Capstone Project

November 24, 2020

1 Capstone Project

1.1 Image classifier for the SVHN dataset

1.1.1 Instructions

In this notebook, you will create a neural network that classifies real-world images digits. You will use concepts from throughout this course in building, training, testing, validating and saving your Tensorflow classifier model.

This project is peer-assessed. Within this notebook you will find instructions in each section for how to complete the project. Pay close attention to the instructions as the peer review will be carried out according to a grading rubric that checks key parts of the project instructions. Feel free to add extra cells into the notebook as required.

1.1.2 How to submit

When you have completed the Capstone project notebook, you will submit a pdf of the notebook for peer review. First ensure that the notebook has been fully executed from beginning to end, and all of the cell outputs are visible. This is important, as the grading rubric depends on the reviewer being able to view the outputs of your notebook. Save the notebook as a pdf (File -> Download as -> PDF via LaTeX). You should then submit this pdf for review.

1.1.3 Let's get started!

We'll start by running some imports, and loading the dataset. For this project you are free to make further imports throughout the notebook as you wish.

1.2 ### Personal Information

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Date: 24/11/2020

```
In [2]: import tensorflow as tf
        from scipy.io import loadmat
```


For the capstone project, you will use the SVHN dataset. This is an image dataset of over 600,000 digit images in all, and is a harder dataset than MNIST as the numbers appear in the context of natural scene images. SVHN is obtained from house numbers in Google Street View images.

- Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu and A. Y. Ng. "Reading Digits in Natural Images with Unsupervised Feature Learning". NIPS Workshop on Deep Learning and Unsupervised Feature Learning, 2011.

Your goal is to develop an end-to-end workflow for building, training, validating, evaluating and saving a neural network that classifies a real-world image into one of ten classes.

```
In [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.

1.3 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]: #import essentially packages
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
```

1.4 ### Task 1.1

Extract the training and test images and labels separately from the train and test dictionaries loaded for you

```
In [5]: def hsvn_preprocess(train, test):
            x_train = np.array(train['X'])
            x_train = np.moveaxis(x_train, -1, 0)
            x_train = x_train/255.
            y_train = train['y']
            x_test = np.array(test['X'])
            x_test = np.moveaxis(x_test, -1, 0)
            x_test = x_test/255.
            y_test = test['y']
            return x_train, y_train, x_test, y_test
```

```
In [6]: #execute task 1.1
        x_train, y_train, x_test, y_test = hsvn_preprocess(train, test)
        print('Dimension x_train: ', x_train.shape)
        print('Dimension y_train: ', y_train.shape)
        print('Dimension x_test: ', x_test.shape)
        print('Dimension y_test', y_test.shape)
```

```
Dimension x_train:  (73257, 32, 32, 3)
Dimension y_train:  (73257, 1)
Dimension x_test:  (26032, 32, 32, 3)
Dimension y_test (26032, 1)
```

1.5 ### Task 1.2

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

```
In [6]: def display_images(x, y, quantity):
            if quantity >= 10:
                random_idx = np.random.choice(x.shape[0], quantity)
                fig = plt.figure(figsize = (20, 8))
                for idx in range(10):
                    index = random_idx[idx]
                    ax = fig.add_subplot(2, quantity/2, idx+1, xticks = [], yticks = [])
                    img = np.squeeze(x[index, ...])
                    ax.imshow(img)
                    ax.set_title(str(y[index, ...]), color = 'green')
                plt.show()
            else:
                print('Display least 10 images')
```

```
In [7]: #execute task 1.2 ==> display train images
        display_images(x_train, y_train, quantity = 10)
```


```
In [8]: #execute task 1.2 ==> display test images
        display_images(x_test, y_test, quantity = 10)
```

1.6 ### Task 1.3

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 [7]: #RGB shape of images
        print('RGB-Dimension x_train: ', x_train.shape)
        print('RGB-Dimension x_test: ', x_test.shape)
```

```
RGB-Dimension x_train:  (73257, 32, 32, 3)
RGB-Dimension x_test:  (26032, 32, 32, 3)
```

In [8]:
```python
#if keepdims = true, retains reduced dimensions with length 1
def convert_grayscale(images):
    img = tf.convert_to_tensor(images)
    img_gray = tf.reduce_mean(img, axis = 3, keepdims = True)
    img_gray.numpy()
    return img_gray
```

In [9]:
```python
#execute task 1.3 ==> convert x_train
xgray_train = convert_grayscale(x_train)
print('Grayscale-Dimension x_train: ', xgray_train.shape)
```

```
Grayscale-Dimension x_train:  (73257, 32, 32, 1)
```

In [10]:
```python
#execute task 1.3 ==> convert x_test
xgray_test = convert_grayscale(x_test)
print('Grayscale-Dimension x_test: ', xgray_test.shape)
```

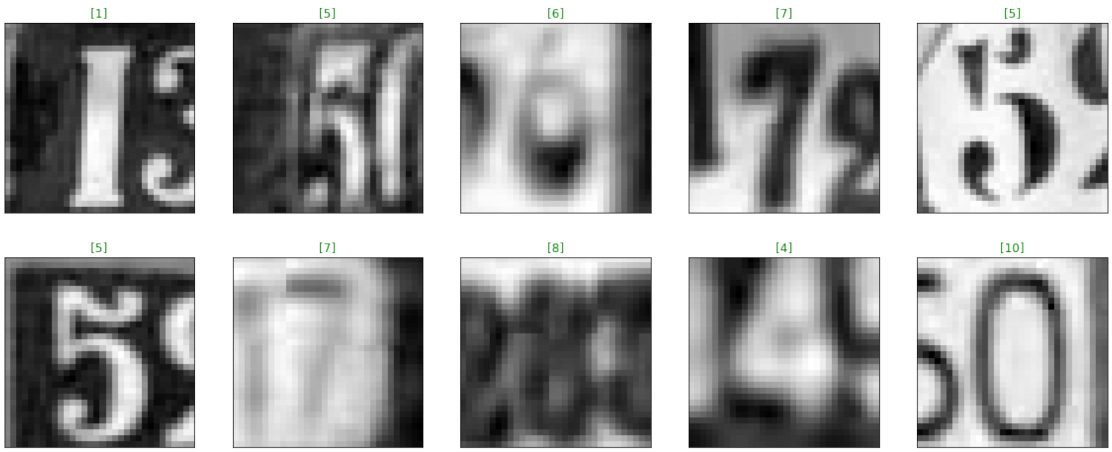
```
Grayscale-Dimension x_test:  (26032, 32, 32, 1)
```

1.7 ### Task 1.4

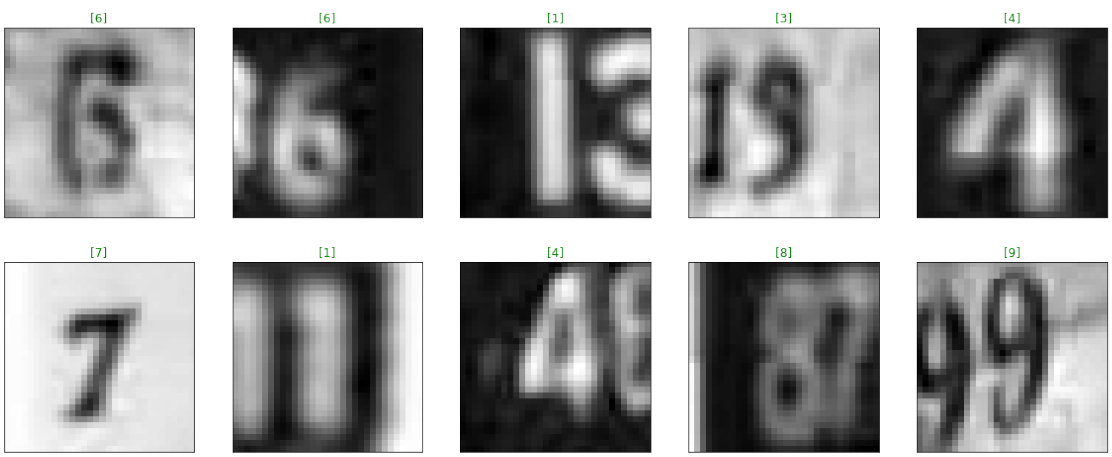
Select a random sample of grayscale images and corresponding labels from the dataset (at least 10), and display them in a figure

In [13]:
```python
import matplotlib

def display_gray_images(x, y, quantity):
    if quantity >= 10:
        random_idx = np.random.choice(x.shape[0], quantity)
        fig = plt.figure(figsize = (20, 8))
        for idx in range(10):
            index = random_idx[idx]
            ax = fig.add_subplot(2, quantity/2, idx+1, xticks = [], yticks = [])
            img = np.squeeze(x[index, ...])
            ax.imshow(img, cmap = matplotlib.cm.gray)
            ax.set_title(str(y[index, ...]), color = 'green')
        plt.show()
    else:
        print('Display least 10 images')
```

In [14]:
```python
#execute task 1.4 ==> display train images
display_gray_images(xgray_train, y_train, quantity = 10)
```




```
In [15]: #execute task 1.4 ==> display test images
         display_gray_images(xgray_test, y_test, quantity = 10)
```




```
In [ ]:
```

1.8 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 [11]:
```
#import essentially packages
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Flatten, Dense
from tensorflow.keras import initializers, regularizers
```

1.9 ### Task 2.1

- Build an MLP classifier model using Sequential API. Your model should be 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

In [12]:
```
def build_model(d1, d2):
    model = Sequential([
        Flatten(input_shape = (d1, d2), name = 'flatten_1'),
        Dense(units = 512, activation = 'relu', name = 'fc_1',
                  kernel_initializer = initializers.he_uniform(seed = None),
                  bias_initializer = initializers.Ones()),
        Dense(units = 256, activation = 'relu', name = 'fc_2'),
        Dense(units = 64, activation = 'relu', name = 'fc_3'),
        Dense(units = 10, activation = 'softmax', name = 'fc_4')
    ])

    #Compile model
    model.compile(optimizer = tf.keras.optimizers.Adam(lr = 1e-3),
                  loss = 'categorical_crossentropy',
                  metrics = ['accuracy'])

    return model
```

1.10 ### Task 2.2

Print out the model summary

In [23]:
```
model = build_model(32, 32)
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
flatten_1 (Flatten)          (None, 1024)             0
_________________________________________________________________
fc_1 (Dense)                 (None, 512)              524800
_________________________________________________________________
fc_2 (Dense)                 (None, 256)              131328
_________________________________________________________________
fc_3 (Dense)                 (None, 64)               16448
_________________________________________________________________
fc_4 (Dense)                 (None, 10)               650
=================================================================
Total params: 673,226
Trainable params: 673,226
Non-trainable params: 0
_________________________________________________________________
```

1.11 ### Task 2.3

- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during a training run
- Your model should track at least one appropiate metric, and use at least two callbacks during training, one of which should be ModelCheckpoint callback
- As a guide, you should aim to achieve a final categorical cross entropy training loss of less than 1.0

In [19]:
```
#adapt outputs to apply categorical_crossentropy loss
from sklearn.preprocessing import LabelBinarizer
def encoding_outputs(y_train, y_test):
    lb = LabelBinarizer()
    y_train = lb.fit_transform(y_train)
    y_test = lb.fit_transform(y_test)
    return y_train, y_test
```

In [20]:
```
#define 10 binary-labels by class
y_train, y_test = encoding_outputs(y_train, y_test)
print('Dimensions y-train: ', y_train.shape)
print('Dimensions y-test: ', y_test.shape)
```

```
Dimensions y-train:  (73257, 10)
Dimensions y-test:  (26032, 10)
```

In [26]:
```
#import packages
from tensorflow.keras.callbacks \
        import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
```

In [30]:
```
#function to reduce plateau
def reduce_plateau_callback():
    reduce_plateau = ReduceLROnPlateau(
```

