MLP & CNN for Google Street View House Numbers

January 3, 2021

1 Capstone Project

1.1 Image classifier for the Street View House Numbers dataset

The task is to develop MLP and CNN models in order to verify their performance as well as generalization on the test set. The assumption is that CNN will have less parameters requiring a bit longer training time, but resulting in better generalization on unseen set.

Both models' types will use the same optimizer and loss, as well as metrics.

[1]:
```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt

from scipy.io import loadmat
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, BatchNormalization, Dense, Dropout,␣
 ↪Flatten, MaxPooling2D
from tensorflow.keras.regularizers import l1_l2
from tensorflow.keras.activations import relu, softmax
from tensorflow.keras.initializers import he_uniform, ones
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import SparseCategoricalCrossentropy
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,␣
 ↪ReduceLROnPlateau
```

1.1.1 Load and inspect the sets

[3]:
```
train_data = loadmat('./project_svhn_classification/assets/train_32x32.mat')
test_data = loadmat('./project_svhn_classification/assets/test_32x32.mat')
```

[4]:
```
X_train, y_train = train_data['X'], train_data['y']
X_test, y_test = test_data['X'], test_data['y']

print('X training shape: ', X_train.shape)
print('y train shape: ', y_train.shape)
print('\nUniq labels in the train set: ', np.unique(y_train))
print('Uniq labels in the test set: ', np.unique(y_test))
```

```
X training shape:  (32, 32, 3, 73257)
y train shape:  (73257, 1)

Uniq labels in the train set:  [ 1  2  3  4  5  6  7  8  9 10]
Uniq labels in the test set:  [ 1  2  3  4  5  6  7  8  9 10]
```

Replace the label "10" with "0"

[5]:
```
y_train[y_train == 10] = 0
y_test[y_test == 10] = 0

print('\nUniq labels in the train set: ', np.unique(y_train))
print('Uniq labels in the test set: ', np.unique(y_test))
```

```
Uniq labels in the train set:  [0 1 2 3 4 5 6 7 8 9]
Uniq labels in the test set:  [0 1 2 3 4 5 6 7 8 9]
```

Move the samples axis as first

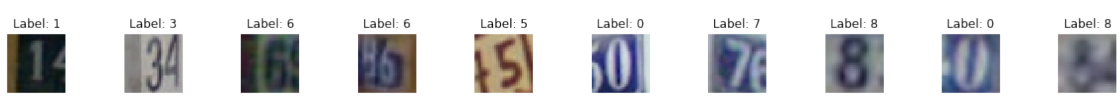
[10]:
```
X_train = np.moveaxis(X_train, -1, 0)
X_test = np.moveaxis(X_test, -1, 0)

print('X training shape: ', X_train.shape)
print('X testing shape: ', X_test.shape)
```

```
X training shape:  (73257, 32, 32, 3)
X testing shape:  (26032, 32, 32, 3)
```

Display images from the "train" set

[21]:
```
def display_sample_images(data_set, labels_setb):
    fig, ax = plt.subplots(nrows=1, ncols=10, figsize=(20, 10))

    for i in range(10):
        idx = np.random.choice(range(data_set.shape[0]))
        ax[i].set_axis_off()
        ax[i].imshow(data_set[idx], interpolation='nearest')
        ax[i].set_title(f'Label: {labels_set[idx][0]}')

    plt.subplots_adjust(wspace=1)
```

[22]:
```
display_sample_images(X_train, y_train)
```



Display images from the "test" set

[24]:
```
display_sample_images(X_test, y_test)
```

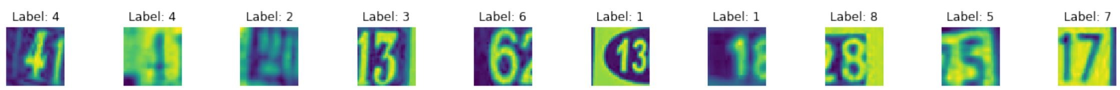
Normalize data

[25]:
```
X_train_inputs = np.mean(X_train, axis=3, keepdims=True) / 255.
X_test_inputs = np.mean(X_test, axis=3, keepdims=True) / 255.

print('X training inputs shape: ', X_train_inputs.shape)
print('X testing inputs shape: ', X_test_inputs.shape)
```

```
X training inputs shape:  (73257, 32, 32, 1)
X testing inputs shape:  (26032, 32, 32, 1)
```

Display normalized images - train set

[28]:
```
display_sample_images(X_train_inputs, y_train)
```



1.1.2 The MLP model

[31]:
```
def build_mlp_model(input_shape):
    model = Sequential([
        Flatten(input_shape=input_shape, name='flatten'),
        Dense(units=128,
              activation=relu,
              kernel_initializer=he_uniform(),
              bias_initializer=he_uniform(),
              name='dense_1'),
        Dense(units=64,
              activation=relu,
              kernel_initializer=he_uniform(),
              bias_initializer=he_uniform(),
              name='dense_2'),
        Dense(units=32,
              activation=relu,
              kernel_initializer=he_uniform(),
              bias_initializer=he_uniform(),
```

```
                name='dense_3'),
        Dense(units=10,
                activation=softmax,
                kernel_initializer=he_uniform(),
                bias_initializer=he_uniform(),
                name='dense_output')
    ])
    model.compile(
        optimizer=Adam(),
        loss=SparseCategoricalCrossentropy(),
        metrics=['accuracy'])
    return model
```

[61]:
```
mlp_model = build_mlp_model(input_shape=X_train_inputs[0].shape)
mlp_model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               131200
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_3 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_output (Dense)         (None, 10)                330
=================================================================
Total params: 141,866
Trainable params: 141,866
Non-trainable params: 0
_________________________________________________________________
```

Learning callbacks

[33]:
```
best_mlp_model_cb = ModelCheckpoint(filepath='most_accurate_model/
 ↪model_{epoch}',
                               monitor='val_accuracy',
                               save_best_only=True,
                               save_weights_only=True,
                               mode='max',
                               verbose=1)

early_stopping_cb = EarlyStopping(monitor='val_loss',
                                  min_delta=1e-2,
                                  patience=4,
```

```
                                 verbose=1)

lr_reduction_cb = ReduceLROnPlateau(monitor='val_loss',
                                   factor=1e-4,
                                   patience=2,
                                   mode='min',
                                   verbose=1)
```

Train MLP model

[62]:
```
mlp_history = mlp_model.fit(x=X_train_inputs,
                            y=y_train,
                            epochs=50,
                            batch_size=64,
                            validation_data=(X_test_inputs, y_test),
                            callbacks=[
                                best_mlp_model_cb,
                                early_stopping_cb,
                                lr_reduction_cb,
                            ])
```

```
Epoch 1/50
1145/1145 [==============================] - 2s 2ms/step - loss: 2.2490 -
accuracy: 0.1855 - val_loss: 1.9035 - val_accuracy: 0.3633

Epoch 00001: val_accuracy did not improve from 0.74977
Epoch 2/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.6686 -
accuracy: 0.4295 - val_loss: 1.4014 - val_accuracy: 0.5515

Epoch 00002: val_accuracy did not improve from 0.74977
Epoch 3/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.3076 -
accuracy: 0.5754 - val_loss: 1.3510 - val_accuracy: 0.5759

Epoch 00003: val_accuracy did not improve from 0.74977
Epoch 4/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.2059 -
accuracy: 0.6158 - val_loss: 1.2785 - val_accuracy: 0.6007

Epoch 00004: val_accuracy did not improve from 0.74977
Epoch 5/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.1502 -
accuracy: 0.6370 - val_loss: 1.2570 - val_accuracy: 0.6099

Epoch 00005: val_accuracy did not improve from 0.74977
Epoch 6/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.1224 -
```

```
accuracy: 0.6480 - val_loss: 1.2407 - val_accuracy: 0.6117

Epoch 00006: val_accuracy did not improve from 0.74977
Epoch 7/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.0867 -
accuracy: 0.6595 - val_loss: 1.2329 - val_accuracy: 0.6280

Epoch 00007: val_accuracy did not improve from 0.74977
Epoch 8/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.0533 -
accuracy: 0.6739 - val_loss: 1.1785 - val_accuracy: 0.6425

Epoch 00008: val_accuracy did not improve from 0.74977
Epoch 9/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.0299 -
accuracy: 0.6795 - val_loss: 1.1726 - val_accuracy: 0.6483

Epoch 00009: val_accuracy did not improve from 0.74977
Epoch 10/50
1145/1145 [==============================] - 2s 2ms/step - loss: 1.0145 -
accuracy: 0.6869 - val_loss: 1.1777 - val_accuracy: 0.6423

Epoch 00010: val_accuracy did not improve from 0.74977
Epoch 11/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9961 -
accuracy: 0.6945 - val_loss: 1.1182 - val_accuracy: 0.6626

Epoch 00011: val_accuracy did not improve from 0.74977
Epoch 12/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9920 -
accuracy: 0.6932 - val_loss: 1.1509 - val_accuracy: 0.6524

Epoch 00012: val_accuracy did not improve from 0.74977
Epoch 13/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9865 -
accuracy: 0.6959 - val_loss: 1.0840 - val_accuracy: 0.6718

Epoch 00013: val_accuracy did not improve from 0.74977
Epoch 14/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9814 -
accuracy: 0.6964 - val_loss: 1.1432 - val_accuracy: 0.6481

Epoch 00014: val_accuracy did not improve from 0.74977
Epoch 15/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9645 -
accuracy: 0.7019 - val_loss: 1.0925 - val_accuracy: 0.6694

Epoch 00015: val_accuracy did not improve from 0.74977
```

```
Epoch 00015: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-07.
Epoch 16/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9480 -
accuracy: 0.7076 - val_loss: 1.0825 - val_accuracy: 0.6728

Epoch 00016: val_accuracy did not improve from 0.74977
Epoch 17/50
1145/1145 [==============================] - 2s 2ms/step - loss: 0.9340 -
accuracy: 0.7139 - val_loss: 1.0755 - val_accuracy: 0.6753

Epoch 00017: val_accuracy did not improve from 0.74977
Epoch 00017: early stopping
```

[36]:
```
def evaluate_model(model, name, set_inputs, labels):
    test_loss, test_accuracy = model.evaluate(x=set_inputs, y=labels, verbose=0)
    print(f'Evaluating model {name}')
    print(f'* Test accuracy: {np.round(test_accuracy, 3)}')
    print(f'* Test loss: {np.round(test_loss, 3)}')
```

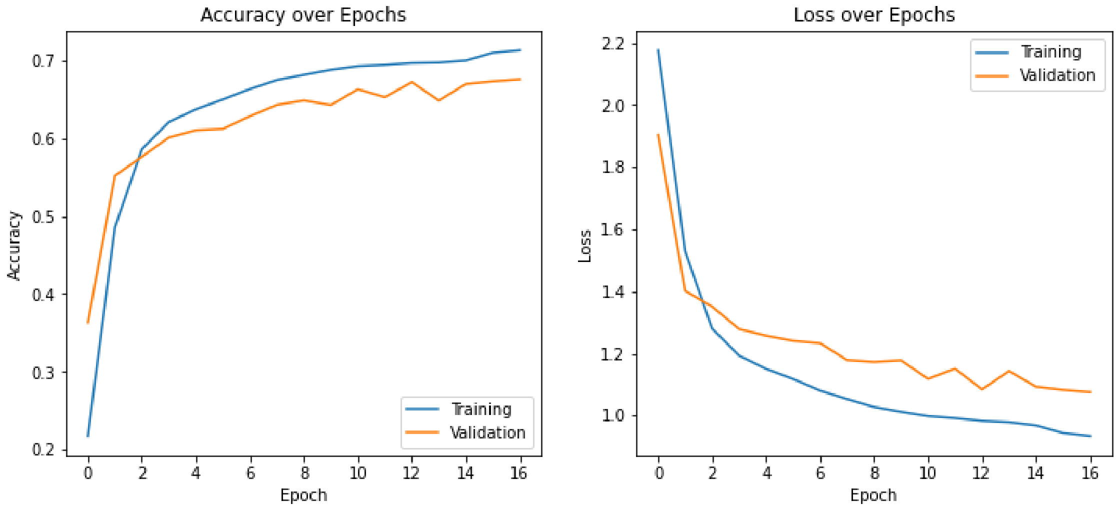
[63]:
```
evaluate_model(mlp_model, name='MLP', set_inputs=X_test_inputs, labels=y_test)
```

```
Evaluating model MLP
* Test accuracy: 0.675
* Test loss: 1.076
```

MLP model's performance: accuracy and sparse categorical crossentropy loss over epochs

[59]:
```
def plot_history_performance(history):
    fig = plt.figure(figsize=(12, 5))
    fig.add_subplot(121)
    plt.plot(history['accuracy'])
    plt.plot(history['val_accuracy'])
    plt.title('Accuracy over Epochs')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['Training', 'Validation'], loc='lower right')

    fig.add_subplot(122)
    plt.plot(history['loss'])
    plt.plot(history['val_loss'])
    plt.title('Loss over Epochs')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['Training', 'Validation'], loc='upper right')
```

[64]:
```
plot_history_performance(mlp_history.history)
```



1.1.3 The CNN model

[44]:
```
def build_cnn_model(input_shape):
    model = Sequential([
        Conv2D(filters=16,
               kernel_size=(3, 3),
               input_shape=input_shape,
               padding='same',
               activation=relu,
               kernel_initializer=he_uniform(),
               kernel_regularizer=l1_l2(l1=1e-3, l2=1e-3),
               bias_initializer=he_uniform(),
               bias_regularizer=l1_l2(l1=1e-3, l2=1e-3),
               name='conv2d_1'),
        Conv2D(filters=8,
               kernel_size=(3, 3),
               padding='same',
               activation=relu,
               kernel_initializer=he_uniform(),
               kernel_regularizer=l1_l2(l1=1e-3, l2=1e-3),
               bias_initializer=he_uniform(),
               bias_regularizer=l1_l2(l1=1e-3, l2=1e-3),
               name='conv2d_2'),
        MaxPooling2D(pool_size=(3, 3), name='max_pooling_2d_1'),
        BatchNormalization(name='batch_normalization_1'),
        Dropout(rate=0.3, name='dropout_1'),
        Conv2D(filters=8,
               kernel_size=(3, 3),
               padding='same',
```

```
               activation=relu,
               kernel_initializer=he_uniform(),
               kernel_regularizer=l1_l2(l1=1e-3, l2=1e-3),
               bias_initializer=he_uniform(),
               bias_regularizer=l1_l2(l1=1e-3, l2=1e-3),
               name='conv2d_3'),
        MaxPooling2D(pool_size=(3, 3), name='max_pooling_2d_2'),
        Flatten(name='flatten'),
        Dense(units=32,
              activation=relu,
              kernel_initializer=he_uniform(),
              kernel_regularizer=l1_l2(l1=1e-3, l2=1e-3),
              bias_initializer=he_uniform(),
              bias_regularizer=l1_l2(l1=1e-3, l2=1e-3),
              name='dense_1'),
        Dropout(0.3, name='dropout_2'),
        Dense(units=16,
              activation=relu,
              kernel_initializer=he_uniform(),
              bias_initializer=he_uniform(),
              kernel_regularizer=l1_l2(l1=1e-3, l2=1e-3),
              name='dense_2'),
        Dense(units=10,
              activation=softmax,
              kernel_initializer=he_uniform(),
              kernel_regularizer=l1_l2(l1=1e-3, l2=1e-3),
              bias_initializer=he_uniform(),
              bias_regularizer=l1_l2(l1=1e-3, l2=1e-3),
              name='dense_output')
    ])
    model.compile(
        optimizer=Adam(),
        loss=SparseCategoricalCrossentropy(),
        metrics=['accuracy'])
    return model
```

[45]:

```
cnn_model = build_cnn_model(input_shape=X_train_inputs[0].shape)
cnn_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 32, 32, 16)        160
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 32, 8)         1160
_________________________________________________________________
```

```
max_pooling_2d_1 (MaxPooling (None, 10, 10, 8)         0
_________________________________________________________________
batch_normalization_1 (Batch (None, 10, 10, 8)         32
_________________________________________________________________
dropout_1 (Dropout)          (None, 10, 10, 8)         0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 10, 10, 8)         584
_________________________________________________________________
max_pooling_2d_2 (MaxPooling (None, 3, 3, 8)           0
_________________________________________________________________
flatten (Flatten)            (None, 72)                0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                2336
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_2 (Dense)              (None, 16)                528
_________________________________________________________________
dense_output (Dense)         (None, 10)                170
=================================================================
Total params: 4,970
Trainable params: 4,954
Non-trainable params: 16
_________________________________________________________________
```

[46]:
```
best_cnn_model_cb = ModelCheckpoint(filepath='most_accurate_cnn_model/
↪model_{epoch}',
                                    monitor='val_accuracy',
                                    save_best_only=True,
                                    save_weights_only=True,
                                    mode='max',
                                    verbose=1)
```

[49]:
```
cnn_history = cnn_model.fit(x=X_train_inputs,
                            y=y_train,
                            epochs=50,
                            batch_size=64,
                            validation_data=(X_test_inputs, y_test),
                            callbacks=[
                                best_cnn_model_cb,
                                early_stopping_cb,
                                lr_reduction_cb,
                            ])
```

```
Epoch 1/50
1145/1145 [==============================] - 32s 27ms/step - loss: 2.6862 -
accuracy: 0.1910 - val_loss: 2.2098 - val_accuracy: 0.2995
```

```
Epoch 00001: val_accuracy did not improve from 0.75192
Epoch 2/50
1145/1145 [==============================] - 32s 28ms/step - loss: 1.9141 -
accuracy: 0.4096 - val_loss: 1.5982 - val_accuracy: 0.5423

Epoch 00002: val_accuracy did not improve from 0.75192
Epoch 3/50
1145/1145 [==============================] - 32s 28ms/step - loss: 1.6568 -
accuracy: 0.5145 - val_loss: 1.4570 - val_accuracy: 0.6044

Epoch 00003: val_accuracy did not improve from 0.75192
Epoch 4/50
1145/1145 [==============================] - 32s 28ms/step - loss: 1.4784 -
accuracy: 0.5929 - val_loss: 1.2287 - val_accuracy: 0.6999

Epoch 00004: val_accuracy did not improve from 0.75192
Epoch 5/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.3742 -
accuracy: 0.6366 - val_loss: 1.1378 - val_accuracy: 0.7372

Epoch 00005: val_accuracy did not improve from 0.75192
Epoch 6/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.3066 -
accuracy: 0.6630 - val_loss: 1.0928 - val_accuracy: 0.7495

Epoch 00006: val_accuracy did not improve from 0.75192
Epoch 7/50
1145/1145 [==============================] - 34s 29ms/step - loss: 1.2490 -
accuracy: 0.6876 - val_loss: 1.0885 - val_accuracy: 0.7523

Epoch 00007: val_accuracy improved from 0.75192 to 0.75234, saving model to
most_accurate_cnn_model/model_7
Epoch 8/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.2205 -
accuracy: 0.6988 - val_loss: 0.9894 - val_accuracy: 0.7888

Epoch 00008: val_accuracy improved from 0.75234 to 0.78880, saving model to
most_accurate_cnn_model/model_8
Epoch 9/50
1145/1145 [==============================] - 34s 29ms/step - loss: 1.1988 -
accuracy: 0.7052 - val_loss: 0.9674 - val_accuracy: 0.7985

Epoch 00009: val_accuracy improved from 0.78880 to 0.79848, saving model to
most_accurate_cnn_model/model_9
Epoch 10/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.1810 -
accuracy: 0.7141 - val_loss: 0.9648 - val_accuracy: 0.7917
```

```
Epoch 00010: val_accuracy did not improve from 0.79848
Epoch 11/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.1691 -
accuracy: 0.7143 - val_loss: 0.9492 - val_accuracy: 0.8005

Epoch 00011: val_accuracy improved from 0.79848 to 0.80051, saving model to
most_accurate_cnn_model/model_11
Epoch 12/50
1145/1145 [==============================] - 32s 28ms/step - loss: 1.1568 -
accuracy: 0.7212 - val_loss: 0.9296 - val_accuracy: 0.8040

Epoch 00012: val_accuracy improved from 0.80051 to 0.80405, saving model to
most_accurate_cnn_model/model_12
Epoch 13/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.1477 -
accuracy: 0.7225 - val_loss: 0.9331 - val_accuracy: 0.8002

Epoch 00013: val_accuracy did not improve from 0.80405
Epoch 14/50
1145/1145 [==============================] - 35s 30ms/step - loss: 1.1409 -
accuracy: 0.7243 - val_loss: 0.9837 - val_accuracy: 0.8022

Epoch 00014: val_accuracy did not improve from 0.80405

Epoch 00014: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-07.
Epoch 15/50
1145/1145 [==============================] - 36s 31ms/step - loss: 1.1222 -
accuracy: 0.7327 - val_loss: 0.9113 - val_accuracy: 0.8137

Epoch 00015: val_accuracy improved from 0.80405 to 0.81369, saving model to
most_accurate_cnn_model/model_15
Epoch 16/50
1145/1145 [==============================] - 37s 32ms/step - loss: 1.1228 -
accuracy: 0.7334 - val_loss: 0.9105 - val_accuracy: 0.8139

Epoch 00016: val_accuracy improved from 0.81369 to 0.81388, saving model to
most_accurate_cnn_model/model_16
Epoch 17/50
1145/1145 [==============================] - 35s 31ms/step - loss: 1.1197 -
accuracy: 0.7327 - val_loss: 0.9096 - val_accuracy: 0.8139

Epoch 00017: val_accuracy did not improve from 0.81388
Epoch 18/50
1145/1145 [==============================] - 33s 29ms/step - loss: 1.1208 -
accuracy: 0.7321 - val_loss: 0.9085 - val_accuracy: 0.8144

Epoch 00018: val_accuracy improved from 0.81388 to 0.81438, saving model to
most_accurate_cnn_model/model_18
```

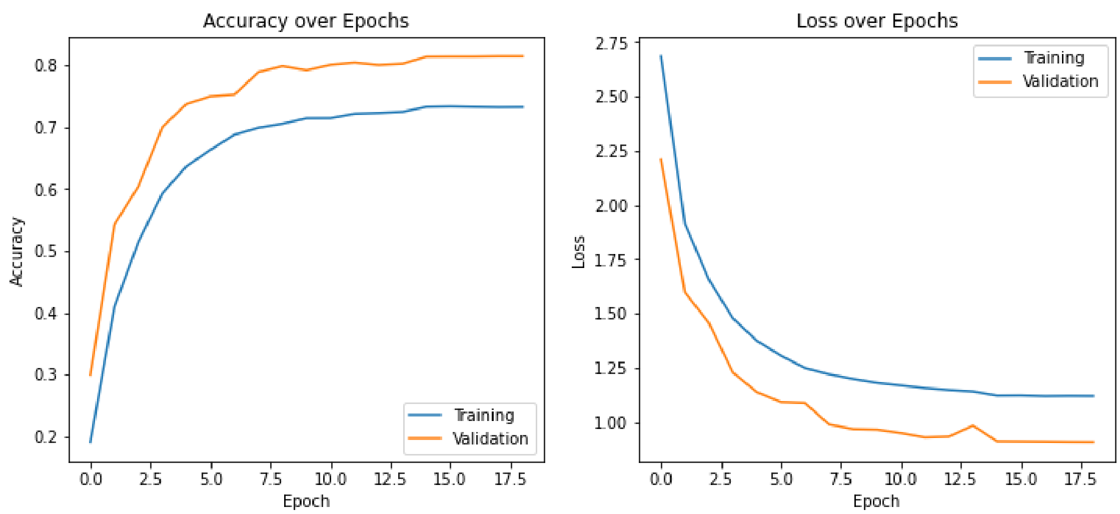
```
Epoch 19/50
1145/1145 [==============================] - 36s 31ms/step - loss: 1.1202 -
accuracy: 0.7323 - val_loss: 0.9080 - val_accuracy: 0.8144

Epoch 00019: val_accuracy did not improve from 0.81438
Epoch 00019: early stopping
```

[50]:
```
evaluate_model(cnn_model, name='CNN', set_inputs=X_test_inputs, labels=y_test)
```

```
Evaluating model CNN
* Test accuracy: 0.814
* Test loss: 0.908
```

MLP model's performance: accuracy and sparse categorical crossentropy loss over epochs

[65]:
```
plot_history_performance(cnn_history.history)
```



1.1.4 Load best models

[55]:
```
best_mlp_model = build_mlp_model(input_shape=X_train_inputs[0].shape)
best_mlp_model.load_weights(tf.train.latest_checkpoint('most_accurate_model'))
evaluate_model(best_mlp_model, name='MLP', set_inputs=X_test_inputs,␣
↪labels=y_test)
```

```
Evaluating model MLP
* Test accuracy: 0.75
* Test loss: 0.857
```

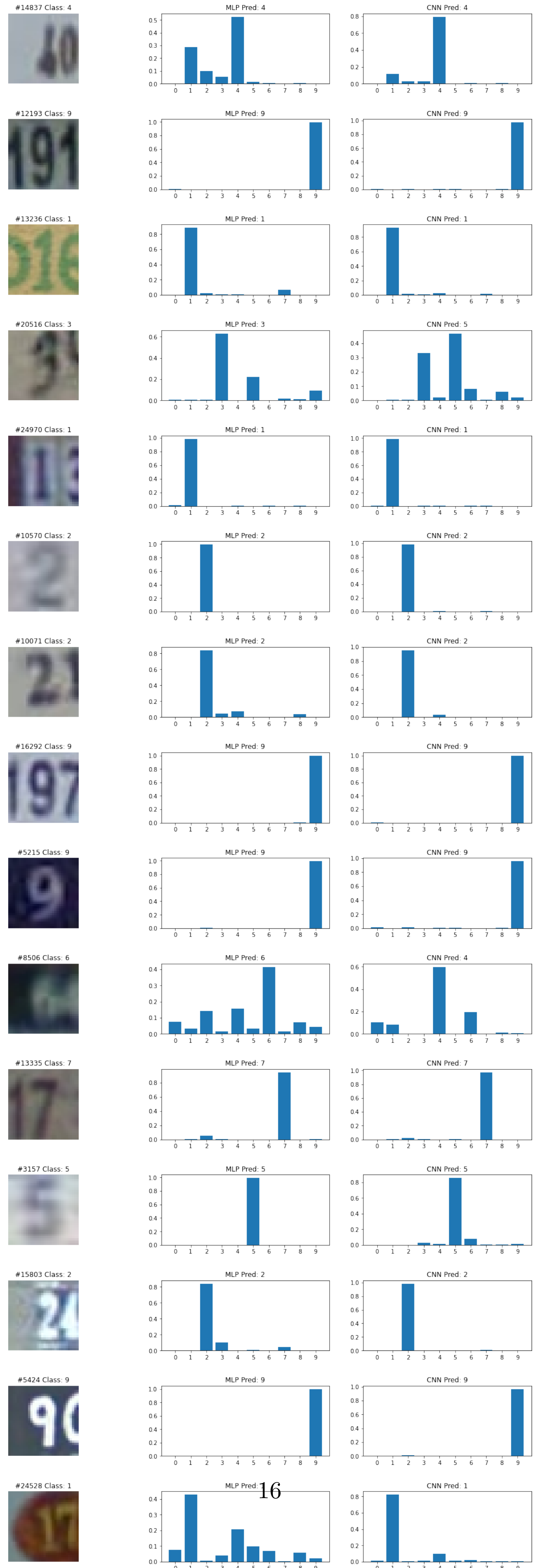
[56]:
```
best_cnn_model = build_cnn_model(input_shape=X_train_inputs[0].shape)
best_cnn_model.load_weights(tf.train.
 ↪latest_checkpoint('most_accurate_cnn_model'))
evaluate_model(best_cnn_model, name='CNN', set_inputs=X_test_inputs,␣
 ↪labels=y_test)
```

```
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.iter
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.beta_1
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.beta_2
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.decay
WARNING:tensorflow:Unresolved object in checkpoint:
(root).optimizer.learning_rate
WARNING:tensorflow:A checkpoint was restored (e.g. tf.train.Checkpoint.restore
or tf.keras.Model.load_weights) but not all checkpointed values were used. See
above for specific issues. Use expect_partial() on the load status object, e.g.
tf.train.Checkpoint.restore(…).expect_partial(), to silence these warnings, or
use assert_consumed() to make the check explicit. See
https://www.tensorflow.org/guide/checkpoint#loading_mechanics for details.
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.iter
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.beta_1
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.beta_2
WARNING:tensorflow:Unresolved object in checkpoint: (root).optimizer.decay
WARNING:tensorflow:Unresolved object in checkpoint:
(root).optimizer.learning_rate
WARNING:tensorflow:A checkpoint was restored (e.g. tf.train.Checkpoint.restore
or tf.keras.Model.load_weights) but not all checkpointed values were used. See
above for specific issues. Use expect_partial() on the load status object, e.g.
tf.train.Checkpoint.restore(…).expect_partial(), to silence these warnings, or
use assert_consumed() to make the check explicit. See
https://www.tensorflow.org/guide/checkpoint#loading_mechanics for details.
Evaluating model CNN
* Test accuracy: 0.814
* Test loss: 0.908
```

Compare predictions using the test set

[75]:
```
fig, ax = plt.subplots(nrows=15, ncols=3, figsize=(18, 50))

x_values = list(range(10))

for i in range(15):
    idx = np.random.choice(range(X_test_inputs.shape[0]))
    ax[i, 0].set_axis_off()
    ax[i, 0].imshow(X_test[idx], interpolation='nearest')
    ax[i, 0].set_title(f'#{idx} Class: {y_test[idx][0]}')

    img_input = X_test_inputs[idx][np.newaxis, ...]
```

```
    mlp_predictions = best_mlp_model.predict(img_input)
    mlp_prediction = np.argmax(mlp_predictions)
    ax[i, 1].set_title(f'MLP Pred: {mlp_prediction}')
    ax[i, 1].bar(x=x_values, height=mlp_predictions[0], tick_label=x_values)

    cnn_predictions = best_cnn_model.predict(img_input)
    cnn_prediction = np.argmax(cnn_predictions)
    ax[i, 2].set_title(f'CNN Pred: {cnn_prediction}')
    ax[i, 2].bar(x=x_values, height=cnn_predictions[0], tick_label=x_values)

plt.subplots_adjust(hspace=.5)
```


#14837 Class: 4
MLP Pred: 4
CNN Pred: 4
#12193 Class: 9
MLP Pred: 9
CNN Pred: 9
#13236 Class: 1
MLP Pred: 1
CNN Pred: 1
#20516 Class: 3
MLP Pred: 3
CNN Pred: 5
#24970 Class: 1
MLP Pred: 1
CNN Pred: 1
#10570 Class: 2
MLP Pred: 2
CNN Pred: 2
#10071 Class: 2
MLP Pred: 2
CNN Pred: 2
#16292 Class: 9
MLP Pred: 9
CNN Pred: 9
#5215 Class: 9
MLP Pred: 9
CNN Pred: 9
#8506 Class: 6
MLP Pred: 6
CNN Pred: 4
#13335 Class: 7
MLP Pred: 7
CNN Pred: 7
#3157 Class: 5
MLP Pred: 5
CNN Pred: 5
#15803 Class: 2
MLP Pred: 2
CNN Pred: 2
#5424 Class: 9
MLP Pred: 9
CNN Pred: 9
#24528 Class: 1
MLP Pred:
CNN Pred: 1