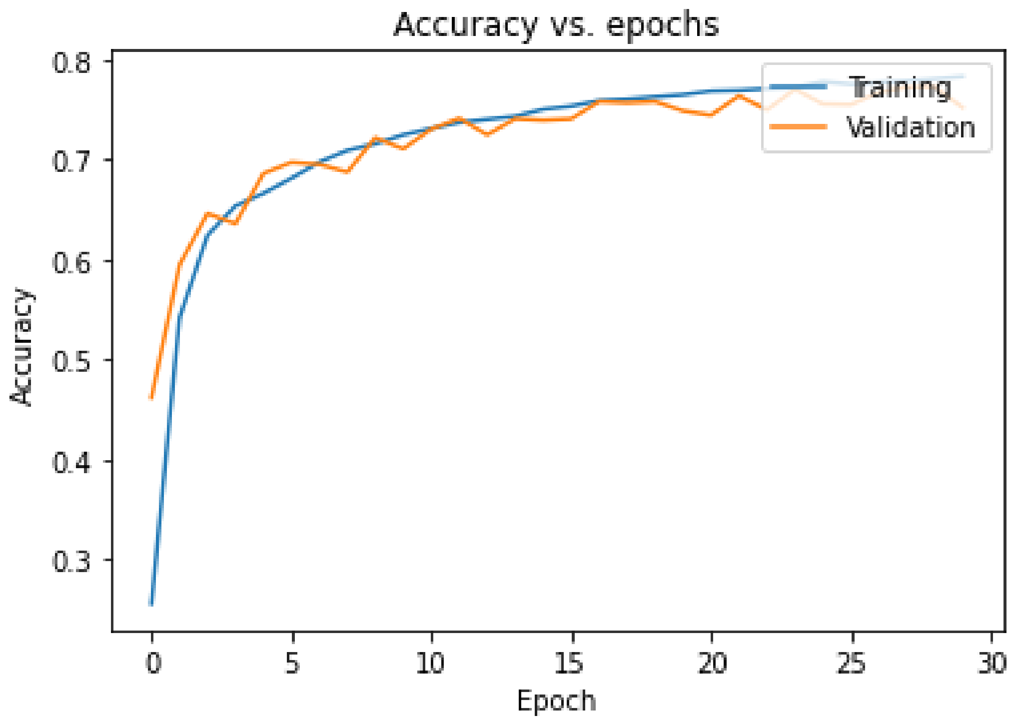
```
Epoch 24: loss improved from 0.73707 to 0.73604, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7360 - accuracy: 0.7717 - val_
Starting epoch 24
Epoch 25/30
972/973 [============================>.] - ETA: 0s - loss: 0.7211 - accuracy: 0.7773
Epoch 25: loss improved from 0.73604 to 0.72102, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7210 - accuracy: 0.7774 - val_
Starting epoch 25
Epoch 26/30
962/973 [============================>.] - ETA: 0s - loss: 0.7224 - accuracy: 0.7749
Epoch 26: loss did not improve from 0.72102
973/973 [==============================] - 2s 2ms/step - loss: 0.7227 - accuracy: 0.7748 - val_
Starting epoch 26
Epoch 27/30
968/973 [============================>.] - ETA: 0s - loss: 0.7181 - accuracy: 0.7765
Epoch 27: loss improved from 0.72102 to 0.71820, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 3s 3ms/step - loss: 0.7182 - accuracy: 0.7766 - val_
Starting epoch 27
Epoch 28/30
957/973 [============================>.] - ETA: 0s - loss: 0.7186 - accuracy: 0.7778
Epoch 28: loss improved from 0.71820 to 0.71766, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 3s 3ms/step - loss: 0.7177 - accuracy: 0.7782 - val_
Starting epoch 28
Epoch 29/30
956/973 [============================>.] - ETA: 0s - loss: 0.7086 - accuracy: 0.7804
Epoch 29: loss improved from 0.71766 to 0.70863, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 3s 3ms/step - loss: 0.7086 - accuracy: 0.7803 - val_
Starting epoch 29
Epoch 30/30
948/973 [============================>.] - ETA: 0s - loss: 0.7006 - accuracy: 0.7824
Epoch 30: loss improved from 0.70863 to 0.70104, saving model to model_checkpoints_best\checkpo
973/973 [==============================] - 2s 2ms/step - loss: 0.7010 - accuracy: 0.7825 - val_
```