```
                                monitor = 'val_loss',
                                factor = 0.1,
                                patience = 3,
                                verbose = 1,
                                mode = 'min',
                                min_lr = 0)
            return reduce_plateau
```

In [31]:
```
#function to early stopping
def early_stopping_callback():
    early_stopping = EarlyStopping(
                        monitor = 'val_accuracy',
                        patience = 8,
                        min_delta = 0.005,
                        verbose = 1,
                        mode = 'max')
    return early_stopping
```

In [32]:
```
#function to save best model
def save_best_checkpoint():
    checkpoint_path = 'mlp_model_run/checkpoint'
    checkpoint = ModelCheckpoint(
                    filepath = checkpoint_path,
                    monitor = 'val_accuracy',
                    save_weights_only = True,
                    save_best_only = True,
                    verbose = 1,
                    mode = 'max')
    return checkpoint
```

In [33]:
```
#create callbacks
reduce_plateau = reduce_plateau_callback()
early_stopping = early_stopping_callback()
best_checkpoint = save_best_checkpoint()
```

In [34]:
```
#define all callbacks
lst_callbacks = [reduce_plateau, early_stopping, best_checkpoint]
```

In [35]:
```
#correct dimension to train
xgray_train[:, :, :, -1].shape
```

Out[35]:
```
TensorShape([73257, 32, 32])
```

In [36]:
```
#Train the mlp model with callbacks
hist_train = model.fit(xgray_train[:, :, :, -1], y_train, epochs = 30,
                    batch_size = 100, validation_split = 0.2,
                    callbacks = lst_callbacks)
```

```
Train on 58605 samples, validate on 14652 samples
Epoch 1/30
```

```
58500/58605 [============================>.] - ETA: 0s - loss: 2.0793 - accuracy: 0.2557
Epoch 00001: val_accuracy improved from -inf to 0.42588, saving model to mlp_model_run/checkpoi
58605/58605 [==============================] - 36s 610us/sample - loss: 2.0783 - accuracy: 0.2
Epoch 2/30
58600/58605 [============================>.] - ETA: 0s - loss: 1.4278 - accuracy: 0.5169
Epoch 00002: val_accuracy improved from 0.42588 to 0.54655, saving model to mlp_model_run/chec
58605/58605 [==============================] - 33s 565us/sample - loss: 1.4277 - accuracy: 0.5
Epoch 3/30
58400/58605 [============================>.] - ETA: 0s - loss: 1.1520 - accuracy: 0.6318
Epoch 00003: val_accuracy did not improve from 0.54655
58605/58605 [==============================] - 32s 548us/sample - loss: 1.1517 - accuracy: 0.6
Epoch 4/30
58600/58605 [============================>.] - ETA: 0s - loss: 1.0547 - accuracy: 0.6680
Epoch 00004: val_accuracy improved from 0.54655 to 0.63070, saving model to mlp_model_run/chec
58605/58605 [==============================] - 33s 561us/sample - loss: 1.0548 - accuracy: 0.6
Epoch 5/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.9631 - accuracy: 0.6990
Epoch 00005: val_accuracy improved from 0.63070 to 0.68782, saving model to mlp_model_run/chec
58605/58605 [==============================] - 33s 570us/sample - loss: 0.9632 - accuracy: 0.6
Epoch 6/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.9010 - accuracy: 0.7184
Epoch 00006: val_accuracy improved from 0.68782 to 0.69165, saving model to mlp_model_run/chec
58605/58605 [==============================] - 32s 554us/sample - loss: 0.9009 - accuracy: 0.7
Epoch 7/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.8518 - accuracy: 0.7347
Epoch 00007: val_accuracy did not improve from 0.69165
58605/58605 [==============================] - 32s 552us/sample - loss: 0.8519 - accuracy: 0.7
Epoch 8/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.8328 - accuracy: 0.7394
Epoch 00008: val_accuracy improved from 0.69165 to 0.72106, saving model to mlp_model_run/chec
58605/58605 [==============================] - 33s 556us/sample - loss: 0.8328 - accuracy: 0.7
Epoch 9/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.7864 - accuracy: 0.7553
Epoch 00009: val_accuracy did not improve from 0.72106
58605/58605 [==============================] - 33s 557us/sample - loss: 0.7865 - accuracy: 0.7
Epoch 10/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.7533 - accuracy: 0.7678
Epoch 00010: val_accuracy improved from 0.72106 to 0.75389, saving model to mlp_model_run/chec
58605/58605 [==============================] - 33s 559us/sample - loss: 0.7533 - accuracy: 0.7
Epoch 11/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.7432 - accuracy: 0.7675
Epoch 00011: val_accuracy did not improve from 0.75389
58605/58605 [==============================] - 32s 548us/sample - loss: 0.7433 - accuracy: 0.7
Epoch 12/30
58400/58605 [============================>.] - ETA: 0s - loss: 0.7192 - accuracy: 0.7753
Epoch 00012: val_accuracy improved from 0.75389 to 0.76153, saving model to mlp_model_run/chec
58605/58605 [==============================] - 33s 557us/sample - loss: 0.7193 - accuracy: 0.7
Epoch 13/30
```

```
58500/58605 [============================>.] - ETA: 0s - loss: 0.7013 - accuracy: 0.7810
Epoch 00013: val_accuracy improved from 0.76153 to 0.76850, saving model to mlp_model_run/check
58605/58605 [==============================] - 33s 559us/sample - loss: 0.7012 - accuracy: 0.78
Epoch 14/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.6806 - accuracy: 0.7894
Epoch 00014: val_accuracy did not improve from 0.76850
58605/58605 [==============================] - 32s 554us/sample - loss: 0.6805 - accuracy: 0.78
Epoch 15/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.6698 - accuracy: 0.7914
Epoch 00015: val_accuracy did not improve from 0.76850
58605/58605 [==============================] - 33s 556us/sample - loss: 0.6698 - accuracy: 0.79
Epoch 16/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.6544 - accuracy: 0.7974
Epoch 00016: val_accuracy improved from 0.76850 to 0.78092, saving model to mlp_model_run/check
58605/58605 [==============================] - 32s 553us/sample - loss: 0.6544 - accuracy: 0.79
Epoch 17/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.6369 - accuracy: 0.8018
Epoch 00017: val_accuracy did not improve from 0.78092
58605/58605 [==============================] - 33s 556us/sample - loss: 0.6369 - accuracy: 0.80
Epoch 18/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.6286 - accuracy: 0.8039
Epoch 00018: val_accuracy improved from 0.78092 to 0.79286, saving model to mlp_model_run/check
58605/58605 [==============================] - 32s 549us/sample - loss: 0.6285 - accuracy: 0.80
Epoch 19/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.6111 - accuracy: 0.8092
Epoch 00019: val_accuracy did not improve from 0.79286
58605/58605 [==============================] - 32s 547us/sample - loss: 0.6111 - accuracy: 0.80
Epoch 20/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.6101 - accuracy: 0.8090
Epoch 00020: val_accuracy improved from 0.79286 to 0.79784, saving model to mlp_model_run/check
58605/58605 [==============================] - 33s 557us/sample - loss: 0.6103 - accuracy: 0.80
Epoch 21/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.5973 - accuracy: 0.8124
Epoch 00021: val_accuracy did not improve from 0.79784
58605/58605 [==============================] - 32s 552us/sample - loss: 0.5973 - accuracy: 0.81
Epoch 22/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.5950 - accuracy: 0.8128
Epoch 00022: val_accuracy did not improve from 0.79784
58605/58605 [==============================] - 34s 572us/sample - loss: 0.5948 - accuracy: 0.81
Epoch 23/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.5810 - accuracy: 0.8190
Epoch 00023: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.

Epoch 00023: val_accuracy did not improve from 0.79784
58605/58605 [==============================] - 32s 554us/sample - loss: 0.5809 - accuracy: 0.81
Epoch 24/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.4673 - accuracy: 0.8557
Epoch 00024: val_accuracy improved from 0.79784 to 0.82446, saving model to mlp_model_run/check
```

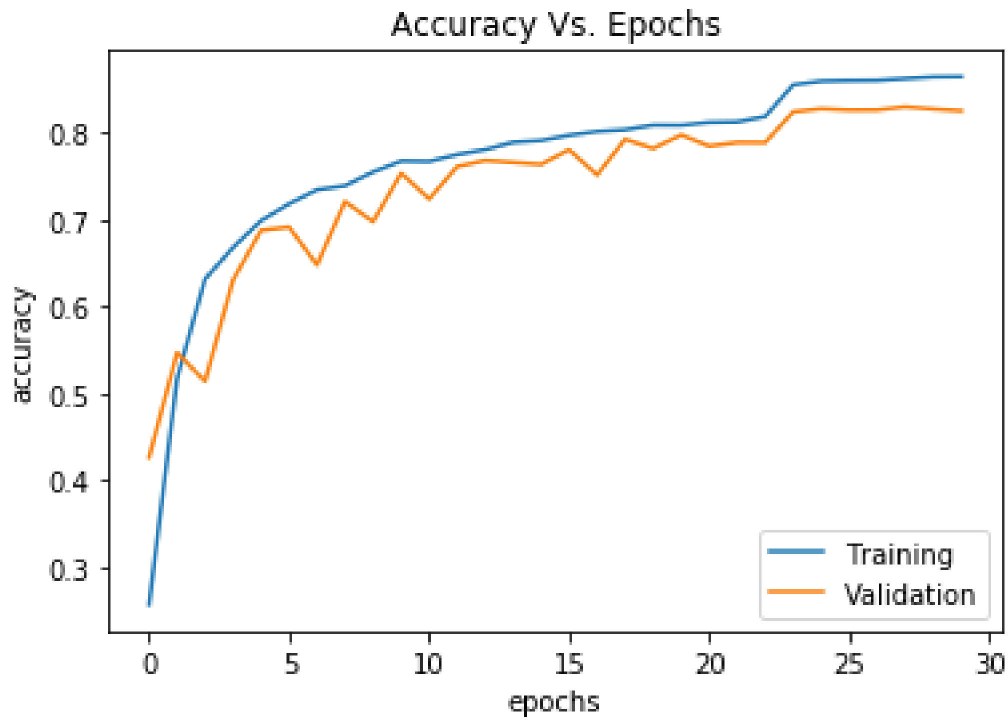
```
58605/58605 [==============================] - 33s 558us/sample - loss: 0.4674 - accuracy: 0.85
Epoch 25/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.4539 - accuracy: 0.8599
Epoch 00025: val_accuracy improved from 0.82446 to 0.82808, saving model to mlp_model_run/check
58605/58605 [==============================] - 33s 559us/sample - loss: 0.4539 - accuracy: 0.85
Epoch 26/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.4505 - accuracy: 0.8606
Epoch 00026: val_accuracy did not improve from 0.82808
58605/58605 [==============================] - 32s 550us/sample - loss: 0.4504 - accuracy: 0.86
Epoch 27/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.4471 - accuracy: 0.8609
Epoch 00027: val_accuracy did not improve from 0.82808
58605/58605 [==============================] - 33s 555us/sample - loss: 0.4471 - accuracy: 0.86
Epoch 28/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.4424 - accuracy: 0.8629
Epoch 00028: val_accuracy improved from 0.82808 to 0.83033, saving model to mlp_model_run/check
58605/58605 [==============================] - 33s 556us/sample - loss: 0.4424 - accuracy: 0.86
Epoch 29/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.4399 - accuracy: 0.8649
Epoch 00029: val_accuracy did not improve from 0.83033
58605/58605 [==============================] - 32s 551us/sample - loss: 0.4399 - accuracy: 0.86
Epoch 30/30
58500/58605 [============================>.] - ETA: 0s - loss: 0.4371 - accuracy: 0.8652
Epoch 00030: val_accuracy did not improve from 0.83033
58605/58605 [==============================] - 32s 548us/sample - loss: 0.4371 - accuracy: 0.86
```

1.12 ### Task 2.4

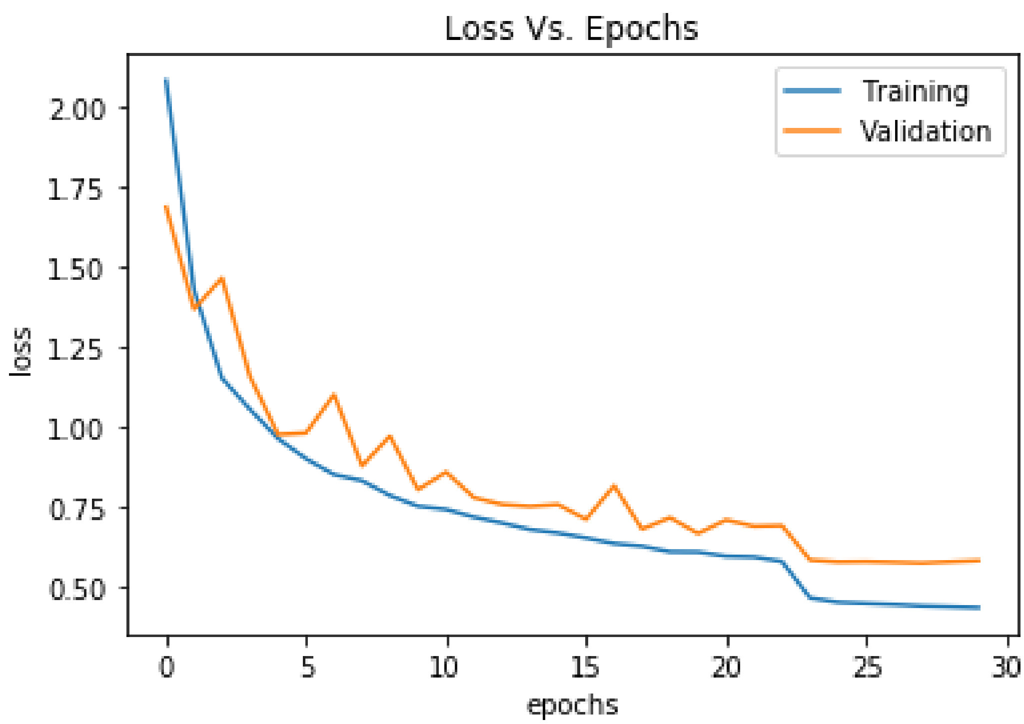
Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets

In [38]:
```
#define function to plot learning curves
def plot_learn_curve(hist, metric, title, pos):
    plt.plot(hist.history[metric])
    plt.plot(hist.history['val_'+metric])
    plt.title(title)
    plt.xlabel('epochs')
    plt.ylabel(metric)
    plt.legend(['Training', 'Validation'], loc = pos+' right')
    plt.show()
```

In [39]:
```
#plot accuracy vs epoch curve
plot_learn_curve(hist_train, 'accuracy', 'Accuracy Vs. Epochs', 'lower')
```




```
In [40]: #plot loss vs epoch curve
         plot_learn_curve(hist_train, 'loss', 'Loss Vs. Epochs', 'upper')
```



1.13 ### Task 2.5

Compute and display the loss and accuracy of the trained model on the test set

```
In [60]: #function to compute test accuracy
         def get_test_accuracy(model, x_test, y_test):
             test_loss, test_accuracy = model.evaluate(x_test, y_test, verbose = 0)
             print('Test-Accuracy: ', round(100 * test_accuracy, 5), '%')
             print('Test-Loss: ', round(test_loss, 6))
```

```
In [61]: #function to load weights of best model
         def get_best_model(model):
             checkpoint_best_epoch = tf.train.latest_checkpoint(
                                         checkpoint_dir = 'mlp_model_run',
                                         latest_filename = None)
             model.load_weights(checkpoint_best_epoch)
             return model
```

```
In [62]: #load best model
         best_mlp = get_best_model(build_model(32, 32))
```

```
In [63]: #display accuracy and loss in test_set
         print('Model with best accuracy: ')
         get_test_accuracy(best_mlp, xgray_test[:, :, :, -1], y_test)
```

```
Model with best accuracy:
Test-Accuracy:  80.29733 %
Test-Loss:  0.70351
```

1.14 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 [13]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers \
        import Conv2D, MaxPool2D, BatchNormalization, Dropout, Flatten, Dense
```

1.15 ### Task 3.1

- Build CNN classifier and compile model.
- The CNN model should use fewer trainable parameters than your MLP model

In [14]:
```
#build CNN architecture

def build_cnn_model(input_shape):
    model = Sequential([
        Conv2D(filters = 16, kernel_size = (3, 3), name = 'conv_1',
               padding = 'same', activation = 'relu',
               input_shape = input_shape),
        BatchNormalization(name = 'bn_1'),
        MaxPool2D(pool_size = (2, 2), name = 'pool_1'),
        Conv2D(filters = 32, kernel_size = (3, 3), name = 'conv_2',
               padding = 'same', activation = 'relu'),
        BatchNormalization(name = 'bn_2'),
        MaxPool2D(pool_size = (2, 2), name = 'pool_2'),
        Flatten(name = 'flatten_1'),
        Dense(units = 256, activation = 'relu', name = 'fc_1'),
        BatchNormalization(name = 'bn_3'),
        Dense(units = 10, activation = 'softmax', name = 'f_2')
    ])

    #Compile model
    model.compile(optimizer = tf.keras.optimizers.Adam(lr = 1e-3),
                  loss = 'categorical_crossentropy',
                  metrics = ['accuracy'])

    return model
```

In [12]:
```
#correct dimensions to CNN
x_train.shape[1:]
```

Out[12]: (32, 32, 3)

In [49]:
```
cnn_model = build_cnn_model(input_shape = x_train.shape[1:])
cnn_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
conv_1 (Conv2D)              (None, 32, 32, 16)        448
_________________________________________________________________
bn_1 (BatchNormalization)    (None, 32, 32, 16)        64
_________________________________________________________________
pool_1 (MaxPooling2D)        (None, 16, 16, 16)        0
_________________________________________________________________
conv_2 (Conv2D)              (None, 16, 16, 32)        4640
_________________________________________________________________
bn_2 (BatchNormalization)    (None, 16, 16, 32)        128
_________________________________________________________________
pool_2 (MaxPooling2D)        (None, 8, 8, 32)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
fc_1 (Dense)                 (None, 256)               524544
_________________________________________________________________
bn_3 (BatchNormalization)    (None, 256)               1024
_________________________________________________________________
f_2 (Dense)                  (None, 10)                2570
=================================================================
Total params: 533,418
Trainable params: 532,810
Non-trainable params: 608
_________________________________________________________________
```

1.16 ### Task 3.2

- Train the model (maximum of 30 epochs), making use of both training and validation sets during the training run
- Your model should track at least one appropiate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback

```
In [50]: #check x_train, y_train and x_test, y_test dimensions
         print('x_train dimension: ', x_train.shape)
         print('y_train dimension: ', y_train.shape)
         print('x_test dimension: ', x_test.shape)
         print('y_test dimension: ', y_test.shape)
```

```
x_train dimension:  (73257, 32, 32, 3)
y_train dimension:  (73257, 10)
x_test dimension:  (26032, 32, 32, 3)
y_test dimension:  (26032, 10)
```

```
In [51]: #import packages
         from tensorflow.keras.callbacks \
                 import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
```

In [52]:
```
#function to reduce plateau
def reduce_plateau_cnncallback():
    reduce_plateau = ReduceLROnPlateau(
                        monitor = 'val_loss',
                        factor = 0.1,
                        patience = 3,
                        verbose = 1,
                        mode = 'min',
                        min_lr = 0)
    return reduce_plateau

#function to early stopping
def early_stopping_cnncallback():
    early_stopping = EarlyStopping(
                        monitor = 'val_accuracy',
                        patience = 8,
                        min_delta = 0.005,
                        verbose = 1,
                        mode = 'max')
    return early_stopping

#function to save best model
def save_best_cnncheckpoint():
    checkpoint_path = 'cnn_model1_run/checkpoint'
    checkpoint = ModelCheckpoint(
                    filepath = checkpoint_path,
                    monitor = 'val_accuracy',
                    save_weights_only = True,
                    save_best_only = True,
                    verbose = 1,
                    mode = 'max')
    return checkpoint
```

In [53]:
```
#create callbacks
cnn_reduce_plateau = reduce_plateau_cnncallback()
cnn_early_stopping = early_stopping_cnncallback()
cnn_save_best = save_best_cnncheckpoint()
```

In [54]:
```
#define callbacks
cnn_callbacks = [cnn_reduce_plateau, cnn_early_stopping, cnn_save_best]
```

In [55]:
```
#train cnn model
cnn_history = cnn_model.fit(x_train, y_train, epochs = 30,
                             validation_split = 0.2,
                             batch_size = 100,
                             callbacks = cnn_callbacks)
```

```
Train on 58605 samples, validate on 14652 samples
Epoch 1/30
```

```
58600/58605 [============================>.] - ETA: 0s - loss: 0.6886 - accuracy: 0.7874
Epoch 00001: val_accuracy improved from -inf to 0.83286, saving model to cnn_model1_run/checkpo
58605/58605 [==============================] - 335s 6ms/sample - loss: 0.6887 - accuracy: 0.787
Epoch 2/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.4302 - accuracy: 0.8703
Epoch 00002: val_accuracy improved from 0.83286 to 0.84023, saving model to cnn_model1_run/chec
58605/58605 [==============================] - 313s 5ms/sample - loss: 0.4302 - accuracy: 0.870
Epoch 3/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.3278 - accuracy: 0.9017
Epoch 00003: val_accuracy improved from 0.84023 to 0.87613, saving model to cnn_model1_run/chec
58605/58605 [==============================] - 333s 6ms/sample - loss: 0.3279 - accuracy: 0.901
Epoch 4/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.2758 - accuracy: 0.9177
Epoch 00004: val_accuracy improved from 0.87613 to 0.89012, saving model to cnn_model1_run/chec
58605/58605 [==============================] - 313s 5ms/sample - loss: 0.2758 - accuracy: 0.917
Epoch 5/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.2249 - accuracy: 0.9337
Epoch 00005: val_accuracy did not improve from 0.89012
58605/58605 [==============================] - 312s 5ms/sample - loss: 0.2249 - accuracy: 0.933
Epoch 6/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.1915 - accuracy: 0.9429
Epoch 00006: val_accuracy did not improve from 0.89012
58605/58605 [==============================] - 305s 5ms/sample - loss: 0.1915 - accuracy: 0.942
Epoch 7/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.1539 - accuracy: 0.9547
Epoch 00007: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.

Epoch 00007: val_accuracy did not improve from 0.89012
58605/58605 [==============================] - 306s 5ms/sample - loss: 0.1539 - accuracy: 0.954
Epoch 8/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0878 - accuracy: 0.9769
Epoch 00008: val_accuracy improved from 0.89012 to 0.90411, saving model to cnn_model1_run/chec
58605/58605 [==============================] - 303s 5ms/sample - loss: 0.0878 - accuracy: 0.976
Epoch 9/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0669 - accuracy: 0.9843
Epoch 00009: val_accuracy did not improve from 0.90411
58605/58605 [==============================] - 309s 5ms/sample - loss: 0.0669 - accuracy: 0.984
Epoch 10/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0609 - accuracy: 0.9859
Epoch 00010: val_accuracy improved from 0.90411 to 0.90431, saving model to cnn_model1_run/chec
58605/58605 [==============================] - 308s 5ms/sample - loss: 0.0609 - accuracy: 0.985
Epoch 11/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0514 - accuracy: 0.9891
Epoch 00011: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.

Epoch 00011: val_accuracy did not improve from 0.90431
58605/58605 [==============================] - 307s 5ms/sample - loss: 0.0514 - accuracy: 0.989
Epoch 12/30
```

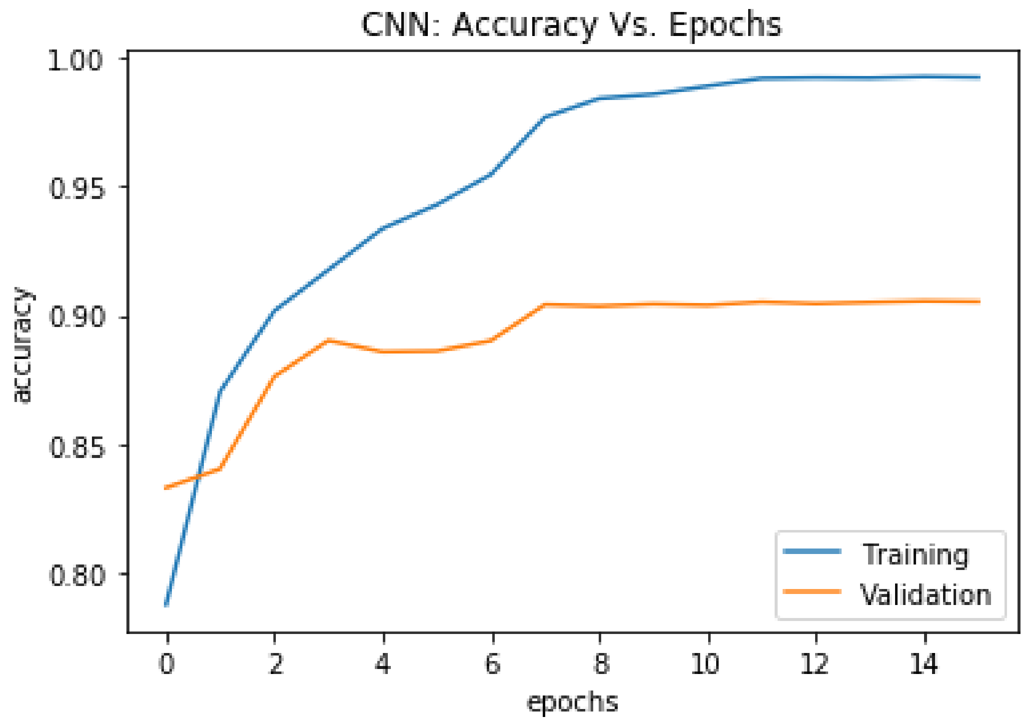
```
58600/58605 [============================>.] - ETA: 0s - loss: 0.0424 - accuracy: 0.9921
Epoch 00012: val_accuracy improved from 0.90431 to 0.90513, saving model to cnn_model1_run/che
58605/58605 [==============================] - 314s 5ms/sample - loss: 0.0424 - accuracy: 0.99
Epoch 13/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0415 - accuracy: 0.9924
Epoch 00013: val_accuracy did not improve from 0.90513
58605/58605 [==============================] - 311s 5ms/sample - loss: 0.0415 - accuracy: 0.99
Epoch 14/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0410 - accuracy: 0.9922
Epoch 00014: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.

Epoch 00014: val_accuracy did not improve from 0.90513
58605/58605 [==============================] - 315s 5ms/sample - loss: 0.0410 - accuracy: 0.99
Epoch 15/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0399 - accuracy: 0.9928
Epoch 00015: val_accuracy improved from 0.90513 to 0.90547, saving model to cnn_model1_run/che
58605/58605 [==============================] - 318s 5ms/sample - loss: 0.0400 - accuracy: 0.99
Epoch 16/30
58600/58605 [============================>.] - ETA: 0s - loss: 0.0399 - accuracy: 0.9925
Epoch 00016: val_accuracy did not improve from 0.90547
58605/58605 [==============================] - 313s 5ms/sample - loss: 0.0399 - accuracy: 0.99
Epoch 00016: early stopping
```

1.17 ### Task 3.3

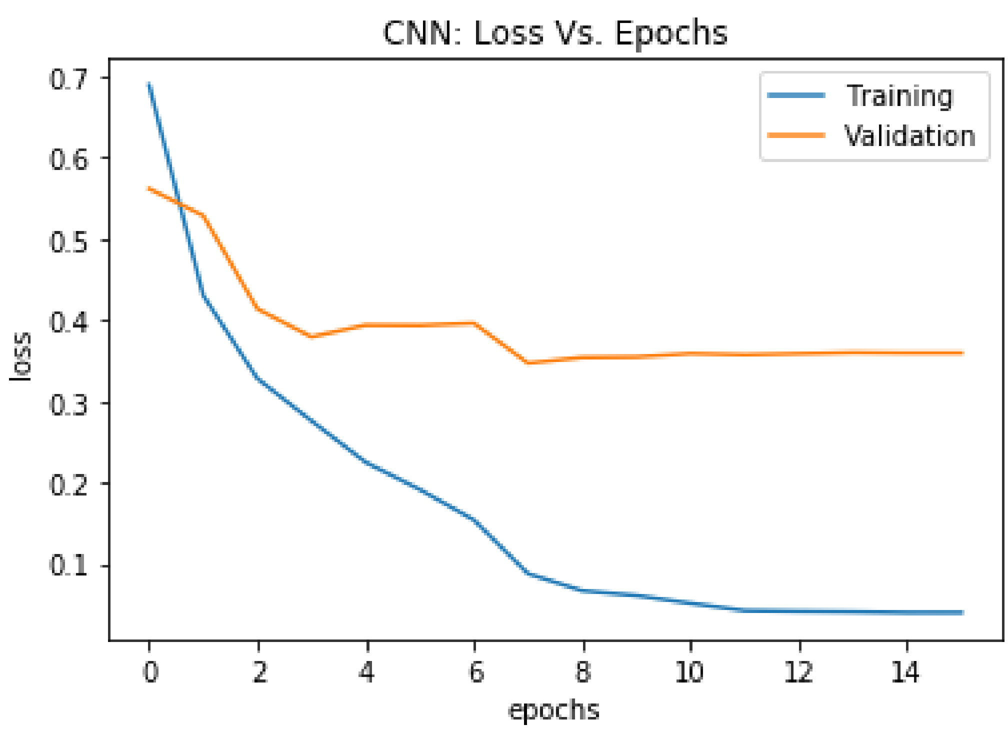
- You should aim beat the MLP performance with fewer parameters!
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets

In [56]:
```
#define function to plot learning curves
def plot_learn_curve(hist, metric, title, pos):
    plt.plot(hist.history[metric])
    plt.plot(hist.history['val_'+metric])
    plt.title(title)
    plt.xlabel('epochs')
    plt.ylabel(metric)
    plt.legend(['Training', 'Validation'], loc = pos+' right')
    plt.show()
```

In [57]:
```
#plot accuracy vs epoch curve
plot_learn_curve(cnn_history, 'accuracy',
                 'CNN: Accuracy Vs. Epochs', 'lower')
```




```
In [58]: #plot loss vs epoch curve
         plot_learn_curve(cnn_history, 'loss', 'CNN: Loss Vs. Epochs', 'upper')
```



1.18 ### Task 3.4

- Compute and display the loss and accuracy of the trained model on test set

```
In [21]: #function to compute test accuracy
         def get_test_accuracy(model, x_test, y_test):
             test_loss, test_accuracy = model.evaluate(x_test, y_test, verbose = 0)
             print('Test-Accuracy: ', round(100 * test_accuracy, 5), '%')
             print('Test-Loss: ', round(test_loss, 6))
```

```
In [22]: #function to load weights of best model
         def get_best_cnnmodel(model):
             checkpoint_best_epoch = tf.train.latest_checkpoint(
                                         checkpoint_dir = 'cnn_model1_run',
                                         latest_filename = None)
             model.load_weights(checkpoint_best_epoch)
             return model
```

```
In [23]: #load best model
         best_cnn = get_best_cnnmodel(build_cnn_model(input_shape = x_train.shape[1:]))
```

```
In [24]: #display accuracy and loss in test_set
         print('Model with best accuracy: ')
         get_test_accuracy(best_cnn, x_test, y_test)
```

```
Model with best accuracy:
Test-Accuracy:  88.9559 %
Test-Loss:  0.423858
```

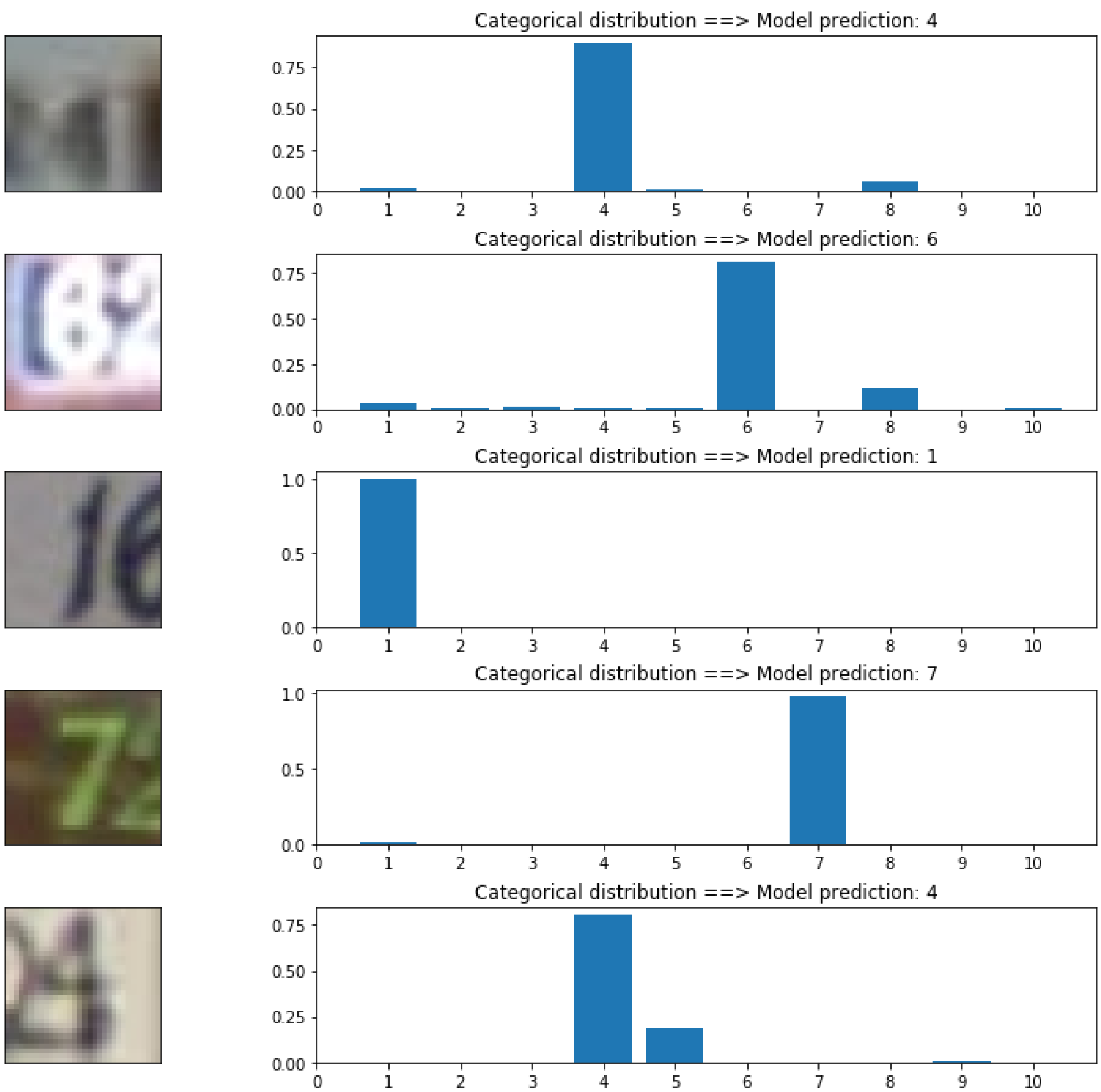
1.19 4. Get model predictions

- 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 [50]: #plot bar chart with final predictions

         def bar_chart_predictions(model, x_test, y_test):
             num_test_images = y_test.shape[0]
             rand_idx = np.random.choice(num_test_images, 5)
             rand_xtest = x_test[rand_idx, ...]
             rand_ytest = y_test[rand_idx, ...]
             predictions = model.predict(rand_xtest)
```

```
    fig, axes = plt.subplots(5, 2, figsize = (16, 12))
    fig.subplots_adjust(hspace = 0.4, wspace = -0.2)

    for i, (prediction, image, label) in enumerate(zip(predictions, rand_xtest, rand_y
        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, 1].bar(np.arange(start = 1, stop = len(prediction)+1), prediction)
        axes[i, 1].set_xticks(np.arange(len(prediction)+1))
        axes[i, 1].set_title(f'Categorical distribution ==> Model prediction: {np.argm
    plt.show()
```

In [59]:
```
#print predicitions of CNN
bar_chart_predictions(best_cnn, x_test, y_test)
```



1.20 Conclusions

1.20.1 CNN Results

Metrics	train	validation	test
accuracy	99.28%	90.55%	88.95%
loss	0.0400	0.3593	0.4238

1.20.2 MLP Results

Metrics	train	validation	test
accuracy	86.29%	83.03%	80.29%
loss	0.4424	0.5761	0.7035

In [ ]:

In [ ]: