Capstone Project

Image classifier for the SVHN dataset

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.

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.

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 scipy.io import loadmat
from tensorflow.compat.v1 import InteractiveSession # This is needed to run on Windows 10 laptop with C
uda

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, BatchNormalization
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
```

In [2]:
```
# This is needed to run on Windows 10 laptop with Cuda
print(tf.__version__)

config = tf.compat.v1.ConfigProto()
config.gpu_options.allow_growth = True
session = InteractiveSession(config=config)
```

```
2.1.0
```

SVHN overview image
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 [3]:
```
# 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. 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 [4]:
```
# Task:
# Extract the training and testing images and labels separately from the train and test dictionaries lo
aded for you.
import numpy as np
X_train = train['X']
y_train = train['y']
X_test = test['X']
y_test = test['y']
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(32, 32, 3, 73257)
(73257, 1)
(32, 32, 3, 26032)
(26032, 1)
```

In [5]:
```
from sklearn.preprocessing import OneHotEncoder

enc = OneHotEncoder().fit(y_train)
y_train = enc.transform(y_train).toarray()
y_test = enc.transform(y_test).toarray()
```

In [6]:
```
print(y_train.shape)
print(y_train[0])
```

```
(73257, 10)
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

In [7]:
```
# Task:
# 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
```

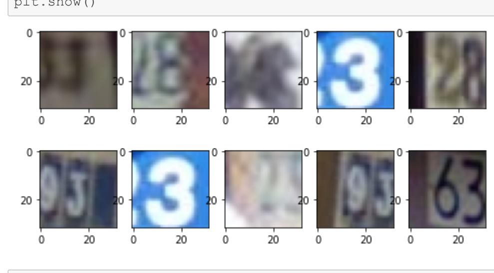
In [8]:
```
X_train_avg = np.swapaxes(X_train, 3,0)
print(X_train_avg.shape)
X_train_avg = np.swapaxes(X_train_avg, 3,2)
X_train_avg = np.swapaxes(X_train_avg, 1,2)
print(X_train_avg.shape)
```

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

In [9]:
```
X_train_avg = np.mean(X_train_avg,axis=3)
X_train_avg =X_train_avg[..., np.newaxis]
print(X_train_avg.shape)
print(X_train_avg[1].shape)
```

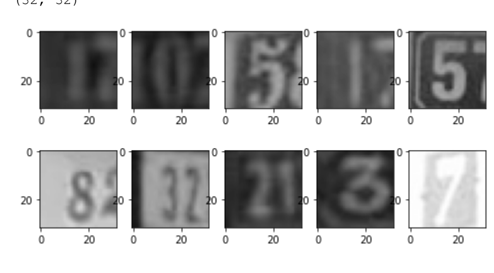
```
(73257, 32, 32, 1)
(32, 32, 1)
```

In [10]:
```
# Task:
# Select a random sample of images and corresponding labels from the dataset (at least 10), and display
 them in a figure.
import numpy as np
import matplotlib.pyplot as plt
import random

w=10
h=2
fig=plt.figure(figsize=(8,4))
columns = 5
rows = 2
shp=(X_train.shape)[0]
#print(random.randint(0,shp))
for i in range(1, columns*rows+1):
    indx = random.randint(0,shp)
    img = X_train[...,indx]
    fig.add_subplot(rows,columns, i)
    plt.imshow(img)
plt.show()
```



In [11]:
```
# Task:
# Select a random sample of the grayscale images and corresponding labels
# from the dataset (at least 10), and display them in a figure.

print(X_train_avg[1].squeeze(axis=2).shape)
w=10
h=2
fig=plt.figure(figsize=(8,4))
columns = 5
rows = 2
shp=(X_train_avg.shape)[0]
#print(random.randint(0,shp))
for i in range(1, columns*rows+1):
    indx = random.randint(0,shp)
    img = X_train_avg[indx].squeeze(axis=2)
    fig.add_subplot(rows,columns, i)
    plt.imshow(img,cmap='gray',vmin=0,vmax=255,label=y_train[indx])
plt.show()
```

