Capstone Project

September 17, 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 (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 [3]: import tensorflow as tf
        import matplotlib.pyplot as plt
        import numpy as np
        import math
        import pandas as pd
        from tensorflow.keras.models import Sequential
        from tensorflow.keras import initializers
        from sklearn.utils.class_weight import compute_class_weight
        from tensorflow.keras.utils import to_categorical
        from tensorflow.keras.layers import Dense,ReLU,LeakyReLU,Softmax,Flatten,BatchNormaliza
        from tensorflow.keras.callbacks import Callback,EarlyStopping,ModelCheckpoint
```

```
from tensorflow.keras.layers import Conv2D,MaxPooling2D,Softmax
from scipy.io import loadmat
```

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 [4]: # 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

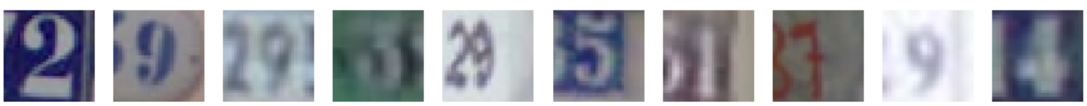
- Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.
- Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.
- Convert the training and test images to grayscale by taking 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 [5]: print(train.keys())
        x_train = train['X']
        y_train = train['y']

        print(test.keys())
        x_test = test["X"]
        y_test = test["y"]

        x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
dict_keys(['__header__', '__version__', '__globals__', 'X', 'y'])
dict_keys(['__header__', '__version__', '__globals__', 'X', 'y'])
```

```
Out[5]: ((32, 32, 3, 73257), (32, 32, 3, 26032), (73257, 1), (26032, 1))
```

```
In [4]: fig,ax = plt.subplots(nrows = 1,ncols= 10,figsize=(15,5))
        for i in range(10):
            chooserandom = np.random.choice(x_train.shape[3])
            images = x_train[:,:,:,chooserandom]
            ax[i].imshow(images)
            ax[i].set_axis_off()
```



```
In [6]: x_trainingray = np.mean(x_train,axis = 2,keepdims=True)
        x_testgray = np.mean(x_test,axis = 2,keepdims=True)
        x_trainingray = np.moveaxis(x_trainingray,2,0)
        x_testgray = np.moveaxis(x_testgray,2,0)
        x_trainingray = np.moveaxis(x_trainingray,3,0)
        x_testgray =np.moveaxis(x_testgray,3,0)
        x_trainingray.shape,x_testgray.shape

        x_trainingray = x_trainingray / 255.0
        x_testgray = x_testgray / 255.
```

```
In [6]: fig,ax = plt.subplots(nrows = 1,ncols= 10,figsize=(15,5))
        for i in range(10):
            chooserandom = np.random.choice(x_trainingray.shape[0])
            images = x_trainingray[chooserandom,0,:,:,]
            ax[i].imshow(images,cmap = "gray")
            ax[i].set_axis_off()
```

```
In [7]: y_train = y_train - 1
        y_test = y_test -1
        y_train = to_categorical(y_train,num_classes=10)
        y_test =to_categorical(y_test,num_classes =10)
```

```
In [8]: y_train[0]
```

```
Out[8]: array([1., 0., 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 [8]: def buildmodel(input_shape,epochs,lr):
            model = Sequential([
                Flatten(input_shape = input_shape,name="Flattening",data_format="channels_firs
                Dense(units =128,activation = LeakyReLU(),name = "dense_1",kernel_initializer=
                      bias_initializer=initializers.Ones()),
                Dense(units =128,activation = LeakyReLU(),name = "dense_2",kernel_initializer=
                      bias_initializer=initializers.Ones()),
                Dense(units =128,activation = ReLU(),name = "dense_3",kernel_initializer=initia
                      bias_initializer=initializers.Ones()),
                Dense(units = 10,activation = Softmax(),name = "Output")
            ],name = "SampisModel")
            METRICS = [tf.keras.metrics.TruePositives(name="TP"),
                      tf.keras.metrics.TrueNegatives(name="TN"),
                      tf.keras.metrics.FalsePositives(name="FP"),
                      tf.keras.metrics.FalseNegatives(name="FN"),
```

```
                 tf.keras.metrics.CategoricalAccuracy(name="ACC"),
                 tf.keras.metrics.AUC(name="AUC")]

        optimizer = tf.keras.optimizers.Adam(lr=lr)
        loss = tf.keras.losses.CategoricalCrossentropy()
        model.compile(loss=loss,optimizer=optimizer,metrics=METRICS)

        return model
```