In [14]:
```python
# Plot the training and validation loss

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 [15]: # Plot the training and validation accuracy

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Accuracy vs. epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='upper right')
plt.show()
```




```
In [16]: model.evaluate(x_test_gray, y_test, verbose=2)
```

```
814/814 - 1s - loss: 0.8815 - accuracy: 0.7351 - 747ms/epoch - 917us/step
```

```
Out[16]: [0.8814964294433594, 0.735133707523346]
```

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 [17]:
```
model2 = Sequential([
        Conv2D(32,(3,3),activation='relu',input_shape=(32,32,1)),
        MaxPooling2D((3,3)),
        Dense(32,  activation="relu",),
        BatchNormalization(),
        Conv2D(16,(3,3),activation='relu'),
        Dense(16,  activation="relu"),
        Dropout(0.3),
        Flatten(),
        Dense(10, activation='softmax', name='output_layer')
        ])

model2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 32)        320

 max_pooling2d (MaxPooling2D  (None, 10, 10, 32)       0
 )

 dense (Dense)               (None, 10, 10, 32)        1056

 batch_normalization (BatchN  (None, 10, 10, 32)       128
 ormalization)

 conv2d_1 (Conv2D)           (None, 8, 8, 16)          4624

 dense_1 (Dense)             (None, 8, 8, 16)          272

 dropout (Dropout)           (None, 8, 8, 16)          0

 flatten (Flatten)           (None, 1024)              0

 output_layer (Dense)        (None, 10)                10250

=================================================================
Total params: 16,650
Trainable params: 16,586
Non-trainable params: 64
_________________________________________________________________
```

In [18]:
```
# Compile the model

model2.compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accu
```

In [19]:
```
# Create Tensorflow checkpoint object

checkpoint_best_path_CNN = 'model_checkpoints_best_CNN\\checkpoint'
checkpoint_best_CNN = ModelCheckpoint(filepath=checkpoint_best_path_CNN, save_weights_
                                      save_best_only=True, verbose=1)
```

In [20]:
```
class TrainingCallback_CNN(Callback):
    def on_epoch_begin(self, epoch, logs=None):
        print(f"Starting epoch {epoch}")

    def on_epoch_end(self, epoch, logs=None):
        print(f"Finished epoch {epoch}")
```

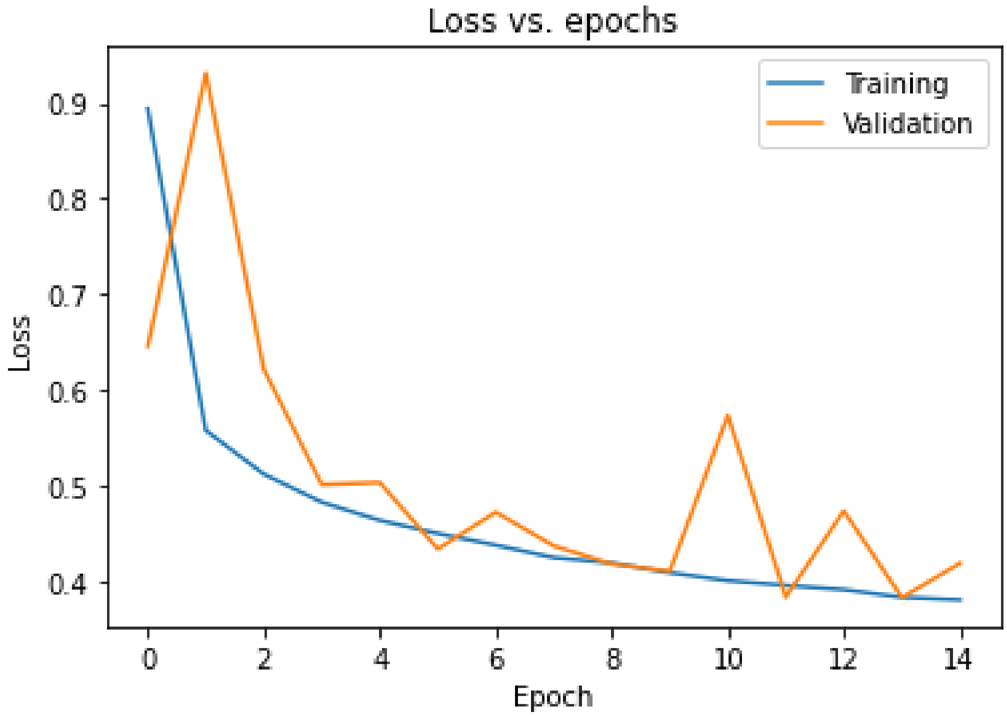
In [21]:
```
# Train the model, with some of the data reserved for validation

history2 = model2.fit(x_train_gray, y_train, epochs=30, validation_split=0.15, batch_s
```

```
Starting epoch 0
Epoch 1/30
972/973 [============================>.] - ETA: 0s - loss: 0.8941 - accuracy: 0.7149Finished ep

Epoch 1: val_accuracy improved from -inf to 0.80608, saving model to model_checkpoints_best_CNN
973/973 [==============================] - 24s 24ms/step - loss: 0.8940 - accuracy: 0.7149 - va
Starting epoch 1
Epoch 2/30
972/973 [============================>.] - ETA: 0s - loss: 0.5567 - accuracy: 0.8349Finished ep

Epoch 2: val_accuracy did not improve from 0.80608
973/973 [==============================] - 22s 23ms/step - loss: 0.5574 - accuracy: 0.8349 - va
Starting epoch 2
Epoch 3/30
972/973 [============================>.] - ETA: 0s - loss: 0.5117 - accuracy: 0.8472Finished ep

Epoch 3: val_accuracy improved from 0.80608 to 0.80644, saving model to model_checkpoints_best_
973/973 [==============================] - 25s 25ms/step - loss: 0.5116 - accuracy: 0.8472 - va
Starting epoch 3
Epoch 4/30
971/973 [============================>.] - ETA: 0s - loss: 0.4821 - accuracy: 0.8559Finished ep

Epoch 4: val_accuracy improved from 0.80644 to 0.84994, saving model to model_checkpoints_best_
973/973 [==============================] - 23s 24ms/step - loss: 0.4822 - accuracy: 0.8559 - va
Starting epoch 4
Epoch 5/30
972/973 [============================>.] - ETA: 0s - loss: 0.4633 - accuracy: 0.8615Finished ep

Epoch 5: val_accuracy improved from 0.84994 to 0.85121, saving model to model_checkpoints_best_
973/973 [==============================] - 23s 24ms/step - loss: 0.4632 - accuracy: 0.8615 - va
Starting epoch 5
```

```
Epoch 6/30
971/973 [============================>.] - ETA: 0s - loss: 0.4491 - accuracy: 0.8661Finished ep

Epoch 6: val_accuracy improved from 0.85121 to 0.87597, saving model to model_checkpoints_best_
973/973 [==============================] - 23s 24ms/step - loss: 0.4494 - accuracy: 0.8661 - va
Starting epoch 6
Epoch 7/30
971/973 [============================>.] - ETA: 0s - loss: 0.4372 - accuracy: 0.8706Finished ep

Epoch 7: val_accuracy did not improve from 0.87597
973/973 [==============================] - 22s 23ms/step - loss: 0.4372 - accuracy: 0.8706 - va
Starting epoch 7
Epoch 8/30
972/973 [============================>.] - ETA: 0s - loss: 0.4240 - accuracy: 0.8745Finished ep

Epoch 8: val_accuracy did not improve from 0.87597
973/973 [==============================] - 22s 23ms/step - loss: 0.4241 - accuracy: 0.8744 - va
Starting epoch 8
Epoch 9/30
971/973 [============================>.] - ETA: 0s - loss: 0.4187 - accuracy: 0.8765Finished ep

Epoch 9: val_accuracy improved from 0.87597 to 0.87615, saving model to model_checkpoints_best_
973/973 [==============================] - 24s 25ms/step - loss: 0.4185 - accuracy: 0.8766 - va
Starting epoch 9
Epoch 10/30
973/973 [==============================] - ETA: 0s - loss: 0.4083 - accuracy: 0.8787Finished ep

Epoch 10: val_accuracy improved from 0.87615 to 0.88024, saving model to model_checkpoints_bes
973/973 [==============================] - 25s 26ms/step - loss: 0.4083 - accuracy: 0.8787 - va
Starting epoch 10
Epoch 11/30
973/973 [==============================] - ETA: 0s - loss: 0.4000 - accuracy: 0.8804Finished ep

Epoch 11: val_accuracy did not improve from 0.88024
973/973 [==============================] - 24s 25ms/step - loss: 0.4000 - accuracy: 0.8804 - va
Starting epoch 11
Epoch 12/30
971/973 [============================>.] - ETA: 0s - loss: 0.3950 - accuracy: 0.8837Finished ep

Epoch 12: val_accuracy improved from 0.88024 to 0.88862, saving model to model_checkpoints_bes
973/973 [==============================] - 23s 24ms/step - loss: 0.3951 - accuracy: 0.8837 - va
Starting epoch 12
Epoch 13/30
972/973 [============================>.] - ETA: 0s - loss: 0.3906 - accuracy: 0.8840Finished ep

Epoch 13: val_accuracy did not improve from 0.88862
973/973 [==============================] - 22s 23ms/step - loss: 0.3907 - accuracy: 0.8840 - va
Starting epoch 13
```

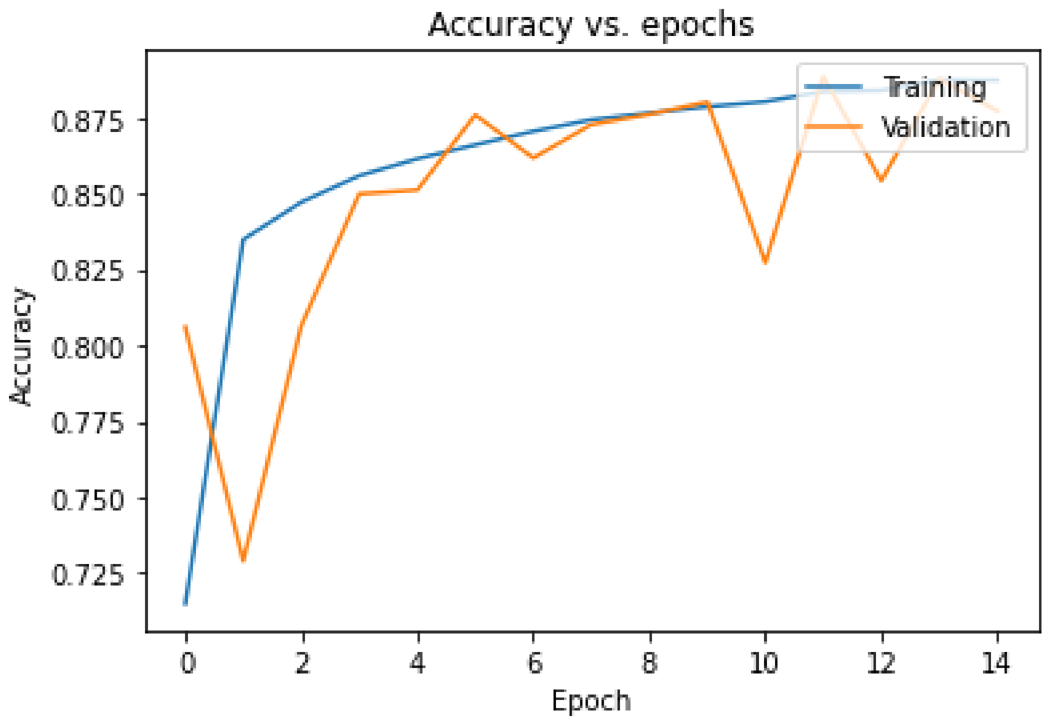
```
Epoch 14/30
973/973 [==============================] - ETA: 0s - loss: 0.3826 - accuracy: 0.8876Finished ep

Epoch 14: val_accuracy did not improve from 0.88862
973/973 [==============================] - 22s 22ms/step - loss: 0.3826 - accuracy: 0.8876 - va
Starting epoch 14
Epoch 15/30
973/973 [==============================] - ETA: 0s - loss: 0.3799 - accuracy: 0.8874Finished ep

Epoch 15: val_accuracy did not improve from 0.88862
973/973 [==============================] - 22s 23ms/step - loss: 0.3799 - accuracy: 0.8874 - va
```

In [22]:
```python
# Plot the training and validation loss

plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('Loss vs. epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='upper right')
plt.show()
```



In [23]:
```python
# Plot the training and validation accuracy
```

```
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])
plt.title('Accuracy vs. epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='upper right')
plt.show()
```




```
In [24]: # Evaluate the model on the test set

         model2.evaluate(x_test_gray, y_test, verbose=2)
```

```
814/814 - 4s - loss: 0.4522 - accuracy: 0.8735 - 4s/epoch - 5ms/step
```

```
Out[24]: [0.4521860182285309, 0.8735018372535706]
```

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.

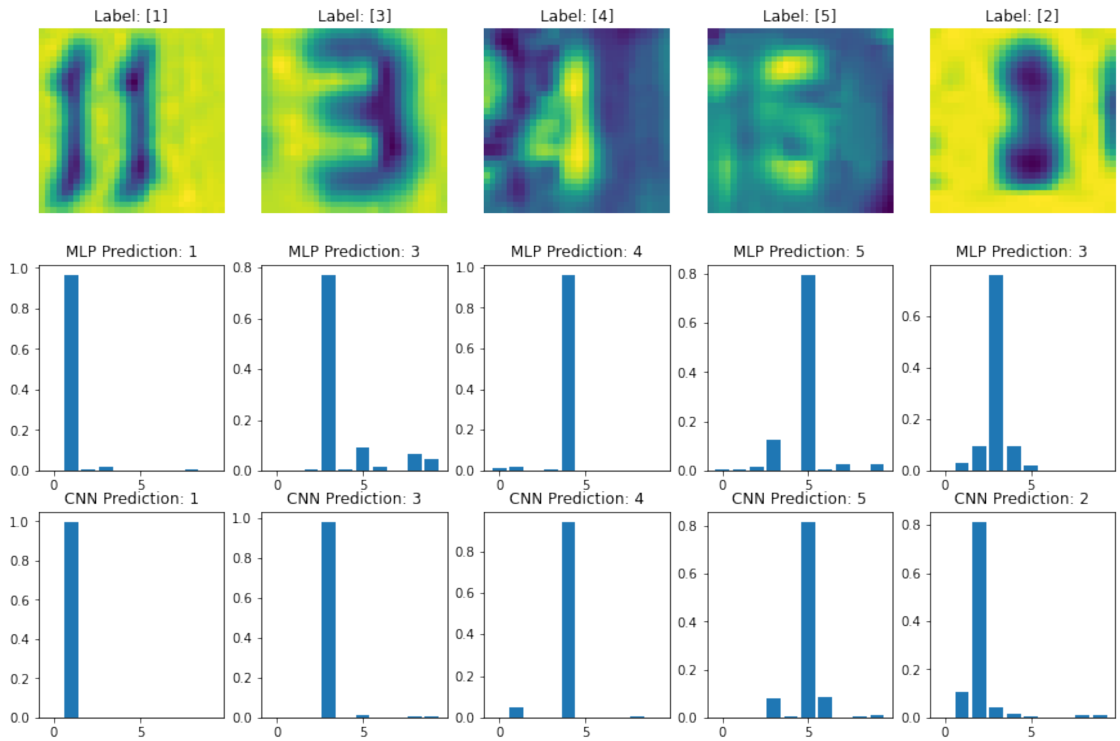
```
In [25]: # Load MLP
         checkpoint_best_path = 'model_checkpoints_best\\checkpoint'
         model.load_weights(checkpoint_best_path)

         model.compile(optimizer='adam',
                       loss='sparse_categorical_crossentropy',
                       metrics=['accuracy'])
```

```
In [26]: # Load CNN
         checkpoint_best_path_CNN = 'model_checkpoints_best_CNN\\checkpoint'
         model2.load_weights(checkpoint_best_path_CNN)

         model2.compile(optimizer='adam',
                       loss='sparse_categorical_crossentropy',
                       metrics=['accuracy'])
```

```
In [27]: # Display random sample of images and labels


         fig, ax = plt.subplots(3, 5, figsize=(15, 10))
         for i in range(5):
             random_inx = np.random.choice(x_test_gray.shape[0])

             ax[0,i].set_axis_off()
             ax[0,i].imshow(x_test_gray[random_inx])
             ax[0,i].set_title(f"Label: {y_test[random_inx]}")

             preds = model.predict(x_test_gray[random_inx][np.newaxis, ...])
             print(preds)
             ax[1,i].bar(list(range(0,10)),preds[0])
             ax[1,i].set_title(f"MLP Prediction: {preds.argmax()}")

             preds2 = model2.predict(x_test_gray[random_inx][np.newaxis, ...])
             ax[2,i].bar(list(range(0,10)),preds2[0])
             ax[2,i].set_title(f"CNN Prediction: {preds2.argmax()}")
```

```
1/1 [==============================] - 0s 117ms/step
[[4.0151618e-04 9.6642381e-01 4.5870664e-03 1.9589698e-02 2.0854585e-03
  1.0726645e-03 3.1256038e-04 1.8664163e-03 3.3767954e-03 2.8399273e-04]]
1/1 [==============================] - 0s 167ms/step
1/1 [==============================] - 0s 23ms/step
[[5.4246688e-05 7.9295406e-04 4.4941436e-03 7.7260339e-01 2.5668326e-03
  9.3385279e-02 1.5991081e-02 7.6208606e-05 6.6653013e-02 4.3382820e-02]]
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 19ms/step
[[1.0061639e-02 1.7648257e-02 6.1293389e-04 2.7950797e-03 9.6180940e-01
  1.1990687e-03 1.5086278e-03 9.4557035e-05 1.9977381e-03 2.2725926e-03]]
1/1 [==============================] - 0s 20ms/step
```

```
1/1 [==============================] - 0s 20ms/step
[[0.00642895 0.00254689 0.01497933 0.12251862 0.00096914 0.79554075
  0.00567877 0.02474732 0.00163968 0.02495056]]
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 19ms/step
[[5.7233032e-04 2.9524481e-02 9.6832275e-02 7.6102531e-01 9.3449436e-02
  1.7505141e-02 2.5802964e-04 3.5080884e-04 4.0504738e-04 7.7069242e-05]]
1/1 [==============================] - 0s 22ms/step
```



In [ ]: