SVHN_Notebook

August 28, 2021

1 Image classifier for the SVHN dataset

In this notebook, I will create a neural network that classifies real-world images digits. I will use concepts such as building, training, testing, validating and saving a Tensorflow classifier model.

1.1 Libraries

[1]:
```python
import tensorflow as tf
from scipy.io import loadmat
import random
import numpy as np
```

```
/Users/tapiatellez/opt/anaconda3/lib/python3.8/site-
packages/tensorflow/python/framework/dtypes.py:471: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/Users/tapiatellez/opt/anaconda3/lib/python3.8/site-
packages/tensorflow/python/framework/dtypes.py:472: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/Users/tapiatellez/opt/anaconda3/lib/python3.8/site-
packages/tensorflow/python/framework/dtypes.py:473: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/Users/tapiatellez/opt/anaconda3/lib/python3.8/site-
packages/tensorflow/python/framework/dtypes.py:474: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/Users/tapiatellez/opt/anaconda3/lib/python3.8/site-
packages/tensorflow/python/framework/dtypes.py:475: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
```

The [SVHN dataset](http://ufldl.stanford.edu/housenumbers/) 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.

My 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.

1.2 Loading the dataset

[2]:
```
train = loadmat('train_32x32.mat')
test = loadmat('test_32x32.mat')
```

Both `train` and `test` are dictionaries with keys `X` and `y` for the input images and labels respectively.

1.3 1. Inspect and preprocess the dataset

1.3.1 Extract the training and testing images and labels separately from the train and test dictionaries

[87]:
```
X_train = train['X']
y_train = train['y']
X_test = test['X']
y_test = test['y']
y_train[y_train == 10] = 0
y_test[y_test == 10] = 0
X_train.shape
X_test.shape
```

[87]: (32, 32, 3, 26032)

1.3.2 Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.

[88]:
```
r_indexes = random.sample(range(0, 73257), 16)
from matplotlib import pyplot as plt
fig = plt.figure(figsize = (6,6)) # figure size in inches
fig.subplots_adjust(left = 0, right = 1, bottom = 0, top = 1, hspace = 0.05,␣
 ↪wspace = 0.05)

for i in range(len(r_indexes)):
    ax = fig.add_subplot(4, 4, i+1, xticks = [], yticks = [])
    ax.imshow(X_train[:,:,:,r_indexes[i]], interpolation = 'nearest')
    ax.text(0, 7, str(y_train[r_indexes[i]][0]), color = 'red', fontsize = 24)
```

1.3.3 Convert the training and test images to grayscale by taking the average across all colour channels for each pixel. I will retain the channel dimension, which will now have size 1.

[89]:
```
X_train_grey = []

for i in range(73257):
    grey_image = np.mean(X_train[:, :, :, i], axis = 2)
    grey_image = grey_image[..., np.newaxis]
    X_train_grey.append(grey_image)
X_train_grey = np.array(X_train_grey)
#X_train_grey = np.moveaxis(X_train_grey, [0], [3])
X_train_grey.shape
```

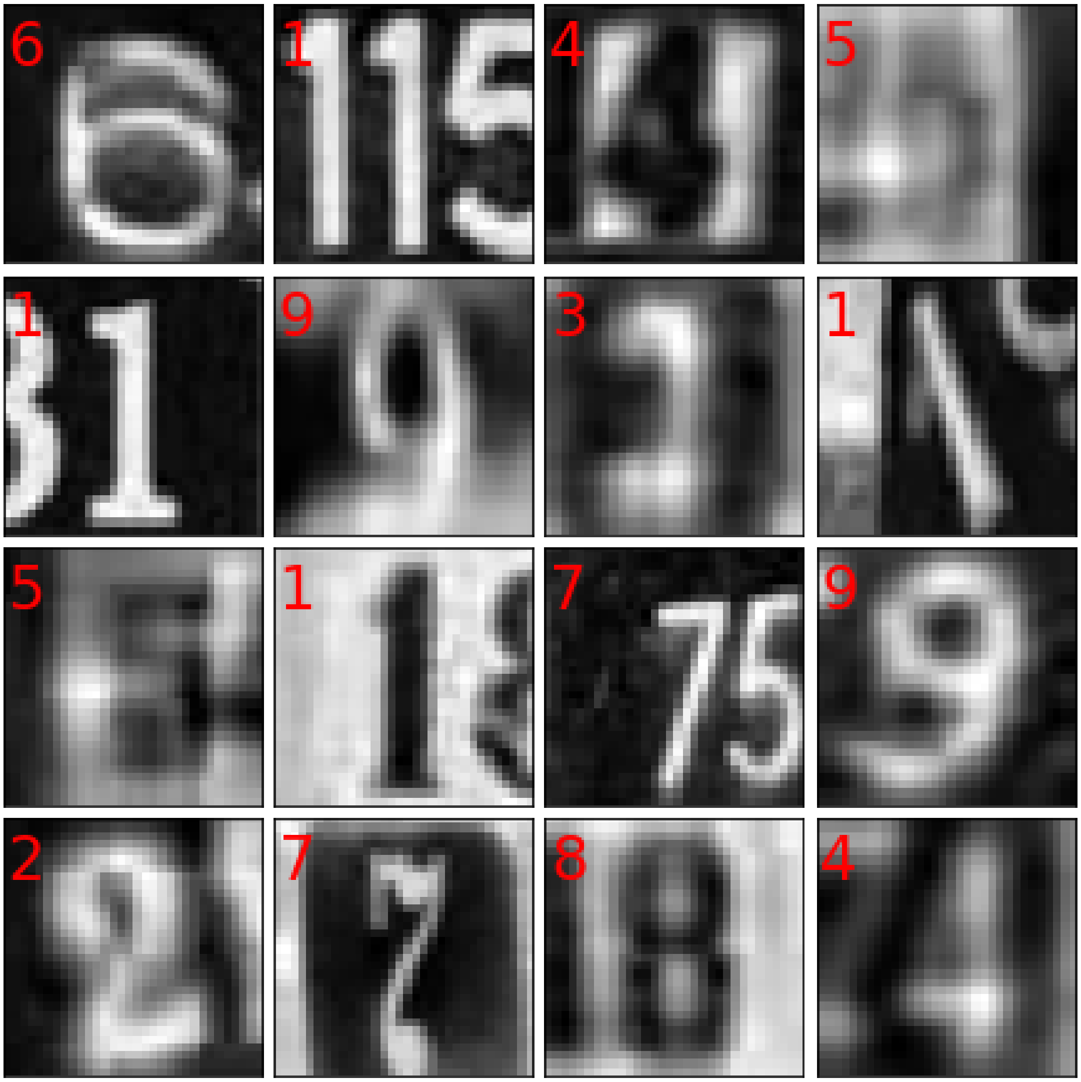
[89]:
```
(73257, 32, 32, 1)
```

[90]:
```
X_test_grey = []
for i in range(26032):
    grey_image = np.mean(X_test[:, :, :, i], axis = 2)
    grey_image = grey_image[..., np.newaxis]
    X_test_grey.append(grey_image)
X_test_grey = np.array(X_test_grey)
#X_test_grey = np.moveaxis(X_test_grey, [0], [3])
X_test_grey.shape
```

[90]:
```
(26032, 32, 32, 1)
```

1.3.4 Select a random sample of the grayscale images and corresponding labels from the dataset and display them in a figure.

[92]:
```
r_indexes = random.sample(range(0, 73257), 16)
from matplotlib import pyplot as plt
fig = plt.figure(figsize = (6,6)) # figure size in inches
fig.subplots_adjust(left = 0, right = 1, bottom = 0, top = 1, hspace = 0.05,␣
↪wspace = 0.05)

for i in range(len(r_indexes)):
    ax = fig.add_subplot(4, 4, i+1, xticks = [], yticks = [])
    ax.imshow(X_train_grey[r_indexes[i], :, :, 0], cmap = plt.cm.binary,␣
↪interpolation = 'nearest')
    ax.text(0, 7, str(y_train[r_indexes[i]][0]), color = 'red', fontsize = 24)
```



1.4 2. MLP neural network classifier

- 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.

Build MLP classifier model(We will only utilize Flatten and Dense layers)

Libraries needed for building the model

[100]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from tensorflow.keras import regularizers
```

[101]:
```
def get_mlp_model():
    model = Sequential([
        Flatten(input_shape = X_train_grey[0].shape),
        Dense(512, kernel_regularizer = regularizers.l2(1e-5), activation =␣
↪"relu"),
        Dense(128, kernel_regularizer = regularizers.l2(1e-5), activation =␣
↪"relu"),
        Dense(64, kernel_regularizer = regularizers.l2(1e-5), activation =␣
↪"relu"),
        Dense(10, activation = "softmax"),
    ])
    return model
```

Model Summary

[162]:
```
model = get_mlp_model()
model.summary()
```

```
Model: "sequential_28"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_28 (Flatten)         (None, 1024)              0

_________________________________________________________________
dense_96 (Dense)             (None, 512)               524800

_________________________________________________________________
dense_97 (Dense)             (None, 128)               65664

_________________________________________________________________
dense_98 (Dense)             (None, 64)                8256

_________________________________________________________________
dense_99 (Dense)             (None, 10)                650
=================================================================
Total params: 599,370
Trainable params: 599,370
Non-trainable params: 0

_________________________________________________________________
```

1.4.1 Compilation for the model

[163]:
```
def compile_models(m):
    m.compile(optimizer = "adam",
              loss = "sparse_categorical_crossentropy",
              metrics = ["accuracy"])
```

[164]:
```
model.compile(optimizer = "adam",
              loss = "sparse_categorical_crossentropy",
             metrics = ["accuracy"])
```

Defining Callbacks

[165]:
```
def get_checkpoint_every_epoch():
    checkpoint_path = "model_checkpoints/checkpoint_{epoch:03d}"
    checkpoint = ModelCheckpoint(filepath = checkpoint_path,
                                 frequency = "epoch",
                                 save_weights_only = True,
                                 verbose = 1)
    return checkpoint

def get_checkpoint_best_only():
    checkpoint_path = "checkpoints_best_only/checkpoint"
    return ModelCheckpoint(filepath = checkpoint_path,
                           save_weights_only= True,
                           monitor = "val_accuracy",
                           save_best_only = True)

def get_checkpoint_best_only_mlp():
    checkpoint_path = "checkpoints_best_only_mlp/checkpoint"
    return ModelCheckpoint(filepath = checkpoint_path,
                           save_weights_only= True,
                           monitor = "val_accuracy",
                           save_best_only = True)
def get_early_stopping():
    return EarlyStopping(monitor = "loss",
                         patience = 3,
                        verbose = 1)
```

[166]:
```
checkpoint_every_epoch = get_checkpoint_every_epoch()
checkpoint_best = get_checkpoint_best_only_mlp()
early_stopping = get_early_stopping()
```

1.4.2 Training the model

[167]:
```
def train_models(m, e):
    callbacks = [get_checkpoint_every_epoch(),
                 get_checkpoint_best_only(),
                 get_early_stopping()]
    history = m.fit(x = X_train_grey,
                    y = y_train,
                    epochs = e,
                    validation_split = 0.15,
                    callbacks = callbacks)
    return history
```

[168]:
```
callbacks = [checkpoint_every_epoch, checkpoint_best, early_stopping]
history = model.fit(x = X_train_grey,
          y = y_train,
          epochs = 30,
          validation_split = 0.15,
          callbacks = callbacks)
```