In [9]:
```
shape = x_trainingray[0,:,:,:].shape
model = buildmodel(shape,30,0.001)
model.summary()
```

```
Model: "SampisModel"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Flattening (Flatten)         (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               131200
_________________________________________________________________
dense_2 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_3 (Dense)              (None, 128)               16512
_________________________________________________________________
Output (Dense)               (None, 10)                1290
=================================================================
Total params: 165,514
Trainable params: 165,514
Non-trainable params: 0
_________________________________________________________________
```

In [11]:
```
def EarlyStopme():

    earlystop = EarlyStopping(monitor = "val_loss",patience=8,verbose=1)

    return earlystop


def create_learning_rate_scheduler(max_learn_rate=0.001,
                                   end_learn_rate = 0.0005,
                                   warmup_epoch_count=5,
                                   total_epoch_count=15):

    def lr_scheduler(epoch):
        if epoch < warmup_epoch_count:
            res = (max_learn_rate)
```

```
            else:
                res = max_learn_rate*math.exp(math.log(end_learn_rate/max_learn_rate)*(epo
            return float(res)
        learning_rate_scheduler = tf.keras.callbacks.LearningRateScheduler(lr_scheduler, v

        return learning_rate_scheduler
    def CheckpointDude():
        Checkpointpath = "checkpointmodel/CheckpointBest"
        Checkpoint = ModelCheckpoint(filepath=Checkpointpath,monitor = "val_loss",
                                    save_best_only = True,save_weights_only=True,frequency
        return Checkpoint

    checkpoint = CheckpointDude()
    EarlyStop = EarlyStopme()
    scheduler = create_learning_rate_scheduler()
```

In [12]:
```
history = model.fit(x = x_traininggray,y=y_train,epochs=15,
          verbose=1,batch_size= 64,
           workers = -1,validation_data=[x_testgray,y_test],
         callbacks=[EarlyStop,scheduler,checkpoint])
```