```
(32, 32)
```



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 [12]:
```
def get_seq_model(input_shape):
    model = Sequential([
                    Dense(128, input_shape=input_shape, activation='relu'),
                    Flatten(),
                    Dense(64, activation='relu'),
                    BatchNormalization(),
                    Dense(64, activation='relu'),
                    Dense(64, activation='relu'),
                    tf.keras.layers.Dropout(0.5),
                    Dense(10, activation='softmax'),
                        ])
    return model
```

In [13]:
```
def compile_seq_model(model):

    model.compile(optimizer='adam',
                loss = ['categorical_crossentropy'],
                metrics=['acc'])
```

In [14]:
```
checkpoint = ModelCheckpoint(filepath = 'SeqModel\mySeqModel', save_best_only=True, save_weights_only=T
rue, monitor='val_loss', verbose=1)
earlystop = EarlyStopping(patience=5, monitor='loss')
```

In [15]:
```
def train_seq_model(model, scaled_train_images, train_labels, epochs):

    history = model.fit(scaled_train_images, train_labels,
                        epochs=epochs,batch_size=40,validation_split=0.15,verbose=1,
                        callbacks=[checkpoint, earlystop])
    return history
```

In [15]:
```
print(X_train_avg[0].shape)
print(y_train[0])
model = get_seq_model(X_train_avg[0].shape)
compile_seq_model(model)
model.summary()
```

```
(32, 32, 1)
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 32, 32, 128)       256
_________________________________________________________________
flatten (Flatten)            (None, 131072)            0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                8388672
_________________________________________________________________
batch_normalization (BatchNo (None, 64)                256
_________________________________________________________________
dense_2 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_3 (Dense)              (None, 64)                4160
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_4 (Dense)              (None, 10)                650
=================================================================
Total params: 8,398,154
Trainable params: 8,398,026
Non-trainable params: 128
_________________________________________________________________
```

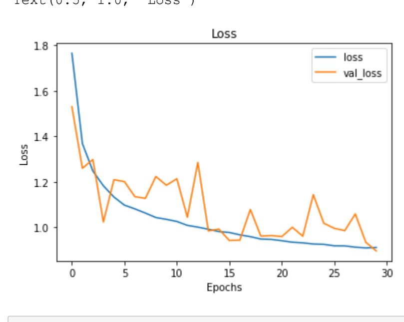
In [17]:
```
history = train_seq_model(model,X_train_avg,y_train,30)
```

```
(32, 32, 1)
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Train on 62268 samples, validate on 10989 samples
Epoch 1/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.7648 - acc: 0.3899
Epoch 00001: val_loss improved from inf to 1.52954, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 48s 768us/sample - loss: 1.7644 - acc: 0.3900 - val_lo
ss: 1.5295 - val_acc: 0.4964
Epoch 2/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.3678 - acc: 0.5580
Epoch 00002: val_loss improved from 1.52954 to 1.25956, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 46s 731us/sample - loss: 1.3677 - acc: 0.5580 - val_lo
ss: 1.2596 - val_acc: 0.5786
Epoch 3/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.2472 - acc: 0.6059
Epoch 00003: val_loss did not improve from 1.25956
62268/62268 [==============================] - 45s 724us/sample - loss: 1.2471 - acc: 0.6059 - val_lo
ss: 1.2976 - val_acc: 0.5563
Epoch 4/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.1825 - acc: 0.6288
Epoch 00004: val_loss improved from 1.25956 to 1.02338, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 45s 731us/sample - loss: 1.1824 - acc: 0.6288 - val_lo
ss: 1.0234 - val_acc: 0.6718
Epoch 5/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.1334 - acc: 0.6492
Epoch 00005: val_loss did not improve from 1.02338
62268/62268 [==============================] - 45s 723us/sample - loss: 1.1333 - acc: 0.6492 - val_lo
ss: 1.2090 - val_acc: 0.6238
Epoch 6/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.0976 - acc: 0.6584
Epoch 00006: val_loss did not improve from 1.02338
62268/62268 [==============================] - 45s 721us/sample - loss: 1.0976 - acc: 0.6584 - val_lo
ss: 1.2010 - val_acc: 0.6370
Epoch 7/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0810 - acc: 0.6650
Epoch 00007: val_loss did not improve from 1.02338
62268/62268 [==============================] - 45s 721us/sample - loss: 1.0810 - acc: 0.6649 - val_lo
ss: 1.1347 - val_acc: 0.6558
Epoch 8/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0627 - acc: 0.6713
Epoch 00008: val_loss did not improve from 1.02338
62268/62268 [==============================] - 46s 737us/sample - loss: 1.0626 - acc: 0.6713 - val_lo
ss: 1.1274 - val_acc: 0.6763
Epoch 9/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0431 - acc: 0.6767
Epoch 00009: val_loss did not improve from 1.02338
62268/62268 [==============================] - 47s 750us/sample - loss: 1.0431 - acc: 0.6767 - val_lo
ss: 1.2231 - val_acc: 0.6290
Epoch 10/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.0352 - acc: 0.6769
Epoch 00010: val_loss did not improve from 1.02338
62268/62268 [==============================] - 47s 747us/sample - loss: 1.0352 - acc: 0.6770 - val_lo
ss: 1.1848 - val_acc: 0.6600
Epoch 11/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0258 - acc: 0.6811
Epoch 00011: val_loss did not improve from 1.02338
62268/62268 [==============================] - 48s 764us/sample - loss: 1.0257 - acc: 0.6811 - val_lo
ss: 1.2133 - val_acc: 0.6397
Epoch 12/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0089 - acc: 0.6896
Epoch 00012: val_loss did not improve from 1.02338
62268/62268 [==============================] - 48s 776us/sample - loss: 1.0087 - acc: 0.6897 - val_lo
ss: 1.0443 - val_acc: 0.7089
Epoch 13/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.0008 - acc: 0.6920
Epoch 00013: val_loss did not improve from 1.02338
62268/62268 [==============================] - 48s 778us/sample - loss: 1.0009 - acc: 0.6921 - val_lo
ss: 1.2846 - val_acc: 0.6721
Epoch 14/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9916 - acc: 0.6933
Epoch 00014: val_loss improved from 1.02338 to 0.98431, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 51s 823us/sample - loss: 0.9916 - acc: 0.6933 - val_lo
ss: 0.9843 - val_acc: 0.7209
Epoch 15/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9814 - acc: 0.6981
Epoch 00015: val_loss did not improve from 0.98431
62268/62268 [==============================] - 50s 798us/sample - loss: 0.9814 - acc: 0.6980 - val_lo
ss: 0.9922 - val_acc: 0.6794
Epoch 16/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.9774 - acc: 0.6989
Epoch 00016: val_loss improved from 0.98431 to 0.94243, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 52s 833us/sample - loss: 0.9774 - acc: 0.6989 - val_lo
ss: 0.9424 - val_acc: 0.7154
Epoch 17/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.9668 - acc: 0.7029
Epoch 00017: val_loss did not improve from 0.94243
62268/62268 [==============================] - 51s 826us/sample - loss: 0.9671 - acc: 0.7028 - val_lo
ss: 0.9438 - val_acc: 0.7094
Epoch 18/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9590 - acc: 0.7059
Epoch 00018: val_loss did not improve from 0.94243
62268/62268 [==============================] - 50s 803us/sample - loss: 0.9591 - acc: 0.7058 - val_lo
ss: 1.0784 - val_acc: 0.6922
Epoch 19/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9488 - acc: 0.7074
Epoch 00019: val_loss did not improve from 0.94243
62268/62268 [==============================] - 48s 774us/sample - loss: 0.9486 - acc: 0.7074 - val_lo
ss: 0.9617 - val_acc: 0.7038
Epoch 20/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9469 - acc: 0.7088
Epoch 00020: val_loss did not improve from 0.94243
62268/62268 [==============================] - 49s 790us/sample - loss: 0.9470 - acc: 0.7088 - val_lo
ss: 0.9639 - val_acc: 0.7160
Epoch 21/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9412 - acc: 0.7106
Epoch 00021: val_loss did not improve from 0.94243
62268/62268 [==============================] - 50s 801us/sample - loss: 0.9413 - acc: 0.7106 - val_lo
ss: 0.9597 - val_acc: 0.7189
Epoch 22/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9347 - acc: 0.7116
Epoch 00022: val_loss did not improve from 0.94243
62268/62268 [==============================] - 47s 759us/sample - loss: 0.9347 - acc: 0.7116 - val_lo
ss: 1.0000 - val_acc: 0.6962
Epoch 23/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9316 - acc: 0.7143
Epoch 00023: val_loss did not improve from 0.94243
62268/62268 [==============================] - 47s 756us/sample - loss: 0.9319 - acc: 0.7143 - val_lo
ss: 0.9611 - val_acc: 0.7097
Epoch 24/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9269 - acc: 0.7156
Epoch 00024: val_loss did not improve from 0.94243
62268/62268 [==============================] - 47s 757us/sample - loss: 0.9268 - acc: 0.7156 - val_lo
ss: 1.1435 - val_acc: 0.6527
Epoch 25/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.9253 - acc: 0.7176
Epoch 00025: val_loss did not improve from 0.94243
62268/62268 [==============================] - 47s 754us/sample - loss: 0.9252 - acc: 0.7176 - val_lo
ss: 1.0180 - val_acc: 0.6894
Epoch 26/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.9187 - acc: 0.7192
Epoch 00026: val_loss did not improve from 0.94243
62268/62268 [==============================] - 47s 754us/sample - loss: 0.9190 - acc: 0.7191 - val_lo
ss: 0.9957 - val_acc: 0.7038
Epoch 27/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.9185 - acc: 0.7183
Epoch 00027: val_loss did not improve from 0.94243
62268/62268 [==============================] - 48s 769us/sample - loss: 0.9185 - acc: 0.7183 - val_lo
ss: 0.9856 - val_acc: 0.6920
Epoch 28/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9129 - acc: 0.7200
Epoch 00028: val_loss did not improve from 0.94243
62268/62268 [==============================] - 47s 752us/sample - loss: 0.9129 - acc: 0.7200 - val_lo
ss: 1.0589 - val_acc: 0.6650
Epoch 29/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9097 - acc: 0.7224
Epoch 00029: val_loss improved from 0.94243 to 0.93458, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 48s 763us/sample - loss: 0.9097 - acc: 0.7224 - val_lo
ss: 0.9346 - val_acc: 0.7145
Epoch 30/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.9115 - acc: 0.7209
Epoch 00030: val_loss improved from 0.93458 to 0.89641, saving model to SeqModel\mySeqModel
62268/62268 [==============================] - 47s 761us/sample - loss: 0.9115 - acc: 0.7208 - val_lo
ss: 0.8964 - val_acc: 0.7180
```

In [18]:
```
model.save('seqmodel\\seqmodel.h5')
```

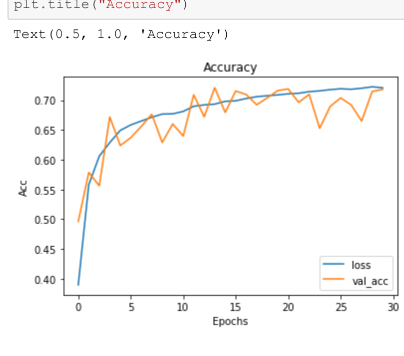
In [19]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(['loss','val_loss'], loc='upper right')
plt.title("Loss")
```