```
Train on 62268 samples, validate on 10989 samples
Epoch 1/30
62176/62268 [============================>.] - ETA: 0s - loss: 5.6903 -
accuracy: 0.1791
Epoch 00001: saving model to model_checkpoints/checkpoint_001
62268/62268 [==============================] - 77s 1ms/sample - loss: 5.6851 -
accuracy: 0.1792 - val_loss: 2.1655 - val_accuracy: 0.2481
Epoch 2/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.9901 -
accuracy: 0.3406
Epoch 00002: saving model to model_checkpoints/checkpoint_002
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.9899 -
accuracy: 0.3407 - val_loss: 1.5617 - val_accuracy: 0.5081
Epoch 3/30
62176/62268 [============================>.] - ETA: 0s - loss: 1.5907 -
accuracy: 0.4927
Epoch 00003: saving model to model_checkpoints/checkpoint_003
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.5907 -
accuracy: 0.4927 - val_loss: 1.5972 - val_accuracy: 0.5022
Epoch 4/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.4615 -
accuracy: 0.5437
Epoch 00004: saving model to model_checkpoints/checkpoint_004
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.4616 -
accuracy: 0.5438 - val_loss: 1.3652 - val_accuracy: 0.5742
Epoch 5/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.3762 -
```

```
accuracy: 0.5745
Epoch 00005: saving model to model_checkpoints/checkpoint_005
62268/62268 [==============================] - 74s 1ms/sample - loss: 1.3763 -
accuracy: 0.5745 - val_loss: 1.3121 - val_accuracy: 0.6030
Epoch 6/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.3187 -
accuracy: 0.5930
Epoch 00006: saving model to model_checkpoints/checkpoint_006
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.3185 -
accuracy: 0.5931 - val_loss: 1.2378 - val_accuracy: 0.6273
Epoch 7/30
62176/62268 [============================>.] - ETA: 0s - loss: 1.2655 -
accuracy: 0.6066
Epoch 00007: saving model to model_checkpoints/checkpoint_007
62268/62268 [==============================] - 74s 1ms/sample - loss: 1.2655 -
accuracy: 0.6067 - val_loss: 1.1788 - val_accuracy: 0.6364
Epoch 8/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.2281 -
accuracy: 0.6186
Epoch 00008: saving model to model_checkpoints/checkpoint_008
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.2284 -
accuracy: 0.6186 - val_loss: 1.2501 - val_accuracy: 0.6054
Epoch 9/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.1722 -
accuracy: 0.6371
Epoch 00009: saving model to model_checkpoints/checkpoint_009
62268/62268 [==============================] - 74s 1ms/sample - loss: 1.1722 -
accuracy: 0.6371 - val_loss: 1.1152 - val_accuracy: 0.6551
Epoch 10/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.1440 -
accuracy: 0.6491
Epoch 00010: saving model to model_checkpoints/checkpoint_010
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.1442 -
accuracy: 0.6491 - val_loss: 1.1992 - val_accuracy: 0.6225
Epoch 11/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.1165 -
accuracy: 0.6573
Epoch 00011: saving model to model_checkpoints/checkpoint_011
62268/62268 [==============================] - 74s 1ms/sample - loss: 1.1164 -
accuracy: 0.6574 - val_loss: 1.1486 - val_accuracy: 0.6335
Epoch 12/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.1063 -
accuracy: 0.6618
Epoch 00012: saving model to model_checkpoints/checkpoint_012
62268/62268 [==============================] - 74s 1ms/sample - loss: 1.1061 -
accuracy: 0.6618 - val_loss: 1.0526 - val_accuracy: 0.6820
Epoch 13/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0889 -
```

```
accuracy: 0.6688
Epoch 00013: saving model to model_checkpoints/checkpoint_013
62268/62268 [==============================] - 79s 1ms/sample - loss: 1.0888 -
accuracy: 0.6689 - val_loss: 1.0993 - val_accuracy: 0.6646
Epoch 14/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0825 -
accuracy: 0.6701 ETA: 0s - loss: 1.0826 - accu
Epoch 00014: saving model to model_checkpoints/checkpoint_014
62268/62268 [==============================] - 85s 1ms/sample - loss: 1.0824 -
accuracy: 0.6701 - val_loss: 1.0418 - val_accuracy: 0.6820
Epoch 15/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0708 -
accuracy: 0.6749
Epoch 00015: saving model to model_checkpoints/checkpoint_015
62268/62268 [==============================] - 85s 1ms/sample - loss: 1.0709 -
accuracy: 0.6749 - val_loss: 0.9936 - val_accuracy: 0.6997
Epoch 16/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.0462 -
accuracy: 0.6827
Epoch 00016: saving model to model_checkpoints/checkpoint_016
62268/62268 [==============================] - 77s 1ms/sample - loss: 1.0462 -
accuracy: 0.6827 - val_loss: 1.1800 - val_accuracy: 0.6366
Epoch 17/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0405 -
accuracy: 0.6853 ETA: 0s - loss: 1.0407 - accuracy
Epoch 00017: saving model to model_checkpoints/checkpoint_017
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.0406 -
accuracy: 0.6853 - val_loss: 1.0458 - val_accuracy: 0.6830
Epoch 18/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.0317 -
accuracy: 0.6873
Epoch 00018: saving model to model_checkpoints/checkpoint_018
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.0318 -
accuracy: 0.6872 - val_loss: 1.1840 - val_accuracy: 0.6429
Epoch 19/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.0153 -
accuracy: 0.6928
Epoch 00019: saving model to model_checkpoints/checkpoint_019
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.0152 -
accuracy: 0.6928 - val_loss: 1.0311 - val_accuracy: 0.6861
Epoch 20/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0089 -
accuracy: 0.6943
Epoch 00020: saving model to model_checkpoints/checkpoint_020
62268/62268 [==============================] - 73s 1ms/sample - loss: 1.0090 -
accuracy: 0.6943 - val_loss: 0.9760 - val_accuracy: 0.7060
Epoch 21/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0154 -
```

```
accuracy: 0.6933
Epoch 00021: saving model to model_checkpoints/checkpoint_021
62268/62268 [==============================] - 85s 1ms/sample - loss: 1.0154 -
accuracy: 0.6934 - val_loss: 1.0370 - val_accuracy: 0.6900
Epoch 22/30
62240/62268 [============================>.] - ETA: 0s - loss: 1.0026 -
accuracy: 0.6990
Epoch 00022: saving model to model_checkpoints/checkpoint_022
62268/62268 [==============================] - 88s 1ms/sample - loss: 1.0026 -
accuracy: 0.6990 - val_loss: 1.1709 - val_accuracy: 0.6436
Epoch 23/30
62208/62268 [============================>.] - ETA: 0s - loss: 1.0041 -
accuracy: 0.6983
Epoch 00023: saving model to model_checkpoints/checkpoint_023
62268/62268 [==============================] - 88s 1ms/sample - loss: 1.0039 -
accuracy: 0.6984 - val_loss: 1.0448 - val_accuracy: 0.6880
Epoch 24/30
62208/62268 [============================>.] - ETA: 0s - loss: 0.9975 -
accuracy: 0.7009
Epoch 00024: saving model to model_checkpoints/checkpoint_024
62268/62268 [==============================] - 88s 1ms/sample - loss: 0.9976 -
accuracy: 0.7009 - val_loss: 1.0794 - val_accuracy: 0.6736
Epoch 25/30
62208/62268 [============================>.] - ETA: 0s - loss: 0.9982 -
accuracy: 0.7006
Epoch 00025: saving model to model_checkpoints/checkpoint_025
62268/62268 [==============================] - 89s 1ms/sample - loss: 0.9980 -
accuracy: 0.7006 - val_loss: 1.1738 - val_accuracy: 0.6384
Epoch 26/30
62176/62268 [============================>.] - ETA: 0s - loss: 0.9865 -
accuracy: 0.7069
Epoch 00026: saving model to model_checkpoints/checkpoint_026
62268/62268 [==============================] - 80s 1ms/sample - loss: 0.9869 -
accuracy: 0.7068 - val_loss: 0.9951 - val_accuracy: 0.7052
Epoch 27/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9808 -
accuracy: 0.7071
Epoch 00027: saving model to model_checkpoints/checkpoint_027
62268/62268 [==============================] - 73s 1ms/sample - loss: 0.9807 -
accuracy: 0.7071 - val_loss: 0.9979 - val_accuracy: 0.7028
Epoch 28/30
62176/62268 [============================>.] - ETA: 0s - loss: 0.9834 -
accuracy: 0.7071
Epoch 00028: saving model to model_checkpoints/checkpoint_028
62268/62268 [==============================] - 72s 1ms/sample - loss: 0.9832 -
accuracy: 0.7071 - val_loss: 1.0707 - val_accuracy: 0.6760
Epoch 29/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9868 -
```

```
accuracy: 0.7056
Epoch 00029: saving model to model_checkpoints/checkpoint_029
62268/62268 [==============================] - 74s 1ms/sample - loss: 0.9868 -
accuracy: 0.7056 - val_loss: 1.0023 - val_accuracy: 0.7014
Epoch 30/30
62240/62268 [============================>.] - ETA: 0s - loss: 0.9719 -
accuracy: 0.7121
Epoch 00030: saving model to model_checkpoints/checkpoint_030
62268/62268 [==============================] - 74s 1ms/sample - loss: 0.9719 -
accuracy: 0.7121 - val_loss: 1.0092 - val_accuracy: 0.7039
```

Model Evaluation

[145]:
```python
def evaluate_models(m):
    test_loss, test_accuracy = m.evaluate(X_test_grey, y_test, verbose = 2)
    print("Test loss: {}".format(test_loss))
    print("Test accuracy: {}".format(test_accuracy))
```

[156]:
```python
test_loss, test_accuracy = model.evaluate(X_test_grey, y_test, verbose = 2)
print("Test loss: {}".format(test_loss))
print("Test accuracy: {}".format(test_accuracy))
```

```
26032/1 - 10s - loss: 0.9698 - accuracy: 0.6969
Test loss: 1.0533421285400086
Test accuracy: 0.6969115138053894
```

Graphs (Check for overfitting)

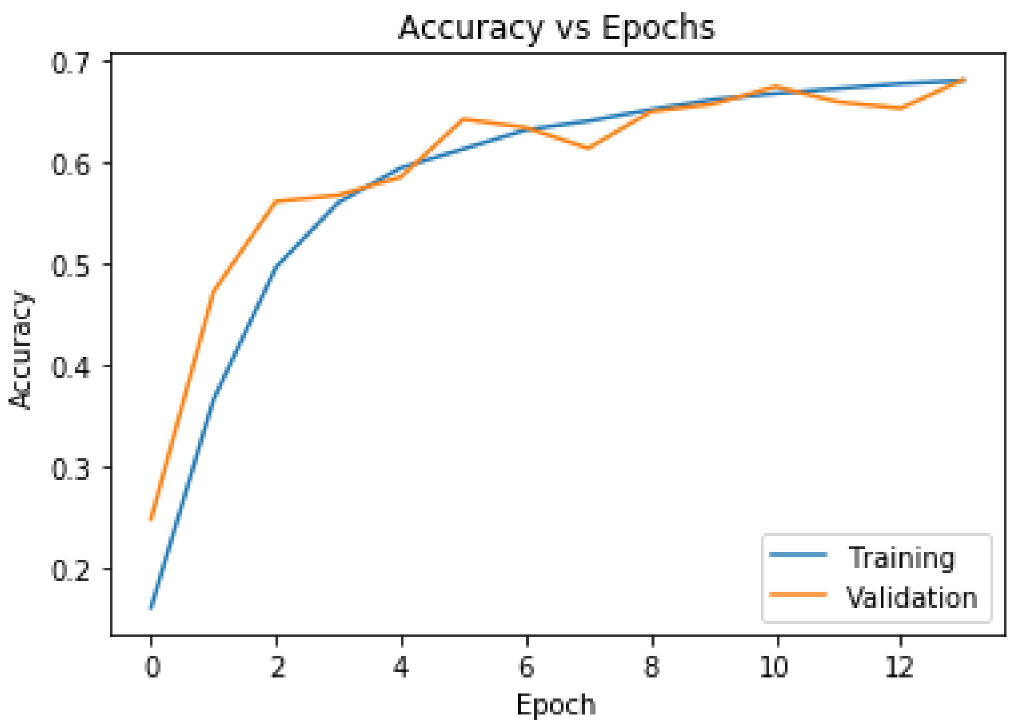
[147]:
```python
import pandas as pd
frame = pd.DataFrame(history.history)
frame.head()
```

[147]:

	loss	accuracy	val_loss	val_accuracy
0	5.932148	0.160114	2.162475	0.247611
1	1.927464	0.365324	1.634188	0.471926
2	1.582403	0.495969	1.462529	0.561016
3	1.424135	0.559902	1.390332	0.567113
4	1.325090	0.594206	1.352927	0.585131

[148]:
```python
def plot_acc(h):
    plt.plot(h.history['accuracy'])
    plt.plot(h.history['val_accuracy'])
    plt.title("Accuracy vs Epochs")
    plt.ylabel('Accuracy')
    plt.xlabel("Epoch")
    plt.legend(['Training', 'Validation'], loc = "lower right")
    plt.show()
```

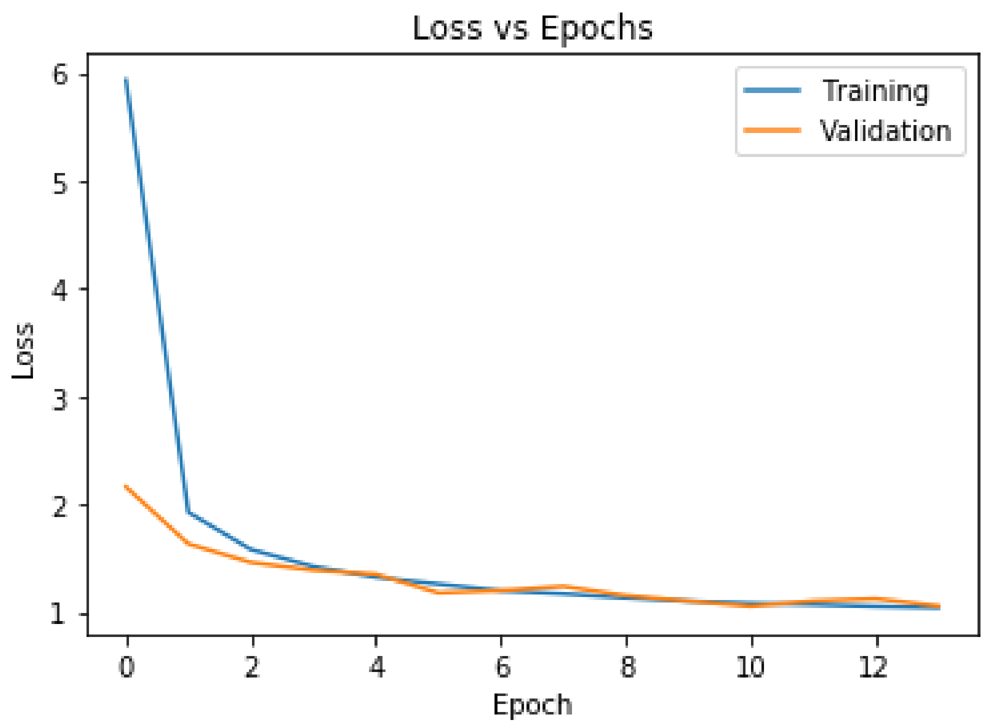
[149]:
```python
import matplotlib.pyplot as plt

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 = "lower right")
plt.show()
```



[150]:
```python
def plot_loss(h):
    plt.plot(h.history['loss'])
    plt.plot(h.history['val_loss'])
    plt.title("Loss vs Epochs")
    plt.ylabel('Loss')
    plt.xlabel("Epoch")
    plt.legend(['Training', 'Validation'], loc = "upper right")
    plt.show()
```

[151]:
```python
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()
```



1.5 3. CNN neural network classifier

- 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.

1.5.1 CNN Construction (We will only use Conv2D, MaxPool2D, BatchNormalization, Flatten, Dense and Dropout layers.)

Missing libraries

[122]:
```python
from tensorflow.keras.layers import Conv2D, MaxPooling2D
```

[123]:
```python
def get_cnn_model(input_shape):
    model = Sequential([
        Conv2D(16, (3, 3),
               padding = "SAME",
               activation = "relu",
               input_shape = input_shape),
        Conv2D(8, (3, 3),
               padding = "SAME",
               activation = "relu"),
        MaxPooling2D(pool_size = (8, 8)),
        Flatten(),
        Dense(128, activation = "relu", kernel_regularizer = regularizers.
 ↪l2(1e-5)),
        Dense(64, activation = "relu", kernel_regularizer = regularizers.
 ↪l2(1e-5)),
        Dense(10, activation = "softmax")
    ])
    return model
```

[124]:
```python
model_cnn = get_cnn_model(X_train_grey[0].shape)
model_cnn.summary()
```

```
Model: "sequential_23"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_28 (Conv2D)           (None, 32, 32, 16)        160
_________________________________________________________________
conv2d_29 (Conv2D)           (None, 32, 32, 8)         1160
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 4, 4, 8)           0
_________________________________________________________________
flatten_23 (Flatten)         (None, 128)               0
_________________________________________________________________
dense_78 (Dense)             (None, 128)               16512
_________________________________________________________________
dense_79 (Dense)             (None, 64)                8256
_________________________________________________________________
dense_80 (Dense)             (None, 10)                650
=================================================================
Total params: 26,738
Trainable params: 26,738
Non-trainable params: 0
_________________________________________________________________
```

1.5.2 Compilation and Trainining

[125]:
```
compile_models(model_cnn)
```

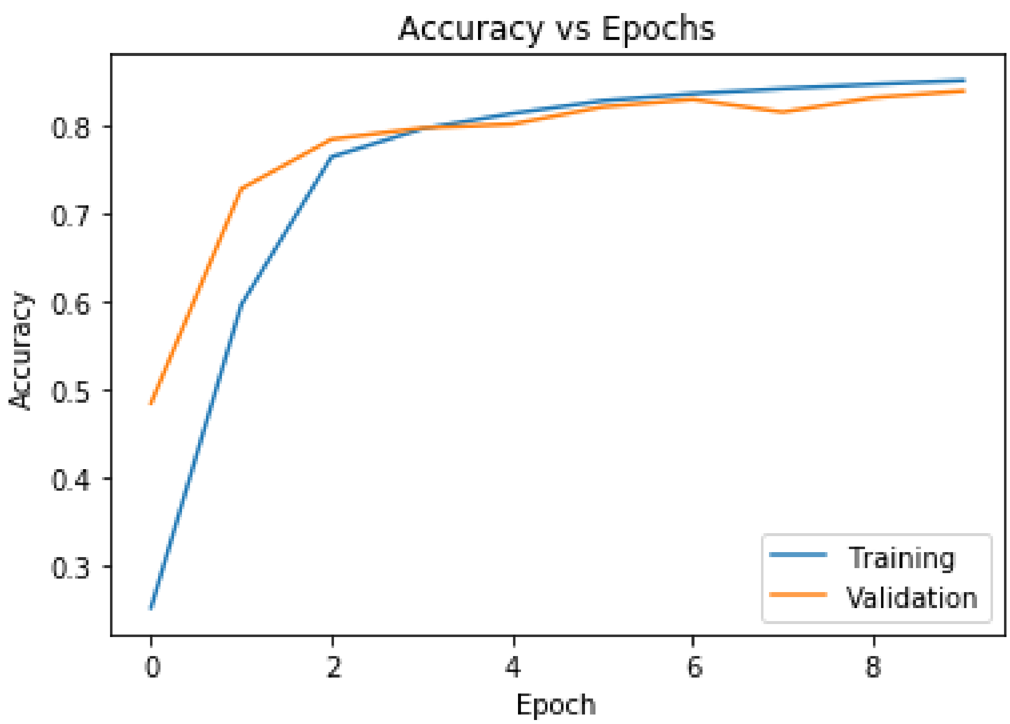
[126]:
```
history = train_models(model_cnn, 10)
```

```
Train on 62268 samples, validate on 10989 samples
Epoch 1/10
62240/62268 [============================>.] - ETA: 0s - loss: 2.1814 -
accuracy: 0.2531
Epoch 00001: saving model to model_checkpoints/checkpoint_001
62268/62268 [==============================] - 363s 6ms/sample - loss: 2.1811 -
accuracy: 0.2532 - val_loss: 1.5694 - val_accuracy: 0.4853
Epoch 2/10
62240/62268 [============================>.] - ETA: 0s - loss: 1.2496 -
accuracy: 0.5967
Epoch 00002: saving model to model_checkpoints/checkpoint_002
62268/62268 [==============================] - 353s 6ms/sample - loss: 1.2493 -
accuracy: 0.5968 - val_loss: 0.8641 - val_accuracy: 0.7284
Epoch 3/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.7637 -
accuracy: 0.7645
Epoch 00003: saving model to model_checkpoints/checkpoint_003
62268/62268 [==============================] - 350s 6ms/sample - loss: 0.7637 -
accuracy: 0.7646 - val_loss: 0.7011 - val_accuracy: 0.7846
Epoch 4/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.6633 -
accuracy: 0.7964
Epoch 00004: saving model to model_checkpoints/checkpoint_004
62268/62268 [==============================] - 346s 6ms/sample - loss: 0.6632 -
accuracy: 0.7964 - val_loss: 0.6493 - val_accuracy: 0.7974
Epoch 5/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.6062 -
accuracy: 0.8138
Epoch 00005: saving model to model_checkpoints/checkpoint_005
62268/62268 [==============================] - 346s 6ms/sample - loss: 0.6062 -
accuracy: 0.8138 - val_loss: 0.6465 - val_accuracy: 0.8017
Epoch 6/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.5650 -
accuracy: 0.8282
Epoch 00006: saving model to model_checkpoints/checkpoint_006
62268/62268 [==============================] - 353s 6ms/sample - loss: 0.5651 -
accuracy: 0.8282 - val_loss: 0.5968 - val_accuracy: 0.8213
Epoch 7/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.5323 -
accuracy: 0.8362
Epoch 00007: saving model to model_checkpoints/checkpoint_007
62268/62268 [==============================] - 351s 6ms/sample - loss: 0.5323 -
```

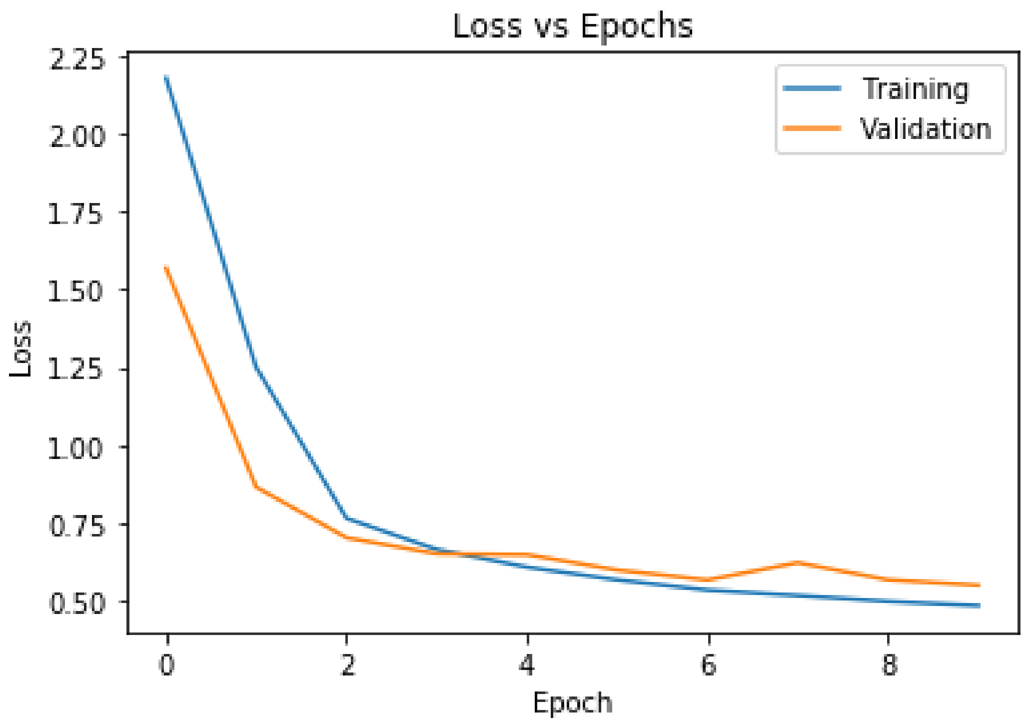
```
accuracy: 0.8362 - val_loss: 0.5650 - val_accuracy: 0.8299
Epoch 8/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.5146 -
accuracy: 0.8419
Epoch 00008: saving model to model_checkpoints/checkpoint_008
62268/62268 [==============================] - 346s 6ms/sample - loss: 0.5148 -
accuracy: 0.8419 - val_loss: 0.6203 - val_accuracy: 0.8155
Epoch 9/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.4959 -
accuracy: 0.8468
Epoch 00009: saving model to model_checkpoints/checkpoint_009
62268/62268 [==============================] - 345s 6ms/sample - loss: 0.4959 -
accuracy: 0.8469 - val_loss: 0.5654 - val_accuracy: 0.8317
Epoch 10/10
62240/62268 [============================>.] - ETA: 0s - loss: 0.4821 -
accuracy: 0.8512
Epoch 00010: saving model to model_checkpoints/checkpoint_010
62268/62268 [==============================] - 349s 6ms/sample - loss: 0.4822 -
accuracy: 0.8512 - val_loss: 0.5478 - val_accuracy: 0.8394
```

Graphs

[127]:
```
plot_acc(history)
```



[128]:
```
plot_loss(history)
```



Evaluation

[129]:
```
evaluate_models(model_cnn)
```

```
26032/1 - 38s - loss: 0.5426 - accuracy: 0.8307
Test loss: 0.5858306852343922
Test accuracy: 0.8306699395179749
```

[130]:
```
!ls checkpoints_best_only_mlp
```

```
checkpoint  checkpoint.data-00000-of-00001  checkpoint.index
```

1.6 4. Get model predictions

I will now load the best weights for the MLP and CNN. I will then randomly select 5 images and their corresponding labels from the test set, and display the images with their labels. Alongside the image and label I will show each model's predictive distribution as a bar chart, and the final final model prediction given by the label with maximum probability.

[131]:
```
def get_model_best_epoch(m):
    checkpoint_path = "checkpoints_best_only/checkpoint"
    m.load_weights(checkpoint_path)
    return m
```

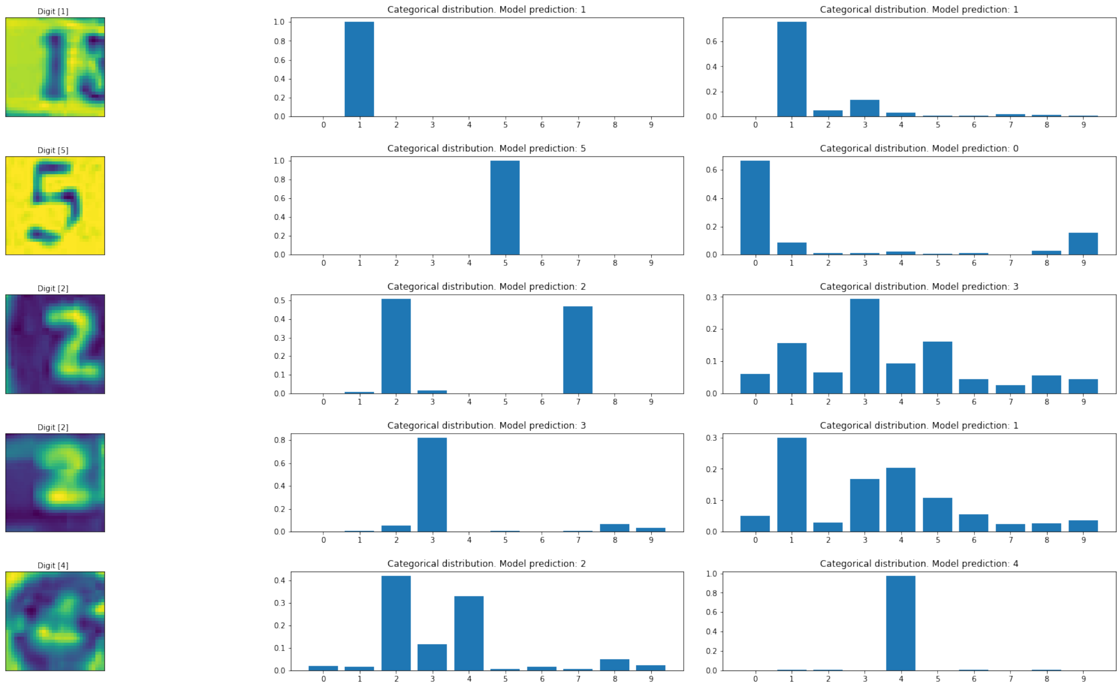
```
def get_model_best_epoch_mlp(m):
    checkpoint_path = "checkpoints_best_only_mlp/checkpoint"
    m.load_weights(checkpoint_path)
    return m
```

Load best models

[132]:
```
best_model_cnn = get_model_best_epoch(get_cnn_model(X_train_grey[0].shape))
best_model_mlp = get_model_best_epoch_mlp(get_mlp_model())
```

Random images and figure

[135]:
```
num_test_images = X_test_grey.shape[0]

random_inx = np.random.choice(num_test_images, 5)
random_test_images = X_test_grey[random_inx, ...]
random_test_labels = y_test[random_inx, ...]

predictions_cnn = best_model_cnn.predict(random_test_images)
predictions_mlp = best_model_mlp.predict(random_test_images)

fig, axes = plt.subplots(5, 3, figsize = (30, 16))
fig.subplots_adjust(hspace = 0.4, wspace = 0.1)

for i, (p_cnn, p_mlp, image, label) in enumerate(zip(predictions_cnn,␣
 ↪predictions_mlp, random_test_images, random_test_labels)):
    axes[i, 0].imshow(np.squeeze(image))
    axes[i, 0].get_xaxis().set_visible(False)
    axes[i, 0].get_yaxis().set_visible(False)
    axes[i, 0].text(10., -1.5, f'Digit {label}')
    axes[i, 1].bar(np.arange(len(p_cnn)), p_cnn)
    axes[i, 1].set_xticks(np.arange(len(p_cnn)))
    axes[i, 1].set_title(f"Categorical distribution. Model prediction: {np.
 ↪argmax(p_cnn)}")
    axes[i, 2].bar(np.arange(len(p_mlp)), p_mlp)
    axes[i, 2].set_xticks(np.arange(len(p_mlp)))
    axes[i, 2].set_title(f"Categorical distribution. Model prediction: {np.
 ↪argmax(p_mlp)}")
```


Digit [1]
Categorical distribution. Model prediction: 1
Categorical distribution. Model prediction: 1
Digit [5]
Categorical distribution. Model prediction: 5
Categorical distribution. Model prediction: 0
Digit [2]
Categorical distribution. Model prediction: 2
Categorical distribution. Model prediction: 3
Digit [2]
Categorical distribution. Model prediction: 3
Categorical distribution. Model prediction: 1
Digit [4]
Categorical distribution. Model prediction: 2
Categorical distribution. Model prediction: 4