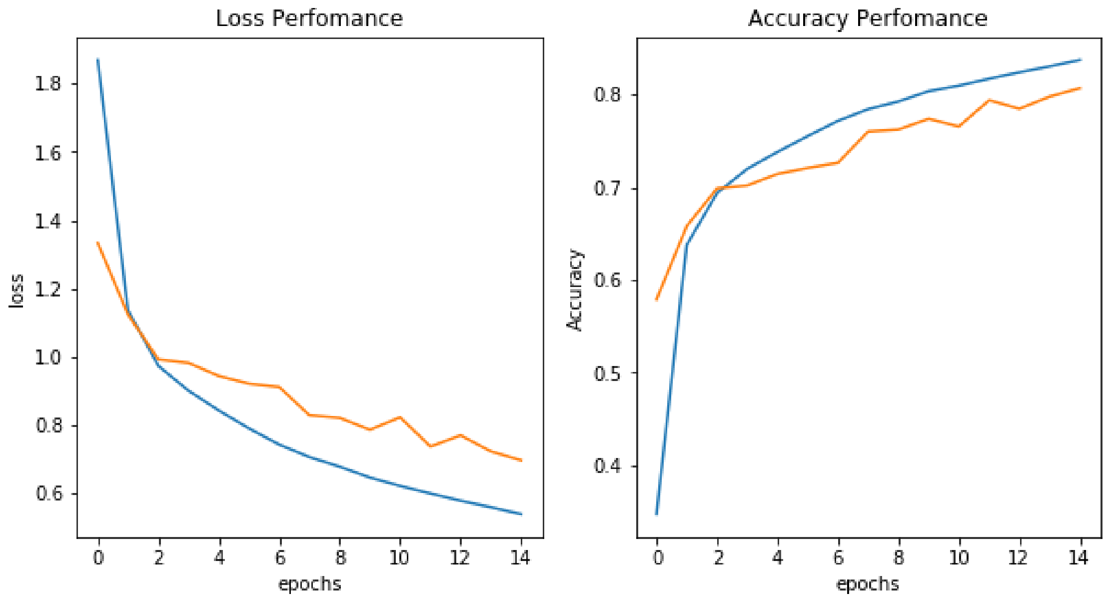
```
Train on 73257 samples, validate on 26032 samples

Epoch 00001: LearningRateScheduler reducing learning rate to 0.001.
Epoch 1/15
73216/73257 [============================>.] - ETA: 0s - loss: 1.8694 - TP: 11535.0000 - TN: 65
Epoch 00001: val_loss improved from inf to 1.33333, saving model to checkpointmodel/CheckpointB
73257/73257 [==============================] - 48s 661us/sample - loss: 1.8689 - TP: 11557.0000

Epoch 00002: LearningRateScheduler reducing learning rate to 0.001.
Epoch 2/15
73152/73257 [============================>.] - ETA: 0s - loss: 1.1363 - TP: 36950.0000 - TN: 64
Epoch 00002: val_loss improved from 1.33333 to 1.12395, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 608us/sample - loss: 1.1363 - TP: 37008.0000

Epoch 00003: LearningRateScheduler reducing learning rate to 0.001.
Epoch 3/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.9736 - TP: 43065.0000 - TN: 65
Epoch 00003: val_loss improved from 1.12395 to 0.99235, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 44s 607us/sample - loss: 0.9737 - TP: 43089.0000

Epoch 00004: LearningRateScheduler reducing learning rate to 0.001.
Epoch 4/15
73152/73257 [============================>.] - ETA: 0s - loss: 0.9011 - TP: 45660.0000 - TN: 65
Epoch 00004: val_loss improved from 0.99235 to 0.98211, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 609us/sample - loss: 0.9010 - TP: 45730.0000

Epoch 00005: LearningRateScheduler reducing learning rate to 0.001.
```

```
Epoch 5/15
73152/73257 [============================>.] - ETA: 0s - loss: 0.8435 - TP: 47586.0000 - TN: 65
Epoch 00005: val_loss improved from 0.98211 to 0.94427, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 609us/sample - loss: 0.8432 - TP: 47661.0000

Epoch 00006: LearningRateScheduler reducing learning rate to 0.0009389309106617063.
Epoch 6/15
73024/73257 [============================>.] - ETA: 0s - loss: 0.7902 - TP: 49252.0000 - TN: 64
Epoch 00006: val_loss improved from 0.94427 to 0.92138, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 608us/sample - loss: 0.7902 - TP: 49406.0000

Epoch 00007: LearningRateScheduler reducing learning rate to 0.0008815912549960212.
Epoch 7/15
73152/73257 [============================>.] - ETA: 0s - loss: 0.7431 - TP: 50928.0000 - TN: 65
Epoch 00007: val_loss improved from 0.92138 to 0.91191, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 610us/sample - loss: 0.7434 - TP: 50992.0000

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0008277532798848107.
Epoch 8/15
73152/73257 [============================>.] - ETA: 0s - loss: 0.7070 - TP: 52193.0000 - TN: 65
Epoch 00008: val_loss improved from 0.91191 to 0.82899, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 608us/sample - loss: 0.7068 - TP: 52272.0000

Epoch 00009: LearningRateScheduler reducing learning rate to 0.0007772031408854596.
Epoch 9/15
73152/73257 [============================>.] - ETA: 0s - loss: 0.6783 - TP: 52952.0000 - TN: 65
Epoch 00009: val_loss improved from 0.82899 to 0.82126, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 44s 606us/sample - loss: 0.6784 - TP: 53028.0000

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0007297400528407231.
Epoch 10/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.6466 - TP: 54147.0000 - TN: 65
Epoch 00010: val_loss improved from 0.82126 to 0.78629, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 608us/sample - loss: 0.6467 - TP: 54175.0000

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0006851754923600619.
Epoch 11/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.6220 - TP: 54867.0000 - TN: 65
Epoch 00011: val_loss did not improve from 0.78629
73257/73257 [==============================] - 44s 602us/sample - loss: 0.6221 - TP: 54898.0000

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0006433324490047158.
Epoch 12/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.5998 - TP: 55530.0000 - TN: 65
Epoch 00012: val_loss improved from 0.78629 to 0.73762, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 610us/sample - loss: 0.5998 - TP: 55557.0000

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0006040447222022236.
```

```
Epoch 13/15
73088/73257 [============================>.] - ETA: 0s - loss: 0.5789 - TP: 56095.0000 - TN: 65
Epoch 00013: val_loss did not improve from 0.73762
73257/73257 [==============================] - 44s 603us/sample - loss: 0.5787 - TP: 56230.0000

Epoch 00014: LearningRateScheduler reducing learning rate to 0.0005671562610977313.
Epoch 14/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.5600 - TP: 56869.0000 - TN: 65
Epoch 00014: val_loss improved from 0.73762 to 0.72354, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 45s 608us/sample - loss: 0.5600 - TP: 56903.0000

Epoch 00015: LearningRateScheduler reducing learning rate to 0.0005325205447199813.
Epoch 15/15
73152/73257 [============================>.] - ETA: 0s - loss: 0.5396 - TP: 57461.0000 - TN: 65
Epoch 00015: val_loss improved from 0.72354 to 0.69736, saving model to checkpointmodel/Checkpo
73257/73257 [==============================] - 43s 594us/sample - loss: 0.5397 - TP: 57545.0000
```