Out[19]: `Text(0.5, 1.0, 'Loss')`



In [22]:
```
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.xlabel('Epochs')
plt.ylabel('Acc')
plt.legend(['loss','val_acc'], loc='lower right')
plt.title("Accuracy")
```

Out[22]: `Text(0.5, 1.0, 'Accuracy')`



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 [23]:
```
def get_conv_model(input_shape):
    model = Sequential([
        Conv2D(filters= 16, kernel_size= 3, activation='relu', input_shape=input_shape),
        MaxPooling2D(pool_size= (3,3), strides=1),
        Conv2D(filters= 32, kernel_size = 3, padding='valid', strides=1, activation='relu'),
        MaxPooling2D(pool_size = (1,1), strides = 3),
        BatchNormalization(),
        Conv2D(filters= 32, kernel_size = 3, padding='valid', strides=2, activation='relu'),
        tf.keras.layers.Dropout(0.5),
        Flatten(),
        Dense(128, activation='relu'),
        Dense(32, activation='relu'),
        tf.keras.layers.Dropout(0.3),
        Dense(10, activation='softmax')
    ])
    return model
```

In [24]:
```
def compile_conv_model(model):

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

In [25]:
```
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
def get_early_stopping():
    """
    This function should return an EarlyStopping callback that stops training when
    the validation (testing) accuracy has not improved in the last 7 epochs.
    HINT: use the EarlyStopping callback with the correct 'monitor' and 'patience'
    """
    earlystoppingcallback = tf.keras.callbacks.EarlyStopping(patience=3, monitor='val_accuracy', mode=
'max')
    return earlystoppingcallback