In [13]:
```python
df = pd.DataFrame(history.history)

f,ax = plt.subplots(1,2,figsize=(10,5))
ax[0].plot(df["loss"])
ax[0].plot(df["val_loss"])
ax[0].set(title="Loss Perfomance",ylabel = "loss",xlabel="epochs")

ax[1].plot(df["ACC"])
ax[1].plot(df["val_ACC"])
ax[1].set(title="Accuracy Perfomance",ylabel = "Accuracy",xlabel="epochs")
```

Out[13]:
```
[Text(0, 0.5, 'Accuracy'),
 Text(0.5, 0, 'epochs'),
 Text(0.5, 1.0, 'Accuracy Perfomance')]
```



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 [10]: def buildmodelCnn(input_shape):
             model = Sequential([
                 Conv2D(filters = 16,kernel_size=(3,3),padding = "SAME",input_shape = input_sha
                        activation = LeakyReLU()),
                 MaxPooling2D(pool_size=(7,7)),
                 BatchNormalization(),
                 Flatten(),
                 Dense(units =128,activation = LeakyReLU(),name = "dense_1",kernel_initializer=
                        bias_initializer=initializers.Ones()),
```

```
        Dense(units =128,activation = LeakyReLU(),name = "dense_2",kernel_initializer=
              bias_initializer=initializers.Ones()),
        Dense(units =128,activation = ReLU(),name = "dense_3",kernel_initializer=init
              bias_initializer=initializers.Ones()),
        Dense(units = 10,activation = Softmax(),name = "Output")

    ])
    opt = tf.keras.optimizers.Adam(0.001)
    loss = tf.keras.losses.CategoricalCrossentropy()
    METRICS = [tf.keras.metrics.TruePositives(name="TP"),
          tf.keras.metrics.TrueNegatives(name="TN"),
          tf.keras.metrics.FalsePositives(name="FP"),
          tf.keras.metrics.FalseNegatives(name="FN"),
          tf.keras.metrics.CategoricalAccuracy(name="ACC"),
          tf.keras.metrics.AUC(name="AUC")]

    model.compile(optimizer=opt,loss=loss,metrics=METRICS)

    return model
```

In [11]:
```
x_trainingray = np.moveaxis(x_trainingray,1,3)
x_testgray =np.moveaxis(x_testgray,1,3)
print(x_trainingray.shape,x_testgray.shape)
shape = x_trainingray[0,:,:,:].shape
print(shape)
modelcnn = buildmodelCnn(shape)
modelcnn.summary()
```

```
(73257, 32, 32, 1) (26032, 32, 32, 1)
(32, 32, 1)
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 16)        160
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 4, 4, 16)          0
_________________________________________________________________
batch_normalization (BatchNo (None, 4, 4, 16)          64
_________________________________________________________________
flatten (Flatten)            (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_2 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_3 (Dense)              (None, 128)               16512
```

```
_________________________________________________________________
Output (Dense)               (None, 10)               1290
=================================================================
Total params: 67,434
Trainable params: 67,402
Non-trainable params: 32
_________________________________________________________________
```

```
In [16]: def CheckpointCNNDude():
             Checkpointpath = "checkpointmodelCNN/CheckpointBest"
             Checkpoint = ModelCheckpoint(filepath=Checkpointpath,monitor = "val_loss",
                                          save_best_only = True,save_weights_only=True,frequency
             return Checkpoint
         checkpoint = CheckpointCNNDude()
         EarlyStop = EarlyStopme()
         scheduler = create_learning_rate_scheduler()
```

```
In [17]: history = modelcnn.fit(x = x_traininggray,y=y_train,epochs=15,
                    verbose=1,batch_size= 64,
                     workers = -1,validation_data=[x_testgray,y_test],
                   callbacks=[EarlyStop,scheduler,checkpoint])
```

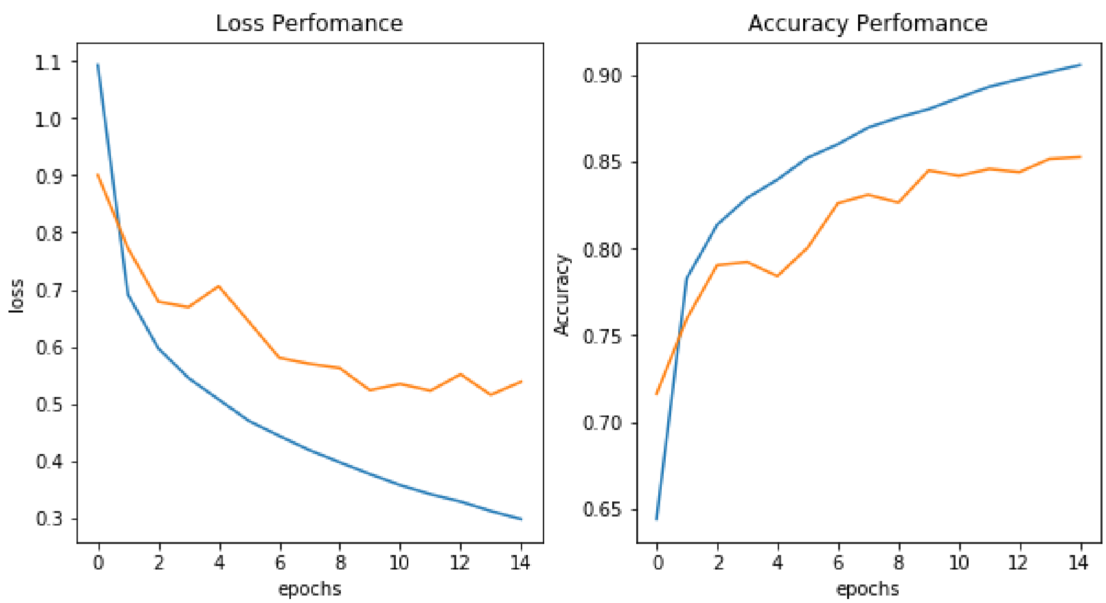
```
Train on 73257 samples, validate on 26032 samples

Epoch 00001: LearningRateScheduler reducing learning rate to 0.001.
Epoch 1/15
73216/73257 [============================>.] - ETA: 0s - loss: 1.0940 - TP: 37400.0000 - TN: 65
Epoch 00001: val_loss improved from inf to 0.90075, saving model to checkpointmodelCNN/Checkpoi
73257/73257 [==============================] - 163s 2ms/sample - loss: 1.0935 - TP: 37471.0000

Epoch 00002: LearningRateScheduler reducing learning rate to 0.001.
Epoch 2/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.6912 - TP: 52300.0000 - TN: 65
Epoch 00002: val_loss improved from 0.90075 to 0.77247, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 154s 2ms/sample - loss: 0.6911 - TP: 52334.0000

Epoch 00003: LearningRateScheduler reducing learning rate to 0.001.
Epoch 3/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.5968 - TP: 55514.0000 - TN: 65
Epoch 00003: val_loss improved from 0.77247 to 0.67863, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 160s 2ms/sample - loss: 0.5967 - TP: 55545.0000

Epoch 00004: LearningRateScheduler reducing learning rate to 0.001.
Epoch 4/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.5450 - TP: 57110.0000 - TN: 65
Epoch 00004: val_loss improved from 0.67863 to 0.66906, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 160s 2ms/sample - loss: 0.5450 - TP: 57144.0000
```

```
Epoch 00005: LearningRateScheduler reducing learning rate to 0.001.
Epoch 5/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.5073 - TP: 58221.0000 - TN: 65
Epoch 00005: val_loss did not improve from 0.66906
73257/73257 [==============================] - 160s 2ms/sample - loss: 0.5072 - TP: 58254.0000

Epoch 00006: LearningRateScheduler reducing learning rate to 0.0009389309106617063.
Epoch 6/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.4692 - TP: 59448.0000 - TN: 65
Epoch 00006: val_loss improved from 0.66906 to 0.64334, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 159s 2ms/sample - loss: 0.4694 - TP: 59481.0000

Epoch 00007: LearningRateScheduler reducing learning rate to 0.0008815912549960212.
Epoch 7/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.4432 - TP: 60231.0000 - TN: 65
Epoch 00007: val_loss improved from 0.64334 to 0.58039, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 157s 2ms/sample - loss: 0.4433 - TP: 60260.0000

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0008277532798848107.
Epoch 8/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.4186 - TP: 61031.0000 - TN: 65
Epoch 00008: val_loss improved from 0.58039 to 0.56964, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 157s 2ms/sample - loss: 0.4186 - TP: 61065.0000

Epoch 00009: LearningRateScheduler reducing learning rate to 0.0007772031408854596.
Epoch 9/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.3972 - TP: 61588.0000 - TN: 65
Epoch 00009: val_loss improved from 0.56964 to 0.56220, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 159s 2ms/sample - loss: 0.3971 - TP: 61620.0000

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0007297400528407231.
Epoch 10/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.3765 - TP: 62208.0000 - TN: 65
Epoch 00010: val_loss improved from 0.56220 to 0.52354, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 159s 2ms/sample - loss: 0.3765 - TP: 62246.0000

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0006851754923600619.
Epoch 11/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.3571 - TP: 62685.0000 - TN: 65
Epoch 00011: val_loss did not improve from 0.52354
73257/73257 [==============================] - 160s 2ms/sample - loss: 0.3571 - TP: 62721.0000

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0006433324490047158.
Epoch 12/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.3411 - TP: 63306.0000 - TN: 65
Epoch 00012: val_loss improved from 0.52354 to 0.52262, saving model to checkpointmodelCNN/Chec
73257/73257 [==============================] - 158s 2ms/sample - loss: 0.3411 - TP: 63340.0000
```

```
Epoch 00013: LearningRateScheduler reducing learning rate to 0.0006040447222022236.
Epoch 13/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.3280 - TP: 63752.0000 - TN: 65
Epoch 00013: val_loss did not improve from 0.52262
73257/73257 [==============================] - 154s 2ms/sample - loss: 0.3280 - TP: 63786.0000

Epoch 00014: LearningRateScheduler reducing learning rate to 0.0005671562610977313.
Epoch 14/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.3116 - TP: 64104.0000 - TN: 65
Epoch 00014: val_loss improved from 0.52262 to 0.51539, saving model to checkpointmodelCNN/Che
73257/73257 [==============================] - 153s 2ms/sample - loss: 0.3117 - TP: 64140.0000

Epoch 00015: LearningRateScheduler reducing learning rate to 0.0005325205447199813.
Epoch 15/15
73216/73257 [============================>.] - ETA: 0s - loss: 0.2976 - TP: 64518.0000 - TN: 65
Epoch 00015: val_loss did not improve from 0.51539
73257/73257 [==============================] - 153s 2ms/sample - loss: 0.2976 - TP: 64555.0000
```

In [18]:
```
df = pd.DataFrame(history.history)

f,ax = plt.subplots(1,2,figsize=(10,5))
ax[0].plot(df["loss"])
ax[0].plot(df["val_loss"])
ax[0].set(title="Loss Perfomance",ylabel = "loss",xlabel="epochs")

ax[1].plot(df["ACC"])
ax[1].plot(df["val_ACC"])
ax[1].set(title="Accuracy Perfomance",ylabel = "Accuracy",xlabel="epochs")
```

Out[18]:
```
[Text(0, 0.5, 'Accuracy'),
 Text(0.5, 0, 'epochs'),
 Text(0.5, 1.0, 'Accuracy Perfomance')]
```



1.5 4. Get model predictions

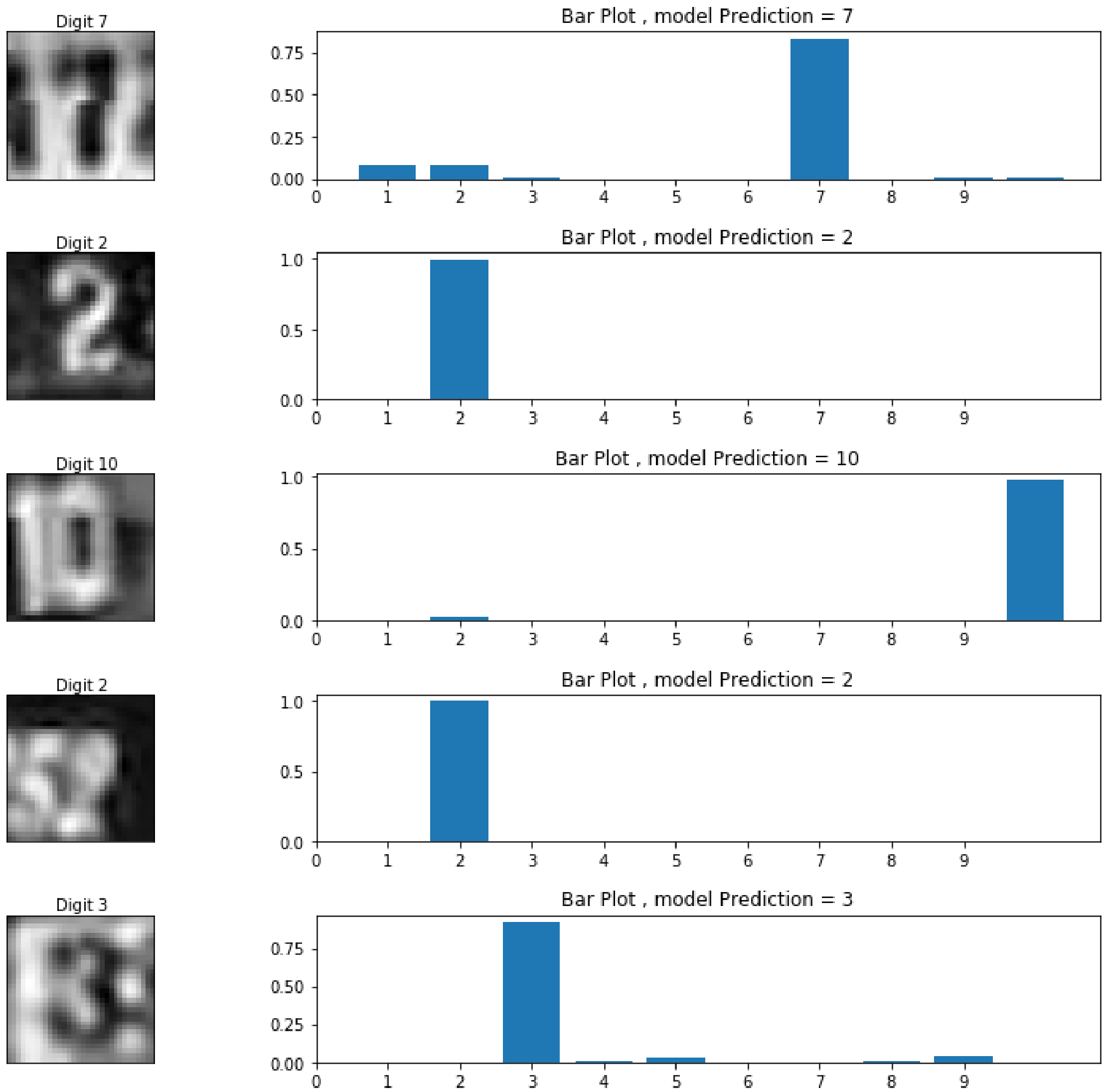
- Load the best weights for the MLP and CNN models that you saved during the training run.
- Randomly select 5 images and corresponding labels from the test set and display the images with their labels.
- Alongside the image and label, show each model's predictive distribution as a bar chart, and the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

In [12]:
```
modelcnn.load_weights(tf.train.latest_checkpoint("checkpointmodelCNN"))
model.load_weights(tf.train.latest_checkpoint("checkpointmodel"))
```

Out[12]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7f8e60e63da0>
```

In [13]:
```
def get_label(labelList):
    iterat = 0
    for i in labelList:
        if i - 1 == 0 :
            return iterat + 1
        iterat = iterat + 1
    return 0

np.random.seed(15)

x_testforMlP = np.moveaxis(x_testgray,3,1)
chooseIndex = np.random.choice(x_testforMlP.shape[0],5)

f,ax = plt.subplots(nrows = 5,ncols = 2,figsize=(16,12))
f.subplots_adjust(hspace=0.5,wspace=-0.2)
```

```
    for iterate,index in enumerate(chooseIndex):
        LabelsMe = get_label(y_test[index,...])
        images = x_testgray[index,:,:,0]
        prediction = model.predict(np.expand_dims(x_testforMlP[index,:,:,:],axis=0)).resha
        ax[iterate,0].imshow((images),cmap="gray")
        ax[iterate,0].text(10, -1.5, f"Digit {LabelsMe}")
        ax[iterate,0].get_xaxis().set_visible(False)
        ax[iterate,0].get_yaxis().set_visible(False)
        ax[iterate,1].bar(np.arange(len(prediction))+1, prediction.reshape(10))
        ax[iterate,1].set_xticks(np.arange(len(prediction)))
        ax[iterate,1].set_title(f"Bar Plot , model Prediction = {np.argmax(prediction) + 1
```




```
In [14]: np.random.seed(15)
```

```python
#x_testforMlP = np.moveaxis(x_testgray,3,1)
chooseIndex = np.random.choice(x_testgray.shape[0],5)

f,ax = plt.subplots(nrows = 5,ncols = 2,figsize=(16,12))
f.subplots_adjust(hspace=0.5,wspace=-0.2)
for iterate,index in enumerate(chooseIndex):
    LabelsMe = get_label(y_test[index,...])
    images = x_testgray[index,:,:,0]
    prediction = modelcnn.predict(np.expand_dims(x_testgray[index,:,:,:],axis=0)).resh
    ax[iterate,0].imshow((images),cmap="gray")
    ax[iterate,0].text(10, -1.5, f"Digit {LabelsMe}")
    ax[iterate,0].get_xaxis().set_visible(False)
    ax[iterate,0].get_yaxis().set_visible(False)
    ax[iterate,1].bar(np.arange(len(prediction))+1, prediction.reshape(10))
    ax[iterate,1].set_xticks(np.arange(len(prediction)))
    ax[iterate,1].set_title(f"Bar Plot , model Prediction = {np.argmax(prediction) + 
```