def get_checkpoint_best_only():
    """
    This function should return a ModelCheckpoint object that:
    - saves only the weights that generate the highest validation (testing) accuracy
    - saves into a directory called 'checkpoints_best_only' inside the current working directory
    - generates a file called 'checkpoints_best_only/checkpoint'
    """
    checkpoint_path =  'checkpoints_best_only\checkpoint'
    checkpoint = ModelCheckpoint(filepath = checkpoint_path,
                                save_weight_only=False,
                                 save_freq='epoch',
                                monitor='val_accuracy',
                                 save_best_only=True,
                                 verbose=1
                                )
    return checkpoint
```

In [26]:
```
checkpoint_best_only = get_checkpoint_best_only()
early_stopping = get_early_stopping()
```

In [27]:
```
def train_conv_model(model, scaled_train_images, train_labels, epochs):
    history = model.fit(scaled_train_images, train_labels,
                        epochs=epochs,batch_size=40,validation_split=0.15,verbose=1,
                        callbacks=[checkpoint_best_only, early_stopping])
    return history
```

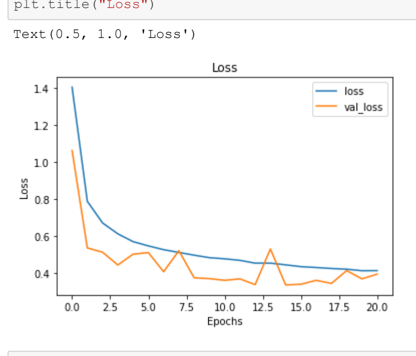
In [28]:
```
model2 = get_conv_model(X_train_avg[0].shape)
compile_conv_model(model2)
history = train_conv_model(model2,X_train_avg,y_train,30)
```

```
Train on 62268 samples, validate on 10989 samples
Epoch 1/30
62080/62268 [============================>.] - ETA: 0s - loss: 1.4067 - accuracy: 0.5260
Epoch 00001: val_accuracy improved from -inf to 0.69451, saving model to checkpoints_best_only\checkp
oint
WARNING:tensorflow:From C:\Users\omkar.karve\.conda\envs\motion\lib\site-packages\tensorflow_core\pyt
hon\ops\resource_variable_ops.py:1786: calling BaseResourceVariable.__init__ (from tensorflow.python.
ops.resource_variable_ops) with constraint is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 20s 328us/sample - loss: 1.4055 - accuracy: 0.5265 - v
al_loss: 1.0636 - val_accuracy: 0.6945
Epoch 2/30
62040/62268 [============================>.] - ETA: 0s - loss: 0.7886 - accuracy: 0.7603
Epoch 00002: val_accuracy improved from 0.69451 to 0.84029, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 18s 285us/sample - loss: 0.7888 - accuracy: 0.7603 - v
al_loss: 0.5371 - val_accuracy: 0.8403
Epoch 3/30
62040/62268 [============================>.] - ETA: 0s - loss: 0.6725 - accuracy: 0.7999
Epoch 00003: val_accuracy improved from 0.84029 to 0.84694, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 18s 285us/sample - loss: 0.6721 - accuracy: 0.8001 - v
al_loss: 0.5140 - val_accuracy: 0.8469
Epoch 4/30
62040/62268 [============================>.] - ETA: 0s - loss: 0.6138 - accuracy: 0.8183
Epoch 00004: val_accuracy improved from 0.84694 to 0.86559, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 18s 288us/sample - loss: 0.6134 - accuracy: 0.8185 - v
al_loss: 0.4450 - val_accuracy: 0.8656
Epoch 5/30
62160/62268 [============================>.] - ETA: 0s - loss: 0.5707 - accuracy: 0.8304
Epoch 00005: val_accuracy did not improve from 0.86559
62268/62268 [==============================] - 16s 260us/sample - loss: 0.5712 - accuracy: 0.8304 - v
al_loss: 0.5034 - val_accuracy: 0.8560
Epoch 6/30
62040/62268 [============================>.] - ETA: 0s - loss: 0.5482 - accuracy: 0.8373
Epoch 00006: val_accuracy did not improve from 0.86559
62268/62268 [==============================] - 16s 262us/sample - loss: 0.5482 - accuracy: 0.8373 - v
al_loss: 0.5120 - val_accuracy: 0.8422
Epoch 7/30
62120/62268 [============================>.] - ETA: 0s - loss: 0.5278 - accuracy: 0.8437
Epoch 00007: val_accuracy improved from 0.86559 to 0.87870, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 18s 291us/sample - loss: 0.5278 - accuracy: 0.8437 - v
al_loss: 0.4088 - val_accuracy: 0.8787
Epoch 8/30
62040/62268 [============================>.] - ETA: 0s - loss: 0.5132 - accuracy: 0.8501
Epoch 00008: val_accuracy did not improve from 0.87870
62268/62268 [==============================] - 16s 260us/sample - loss: 0.5128 - accuracy: 0.8503 - v
al_loss: 0.5222 - val_accuracy: 0.8438
Epoch 9/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.4982 - accuracy: 0.8541
Epoch 00009: val_accuracy improved from 0.87870 to 0.88916, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 19s 308us/sample - loss: 0.4981 - accuracy: 0.8541 - v
al_loss: 0.3761 - val_accuracy: 0.8892
Epoch 10/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.4845 - accuracy: 0.8583
Epoch 00010: val_accuracy improved from 0.88916 to 0.89171, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 21s 343us/sample - loss: 0.4846 - accuracy: 0.8583 - v
al_loss: 0.3713 - val_accuracy: 0.8917
Epoch 11/30
62160/62268 [============================>.] - ETA: 0s - loss: 0.4784 - accuracy: 0.8613
Epoch 00011: val_accuracy improved from 0.89171 to 0.89353, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 20s 314us/sample - loss: 0.4784 - accuracy: 0.8613 - v
al_loss: 0.3624 - val_accuracy: 0.8935
Epoch 12/30
62120/62268 [============================>.] - ETA: 0s - loss: 0.4699 - accuracy: 0.8639
Epoch 00012: val_accuracy did not improve from 0.89353
62268/62268 [==============================] - 17s 268us/sample - loss: 0.4703 - accuracy: 0.8638 - v
al_loss: 0.3700 - val_accuracy: 0.8927
Epoch 13/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.4550 - accuracy: 0.8675
Epoch 00013: val_accuracy improved from 0.89353 to 0.89917, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 19s 303us/sample - loss: 0.4551 - accuracy: 0.8675 - v
al_loss: 0.3390 - val_accuracy: 0.8992
Epoch 14/30
62040/62268 [============================>.] - ETA: 0s - loss: 0.4552 - accuracy: 0.8678
Epoch 00014: val_accuracy did not improve from 0.89917
62268/62268 [==============================] - 17s 267us/sample - loss: 0.4551 - accuracy: 0.8678 - v
al_loss: 0.5317 - val_accuracy: 0.8378
Epoch 15/30
62120/62268 [============================>.] - ETA: 0s - loss: 0.4459 - accuracy: 0.8689
Epoch 00015: val_accuracy improved from 0.89917 to 0.90054, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 19s 300us/sample - loss: 0.4458 - accuracy: 0.8690 - v
al_loss: 0.3374 - val_accuracy: 0.9005
Epoch 16/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.4362 - accuracy: 0.8710
Epoch 00016: val_accuracy improved from 0.90054 to 0.90090, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 19s 297us/sample - loss: 0.4361 - accuracy: 0.8710 - v
al_loss: 0.3412 - val_accuracy: 0.9009
Epoch 17/30
62120/62268 [============================>.] - ETA: 0s - loss: 0.4314 - accuracy: 0.8728
Epoch 00017: val_accuracy did not improve from 0.90090
62268/62268 [==============================] - 17s 267us/sample - loss: 0.4314 - accuracy: 0.8728 - v
al_loss: 0.3622 - val_accuracy: 0.8950
Epoch 18/30
62080/62268 [============================>.] - ETA: 0s - loss: 0.4260 - accuracy: 0.8747
Epoch 00018: val_accuracy improved from 0.90090 to 0.90190, saving model to checkpoints_best_only\che
ckpoint
INFO:tensorflow:Assets written to: checkpoints_best_only\checkpoint\assets
62268/62268 [==============================] - 19s 303us/sample - loss: 0.4262 - accuracy: 0.8746 - v
al_loss: 0.3455 - val_accuracy: 0.9019
Epoch 19/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.4221 - accuracy: 0.8760
Epoch 00019: val_accuracy did not improve from 0.90190
62268/62268 [==============================] - 17s 276us/sample - loss: 0.4223 - accuracy: 0.8760 - v
al_loss: 0.4147 - val_accuracy: 0.8766
Epoch 20/30
62120/62268 [============================>.] - ETA: 0s - loss: 0.4142 - accuracy: 0.8786
Epoch 00020: val_accuracy did not improve from 0.90190
62268/62268 [==============================] - 17s 268us/sample - loss: 0.4142 - accuracy: 0.8785 - v
al_loss: 0.3702 - val_accuracy: 0.8943
Epoch 21/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.4149 - accuracy: 0.8778
Epoch 00021: val_accuracy did not improve from 0.90190
62268/62268 [==============================] - 18s 282us/sample - loss: 0.4148 - accuracy: 0.8778 - v
al_loss: 0.3958 - val_accuracy: 0.8821
```

In [29]:
```
#Save the full model
model2.save('checkpoints_best_only\\bestonly.h5')
```

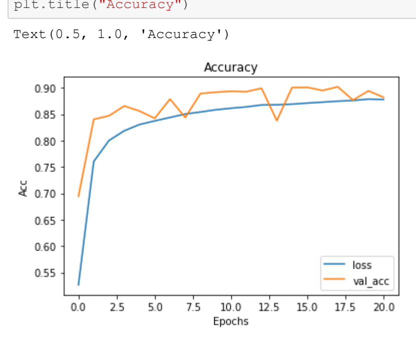
In [30]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(['loss','val_loss'], loc='upper right')
plt.title("Loss")
```

Out[30]: `Text(0.5, 1.0, 'Loss')`



In [31]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.xlabel('Epochs')
plt.ylabel('Acc')
plt.legend(['loss','val_acc'], loc='lower right')
plt.title("Accuracy")
```

Out[31]: `Text(0.5, 1.0, 'Accuracy')`



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.

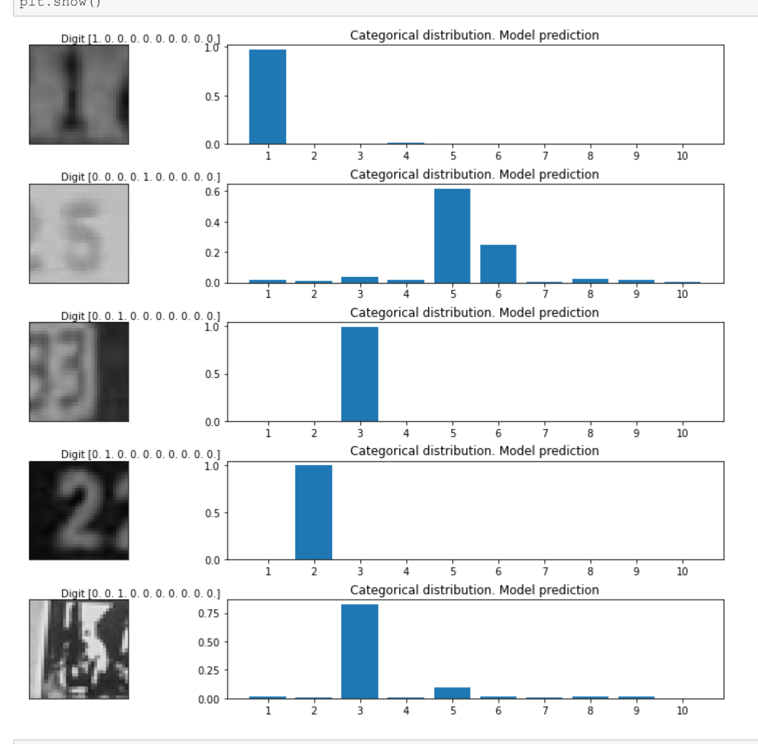
In [32]:
```
from tensorflow.keras.models import load_model
cnnmodel = load_model('checkpoints_best_only\\bestonly.h5')
cnnmodel.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 30, 30, 16)        160
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 28, 28, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 26, 26, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 9, 9, 32)          0
_________________________________________________________________
batch_normalization_2 (Batch (None, 9, 9, 32)          128
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 4, 4, 32)          9248
_________________________________________________________________
dropout_2 (Dropout)          (None, 4, 4, 32)          0
_________________________________________________________________
flatten_2 (Flatten)          (None, 512)               0
_________________________________________________________________
dense_10 (Dense)             (None, 128)               65664
_________________________________________________________________
dense_11 (Dense)             (None, 32)                4128
_________________________________________________________________
dropout_3 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_12 (Dense)             (None, 10)                330
=================================================================
Total params: 84,298
Trainable params: 84,234
Non-trainable params: 64
_________________________________________________________________
```

In [33]:
```
num_test_images = X_train_avg.shape[0]
print(X_train_avg.shape)
predimg=X_train_avg[1,:,:,:]
print(predimg.shape)
predimg = predimg[np.newaxis,...]
print(predimg.shape)
prediction = cnnmodel.predict(predimg)
print(prediction)
```

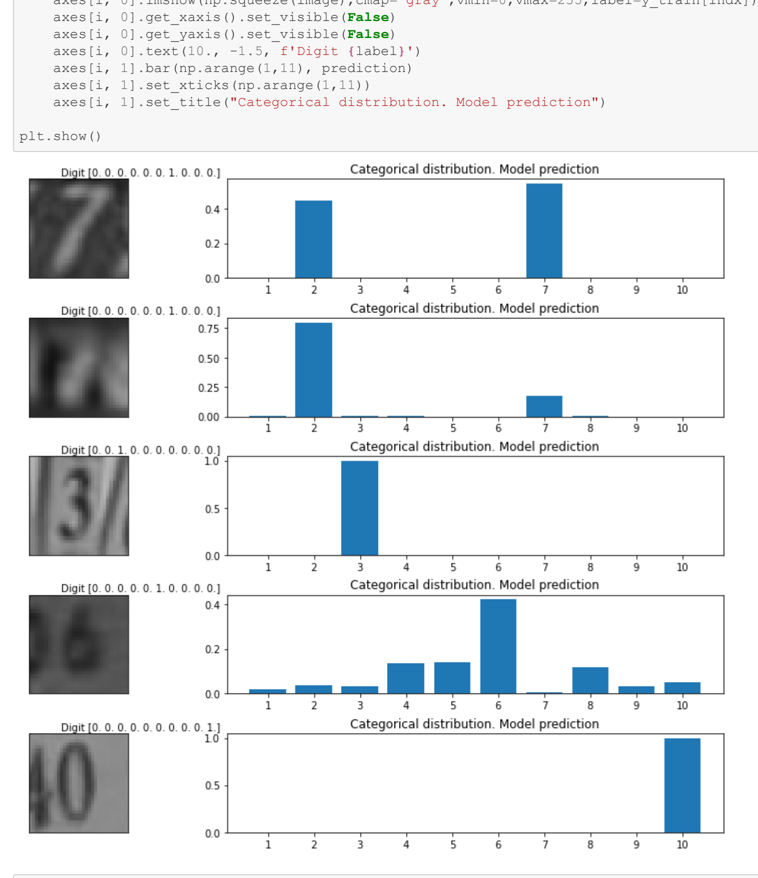
```
(73257, 32, 32, 1)
(32, 32, 1)
(1, 32, 32, 1)
[[3.4819411e-06 7.5843051e-04 2.4716872e-05 7.5845041e-05 6.9711086e-06
  4.3658434e-07 5.0412677e-06 2.9292363e-05 9.9857819e-01 5.1760196e-04]]
```

In [34]:
```
random_inx = np.random.choice(num_test_images, 5)
random_test_images = X_train_avg[random_inx,...]
random_test_labels = y_train[random_inx]
fig, axes = plt.subplots(5, 2, figsize=(16, 12))
fig.subplots_adjust(hspace=0.4, wspace=-0.2)
predictions = cnnmodel.predict(random_test_images)

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].imshow(np.squeeze(image),cmap='gray',vmin=0,vmax=255,label=y_train[indx])
    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(1,11), prediction)
    axes[i, 1].set_xticks(np.arange(1,11))
    axes[i, 1].set_title("Categorical distribution. Model prediction")

plt.show()
```



In [35]:
```
seqmodel = load_model('seqmodel\\seqmodel.h5')
```

In [36]:
```
random_inx = np.random.choice(num_test_images, 5)
random_test_images = X_train_avg[random_inx,...]
random_test_labels = y_train[random_inx]
fig, axes = plt.subplots(5, 2, figsize=(16, 12))
fig.subplots_adjust(hspace=0.4, wspace=-0.2)
predictions = seqmodel.predict(random_test_images)

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].imshow(np.squeeze(image),cmap='gray',vmin=0,vmax=255,label=y_train[indx])
    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(1,11), prediction)
    axes[i, 1].set_xticks(np.arange(1,11))
    axes[i, 1].set_title("Categorical distribution. Model prediction")

plt.show()
```



In [ ]:

In [ ]:

In [ ]: