Capstone_Project

May 12, 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 (you could download the notebook with File -> Download .ipynb, open the notebook locally, and then File -> Download as -> PDF via LaTeX), and 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.

1.1.4 I created this notebook in Google Colab so it downloads the data instead of directly loading from disk

Importing libraries

```
In [0]: import tensorflow as tf
        from scipy.io import loadmat
        import matplotlib.pyplot as plt
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
        from tensorflow.keras.layers import Conv2D, MaxPooling2D, BatchNormalization, Flatten,
```

To downlaod Training dataset

```
In [2]: !wget http://ufldl.stanford.edu/housenumbers/train_32x32.mat
```

```
--2020-05-12 03:05:09--  http://ufldl.stanford.edu/housenumbers/train_32x32.mat
Resolving ufldl.stanford.edu (ufldl.stanford.edu)... 171.64.68.10
Connecting to ufldl.stanford.edu (ufldl.stanford.edu)|171.64.68.10|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 182040794 (174M) [text/plain]
Saving to: train_32x32.mat

train_32x32.mat     100%[===================>] 173.61M  10.7MB/s    in 19s

2020-05-12 03:05:28 (9.34 MB/s) - train_32x32.mat saved [182040794/182040794]
```

To downlaod Testing dataset

```
In [3]: !wget http://ufldl.stanford.edu/housenumbers/test_32x32.mat
```

```
--2020-05-12 03:05:31--  http://ufldl.stanford.edu/housenumbers/test_32x32.mat
Resolving ufldl.stanford.edu (ufldl.stanford.edu)... 171.64.68.10
Connecting to ufldl.stanford.edu (ufldl.stanford.edu)|171.64.68.10|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 64275384 (61M) [text/plain]
Saving to: test_32x32.mat

test_32x32.mat      100%[===================>]  61.30M  11.0MB/s    in 7.7s

2020-05-12 03:05:39 (7.92 MB/s) - test_32x32.mat saved [64275384/64275384]
```

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.

The train and test datasets required for this project can be downloaded from here and here. Once unzipped, you will have two files: `train_32x32.mat` and `test_32x32.mat`. You should store these files in Drive for use in this Colab notebook.

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.

Checking that the files are downloaded

```
In [4]: !ls -lh
```

```
total 235M
drwxr-xr-x 1 root root 4.0K May  4 16:26 sample_data
-rw-r--r-- 1 root root  62M Dec  6  2011 test_32x32.mat
-rw-r--r-- 1 root root 174M Dec  6  2011 train_32x32.mat
```

```
In [0]: # Load the dataset
        def load_data():
            train = loadmat('train_32x32.mat')
            test = loadmat('test_32x32.mat')

            return train, test

        train, test = load_data()
```

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

1.2 1. Inspect and preprocess the dataset

- Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.
- Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.
- Convert the training and test images to grayscale by taking the average across all colour channels for each pixel. *Hint: retain the channel dimension, which will now have size 1.*
- Select a random sample of the grayscale images and corresponding labels from the dataset (at least 10), and display them in a figure.

```
In [0]: import numpy as np

        def transpose_images(images):
            # transposing the image arrays
            imgs = images["X"]
            imgs = np.transpose(imgs, (3, 0, 1, 2))
            labels = images["y"]

            return imgs, labels
```

```
In [0]: train_images, train_labels = transpose_images(train)
        test_images, test_labels = transpose_images(test)
```

1.2.1 If running on local machine then uncomment these 3 cells

Printing the shapes of all data

```
In [8]: print(f"Training image set : {train_images.shape}")
        print(f"Testing image set : {test_images.shape}")
        print('\n')
        print(f"Total images : {train_images.shape[0] + test_images.shape[0]}")
```

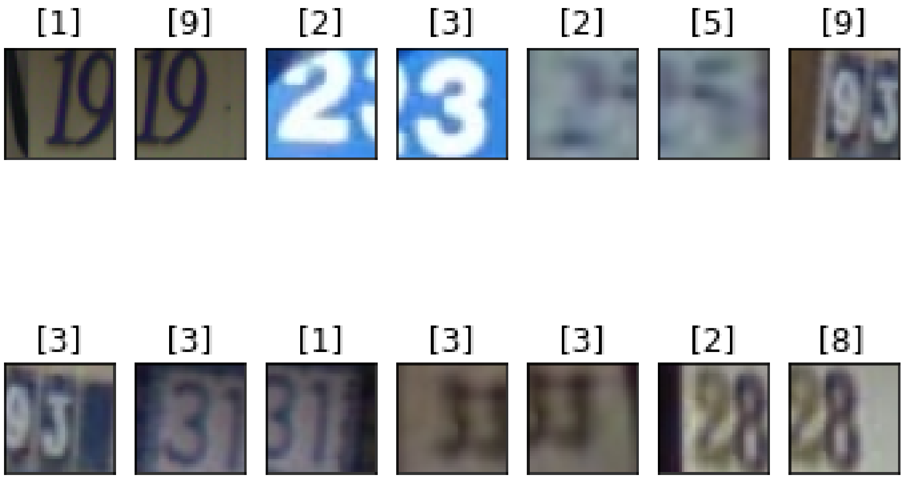
```
Training image set : (73257, 32, 32, 3)
Testing image set : (26032, 32, 32, 3)


Total images : 99289
```

Defining function to plot image smaples

```
In [0]: def plot_images(img, labels, rows=2, cols=5):
            # Plot rows x cols images
            fig, axes = plt.subplots(rows, cols)
            for i, axis in enumerate(axes.flat):
                # For plotting RGB images
                if img[i].shape == (32, 32, 3):
                    axis.imshow(img[i])
                # For plotting Grayscale images by removing last dimension (color)
                else:
                    axis.imshow(img[i,:,:,0])
                axis.set_xticks([])
                axis.set_yticks([])
                axis.set_title(labels[i])
```

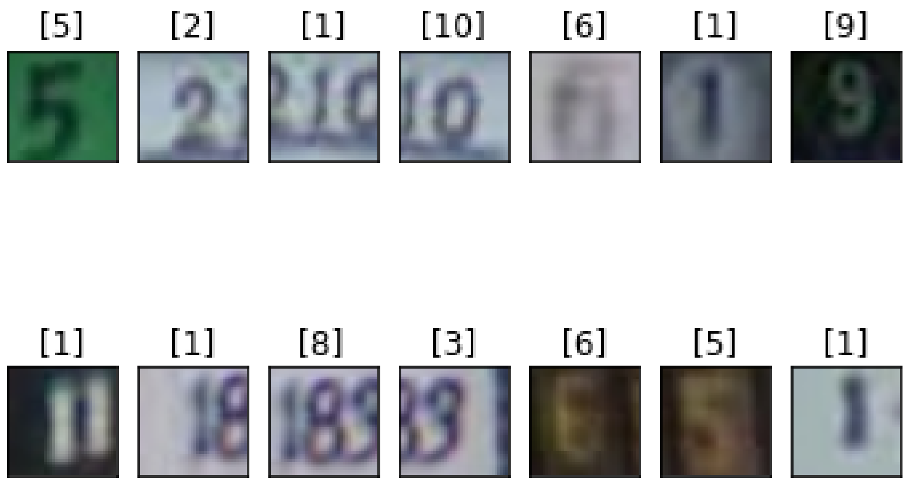
```
In [10]: # Plotting training images
         plot_images(train_images, train_labels,2, 7)
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/text.py:1165: FutureWarning: elementwise comp
  if s != self._text:
```



```
In [11]: # Plotting testing images
         plot_images(test_images, test_labels, 2, 7)
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/text.py:1165: FutureWarning: elementwise comp
  if s != self._text:
```




```
In [12]: # To know all unique labels present in dataset
         print(np.unique(train_labels))
```

```
[ 1  2  3  4  5  6  7  8  9 10]
```

```
In [13]: # Converting label 10 to 0 in labels dataset
         train_labels[train_labels == 10] = 0
         test_labels[test_labels == 10] = 0
         print(np.unique(train_labels))
```

```
[0 1 2 3 4 5 6 7 8 9]
```

Converting RGB images to Grayscale

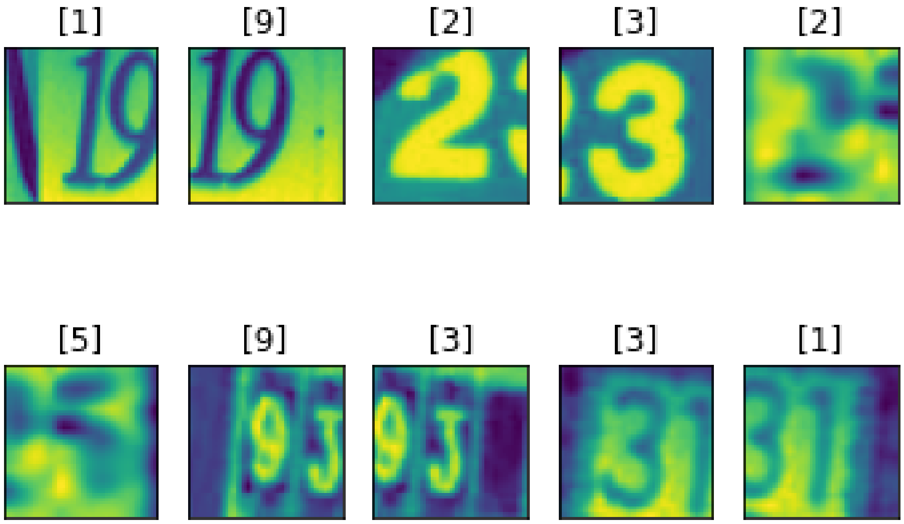
```
In [0]: # To convert rgb to gray images with formula Gray = (0.2990R + 0.5870G + 0.1140B)
        def convert_to_gray(images):
            return np.expand_dims(np.dot(images, [0.2990, 0.5870, 0.1140]), axis=3)
```

```
In [0]: train_grayscale = convert_to_gray(train_images).astype(np.float32)
        test_grayscale = convert_to_gray(test_images).astype(np.float32)
```

PLotting Grayscale images

```
In [16]: # Ploting the Grayscale Image
         plot_images(train_grayscale, train_labels)
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/text.py:1165: FutureWarning: elementwise comp
  if s != self._text:
```



Creating validation split from training dataset

```
In [0]: # To create a validation set of 10% from training set
        from sklearn.model_selection import train_test_split

        train_grayscale, val_grayscale, train_labels, val_labels = train_test_split(train_gray
```

```
In [18]: # Printing new shapes of all datasets
         print("Training Images Set", train_grayscale.shape)
         print("Training Label Set", train_labels.shape)
         print("Testing Images Set", test_grayscale.shape)
         print("Testing Label Set", test_labels.shape)
         print("Validation Images Set", val_grayscale.shape)
         print("Validation Label Set", val_labels.shape)
```

```
Training Images Set (65931, 32, 32, 1)
Training Label Set (65931, 1)
Testing Images Set (26032, 32, 32, 1)
Testing Label Set (26032, 1)
Validation Images Set (7326, 32, 32, 1)
Validation Label Set (7326, 1)
```

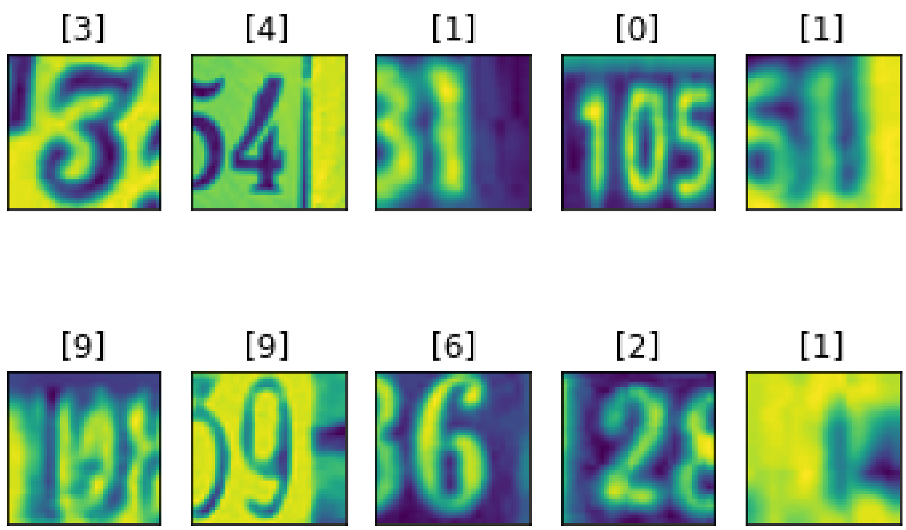
Normalizing the images for easier training

```
In [0]: def normalize_images(imgs):
            # normalize images so pixel values are in range [0,1]
            mean = np.mean(imgs, axis=0)
            std = np.std(imgs, axis=0)
            imgs = (imgs - mean) / std

            return imgs
```

```
In [0]: train_imgs = normalize_images(train_grayscale)
        test_imgs = normalize_images(test_grayscale)
        val_imgs = normalize_images(val_grayscale)
```

```
In [21]: # Ploting the Grayscale Image after normalization
         plot_images(train_grayscale, train_labels)
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/text.py:1165: FutureWarning: elementwise comp
  if s != self._text:
```



Deleting unused variables to clear RAM

```
In [0]: # Deleting unused variables to free RAM
        del train_images, test_images
        del train, test

        # Deleting extra grayscale variables
        del train_grayscale, test_grayscale, val_grayscale
```

```
In [23]: print(f"Training Images : 'train_imgs' , Testing Images : 'test_imgs' , Validation Ima
         print(f"Training labels : 'train_imgs' , Testing labels : 'test_imgs' , Validation lal
```

```
Training Images : 'train_imgs' , Testing Images : 'test_imgs' , Validation Images : 'val_imgs'
Training labels : 'train_imgs' , Testing labels : 'test_imgs' , Validation labels : 'val_imgs'
```

1.3 2. MLP neural network classifier

- Build an MLP classifier model using the Sequential API. Your model should use only Flatten and Dense layers, with the final layer having a 10-way softmax output.
- You should design and build the model yourself. Feel free to experiment with different MLP architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 4 or 5 layers.*
- Print out the model summary (using the summary() method)
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.
- Your model should track at least one appropriate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback.
- As a guide, you should aim to achieve a final categorical cross entropy training loss of less than 1.0 (the validation loss might be higher).
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

Function to test accuarcy and loss of model

```
In [0]: # To get model accuracy and loss

        def test_model(model, x_test, y_test):
            test_loss, test_acc = model.evaluate(x=x_test, y=y_test, verbose=0)

            print(f'Test Accuracy: {test_acc:0.3f}')
            print(f'Test Loss : {test_loss:0.3f}')
```

Function to create and compile a MLP Sequential model

```
In [0]: def get_mlp_model(shape):
            # Returns a MLP model
            model = Sequential([
                Flatten(input_shape=shape),
                Dense(128, activation='relu'),
                Dense(128, activation='relu'),
                Dense(64, activation='relu'),
                Dense(10, activation='softmax')
                ])

            model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['a

            return model
```

Creating a MLP model and prining it's summary

```
In [26]: mlp_model = get_mlp_model(train_imgs[0].shape)
         mlp_model.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 128)               131200
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 156,618
Trainable params: 156,618
Non-trainable params: 0
_________________________________________________________________
```

```
In [27]: # To get testing accuracy and loss before training

         test_model(mlp_model, test_imgs, test_labels)

Test Accuracy: 0.077
Test Loss : 2.473
```

Functions for creating callbacks during model fitting

```
In [0]: # Defining callbacks functions

        def get_checkpoint_every_epoch(folder):
            # Creates checkpoint for every epoch
            path = 'checkpoints/every_epoch/' + folder
            checkpoint_every_epoch = ModelCheckpoint(filepath=path,
                                         frequency='epoch',
                                         save_weights_only=True,
                                         verbose=1)
            return checkpoint_every_epoch

        def get_checkpoint_best_only(folder):
            # Creates checkpoint for best validation accuracy
            path = 'checkpoints/best_only/' + folder + '/checkpoint'
            checkpoints_best_only = ModelCheckpoint(filepath=path,
                                         save_weights_only=True,
```

```
                              save_best_only=True,
                              monitor='val_accuracy',
                              verbose=1)
    return checkpoints_best_only, path

def get_early_stopping(patience=3):
    # Creates earlystopping callback
    return EarlyStopping(monitor='val_accuracy', patience=patience)
```

Creating callbacks for MLP model

```
In [0]: # Creatinng callbacks objects for MLP model
        checkpoint_every_epoch = get_checkpoint_every_epoch('checkpoint_{epoch:03d}')
        checkpoint_best_only, mlp_best_path = get_checkpoint_best_only('mlp')
        early_stopping = get_early_stopping(5)

        callbacks = [checkpoint_every_epoch, checkpoint_best_only, early_stopping]
```

Training (fitting) MLP model and validating it simultaneously and store it's history

```
In [30]: # Fitting the MLP model with callbacks and validation set

         mlp_history = mlp_model.fit(train_imgs,
                                     train_labels,
                                     epochs=30,
                                     validation_data=(val_imgs, val_labels),
                                     callbacks=callbacks,
                                     batch_size=512,
                                     verbose=0)
```

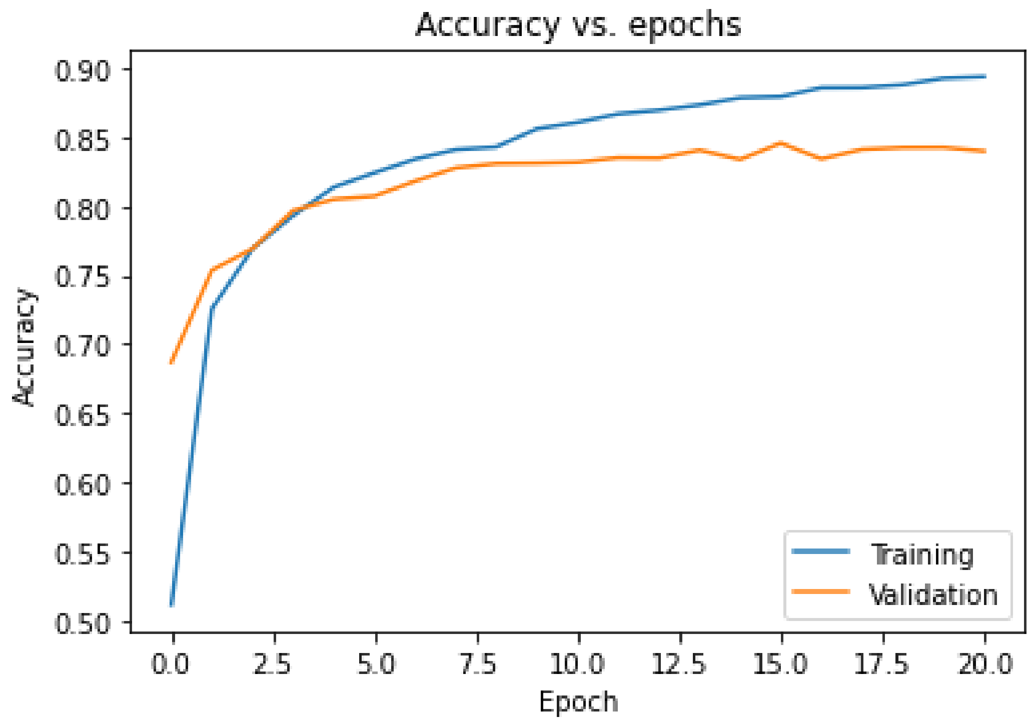
```
Epoch 00001: saving model to checkpoints/every_epoch/checkpoint_001

Epoch 00001: val_accuracy improved from -inf to 0.68687, saving model to checkpoints/best_only/

Epoch 00002: saving model to checkpoints/every_epoch/checkpoint_002

Epoch 00002: val_accuracy improved from 0.68687 to 0.75362, saving model to checkpoints/best_on

Epoch 00003: saving model to checkpoints/every_epoch/checkpoint_003

Epoch 00003: val_accuracy improved from 0.75362 to 0.76904, saving model to checkpoints/best_on

Epoch 00004: saving model to checkpoints/every_epoch/checkpoint_004

Epoch 00004: val_accuracy improved from 0.76904 to 0.79675, saving model to checkpoints/best_on

Epoch 00005: saving model to checkpoints/every_epoch/checkpoint_005
```

```
Epoch 00005: val_accuracy improved from 0.79675 to 0.80480, saving model to checkpoints/best_or

Epoch 00006: saving model to checkpoints/every_epoch/checkpoint_006

Epoch 00006: val_accuracy improved from 0.80480 to 0.80713, saving model to checkpoints/best_or

Epoch 00007: saving model to checkpoints/every_epoch/checkpoint_007

Epoch 00007: val_accuracy improved from 0.80713 to 0.81805, saving model to checkpoints/best_or

Epoch 00008: saving model to checkpoints/every_epoch/checkpoint_008

Epoch 00008: val_accuracy improved from 0.81805 to 0.82760, saving model to checkpoints/best_or

Epoch 00009: saving model to checkpoints/every_epoch/checkpoint_009

Epoch 00009: val_accuracy improved from 0.82760 to 0.83074, saving model to checkpoints/best_or

Epoch 00010: saving model to checkpoints/every_epoch/checkpoint_010

Epoch 00010: val_accuracy improved from 0.83074 to 0.83101, saving model to checkpoints/best_or

Epoch 00011: saving model to checkpoints/every_epoch/checkpoint_011

Epoch 00011: val_accuracy improved from 0.83101 to 0.83170, saving model to checkpoints/best_or

Epoch 00012: saving model to checkpoints/every_epoch/checkpoint_012

Epoch 00012: val_accuracy improved from 0.83170 to 0.83497, saving model to checkpoints/best_or

Epoch 00013: saving model to checkpoints/every_epoch/checkpoint_013

Epoch 00013: val_accuracy did not improve from 0.83497

Epoch 00014: saving model to checkpoints/every_epoch/checkpoint_014

Epoch 00014: val_accuracy improved from 0.83497 to 0.84043, saving model to checkpoints/best_or

Epoch 00015: saving model to checkpoints/every_epoch/checkpoint_015

Epoch 00015: val_accuracy did not improve from 0.84043

Epoch 00016: saving model to checkpoints/every_epoch/checkpoint_016

Epoch 00016: val_accuracy improved from 0.84043 to 0.84548, saving model to checkpoints/best_or

Epoch 00017: saving model to checkpoints/every_epoch/checkpoint_017
```

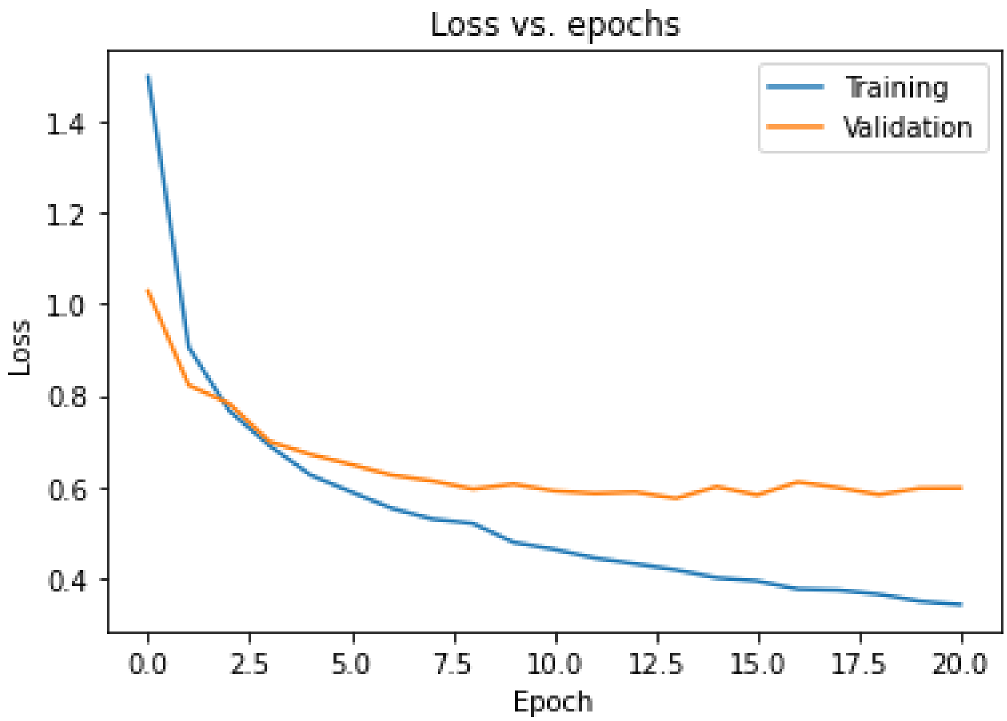
```
Epoch 00017: val_accuracy did not improve from 0.84548

Epoch 00018: saving model to checkpoints/every_epoch/checkpoint_018

Epoch 00018: val_accuracy did not improve from 0.84548

Epoch 00019: saving model to checkpoints/every_epoch/checkpoint_019

Epoch 00019: val_accuracy did not improve from 0.84548

Epoch 00020: saving model to checkpoints/every_epoch/checkpoint_020

Epoch 00020: val_accuracy did not improve from 0.84548

Epoch 00021: saving model to checkpoints/every_epoch/checkpoint_021

Epoch 00021: val_accuracy did not improve from 0.84548
```

Functions for plotting Accuracy and Loss using history of model training

In [31]:
```
# Plotting the Accuracy graph on history
def plot_accuracy_graph(history):
    try:
        plt.plot(history.history['accuracy'])
        plt.plot(history.history['val_accuracy'])
    except KeyError:
        plt.plot(history.history['acc'])
        plt.plot(history.history['val_acc'])
    plt.title('Accuracy vs. epochs')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Training', 'Validation'], loc='lower right')
    plt.show()

plot_accuracy_graph(mlp_history)
```




```
In [32]: # Plotting the Loss graph from history
         def plot_loss_graph(history):
             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()

         plot_loss_graph(mlp_history)
```



In [33]:
```
# To find accuracy and loss on testing data after training

test_model(mlp_model, test_imgs,  test_labels)
```

```
Test Accuracy: 0.815
Test Loss : 0.731
```

In [0]:
```
# Deleting the model to clear RAM

del mlp_model
```

1.4 3. CNN neural network classifier

- Build a CNN classifier model using the Sequential API. Your model should use the Conv2D, MaxPool2D, BatchNormalization, Flatten, Dense and Dropout layers. The final layer should again have a 10-way softmax output.
- You should design and build the model yourself. Feel free to experiment with different CNN architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 2 or 3 convolutional layers and 2 fully connected layers.)*
- The CNN model should use fewer trainable parameters than your MLP model.
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.

- Your model should track at least one appropriate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback.
- You should aim to beat the MLP model performance with fewer parameters!
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

Function to create a CNN model and compile it

In [0]:
```
def get_cnn_model(shape):
    # Returns CNN model and compiles
    model = Sequential([
                        Conv2D(32, kernel_size=3, activation='relu', padding='SAME', input_
                        BatchNormalization(),
                        Conv2D(32, kernel_size=3, activation='relu', padding='SAME'),
                        BatchNormalization(),
                        MaxPooling2D(2),
                        Dropout(0.3),

                        Conv2D(32, kernel_size=3, activation='relu', padding='SAME'),
                        BatchNormalization(),
                        Conv2D(32, kernel_size=3, activation='relu', padding='SAME'),
                        BatchNormalization(),
                        MaxPooling2D(2),
                        Dropout(0.3),

                        Flatten(),
                        Dense(32, activation='relu'),
                        Dropout(0.3),
                        Dense(10, activation='softmax')
            ])

    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['a

    return model
```

In [36]:
```
# Get a CNN model and prining it's summary

cnn_model = get_cnn_model(train_imgs[0].shape)
cnn_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 32)        320
_________________________________________________________________
batch_normalization (BatchNo (None, 32, 32, 32)        128
_________________________________________________________________
```

```
conv2d_1 (Conv2D)            (None, 32, 32, 32)        9248
_________________________________________________________________
batch_normalization_1 (Batch (None, 32, 32, 32)        128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 32)        9248
_________________________________________________________________
batch_normalization_2 (Batch (None, 16, 16, 32)        128
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 32)        9248
_________________________________________________________________
batch_normalization_3 (Batch (None, 16, 16, 32)        128
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 32)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 8, 8, 32)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
dense_4 (Dense)              (None, 32)                65568
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                330
=================================================================
Total params: 94,474
Trainable params: 94,218
Non-trainable params: 256
_________________________________________________________________
```

In [37]:
```
# Testing CNN model accuracy and loss before training

test_model(cnn_model, test_imgs, test_labels)
```

```
Test Accuracy: 0.085
Test Loss : 2.313
```

Creating callbacks for CNN model

In [0]:
```
# Creating callback for CNN model

checkpoint_every_epoch = get_checkpoint_every_epoch('checkpoint_{epoch:03d}')
checkpoint_best_only, cnn_best_path = get_checkpoint_best_only('cnn')
early_stopping = get_early_stopping(5)
```

```
callbacks = [checkpoint_every_epoch, checkpoint_best_only, early_stopping]
```

In [39]:
```
# Fitting the model with batch size of 512 and validating it simultaneously

cnn_history = cnn_model.fit(train_imgs,
                            train_labels,
                            epochs=50,
                            validation_data=(val_imgs, val_labels),
                            callbacks=callbacks,
                            batch_size=512,
                            verbose=0)
```

```
Epoch 00001: saving model to checkpoints/every_epoch/checkpoint_001

Epoch 00001: val_accuracy improved from -inf to 0.20257, saving model to checkpoints/best_only/

Epoch 00002: saving model to checkpoints/every_epoch/checkpoint_002

Epoch 00002: val_accuracy improved from 0.20257 to 0.50519, saving model to checkpoints/best_on

Epoch 00003: saving model to checkpoints/every_epoch/checkpoint_003

Epoch 00003: val_accuracy improved from 0.50519 to 0.75293, saving model to checkpoints/best_on

Epoch 00004: saving model to checkpoints/every_epoch/checkpoint_004

Epoch 00004: val_accuracy improved from 0.75293 to 0.84548, saving model to checkpoints/best_on

Epoch 00005: saving model to checkpoints/every_epoch/checkpoint_005

Epoch 00005: val_accuracy improved from 0.84548 to 0.87906, saving model to checkpoints/best_on

Epoch 00006: saving model to checkpoints/every_epoch/checkpoint_006

Epoch 00006: val_accuracy improved from 0.87906 to 0.88793, saving model to checkpoints/best_on

Epoch 00007: saving model to checkpoints/every_epoch/checkpoint_007

Epoch 00007: val_accuracy improved from 0.88793 to 0.89585, saving model to checkpoints/best_on

Epoch 00008: saving model to checkpoints/every_epoch/checkpoint_008

Epoch 00008: val_accuracy improved from 0.89585 to 0.90227, saving model to checkpoints/best_on

Epoch 00009: saving model to checkpoints/every_epoch/checkpoint_009
```

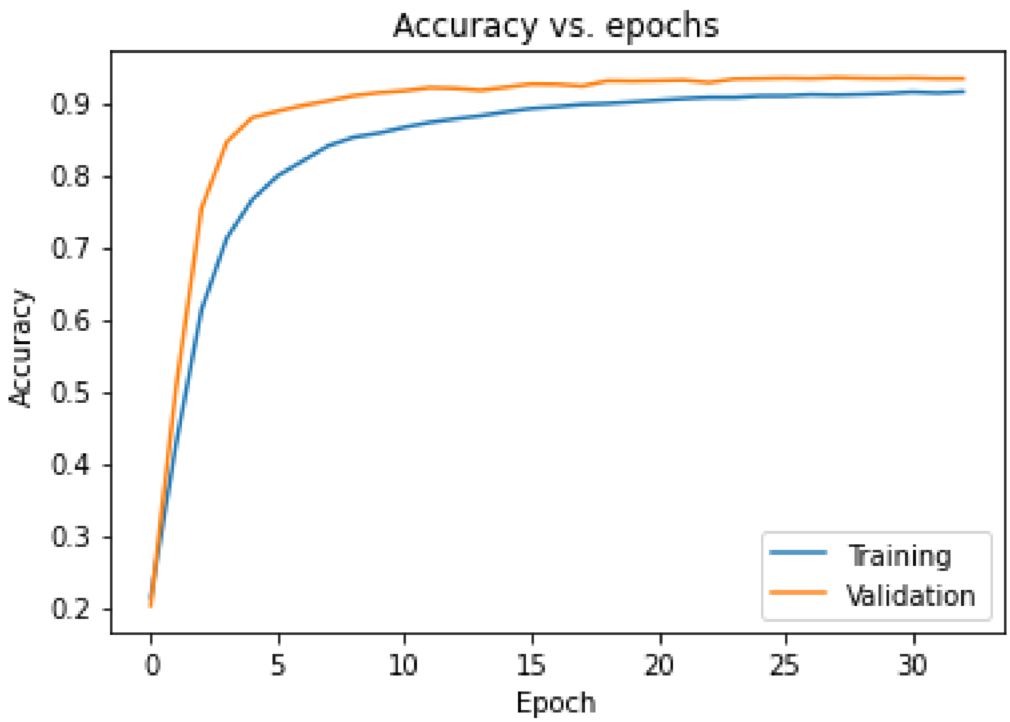
```
Epoch 00009: val_accuracy improved from 0.90227 to 0.90936, saving model to checkpoints/best_or

Epoch 00010: saving model to checkpoints/every_epoch/checkpoint_010

Epoch 00010: val_accuracy improved from 0.90936 to 0.91360, saving model to checkpoints/best_or

Epoch 00011: saving model to checkpoints/every_epoch/checkpoint_011

Epoch 00011: val_accuracy improved from 0.91360 to 0.91619, saving model to checkpoints/best_or

Epoch 00012: saving model to checkpoints/every_epoch/checkpoint_012

Epoch 00012: val_accuracy improved from 0.91619 to 0.92056, saving model to checkpoints/best_or

Epoch 00013: saving model to checkpoints/every_epoch/checkpoint_013

Epoch 00013: val_accuracy did not improve from 0.92056

Epoch 00014: saving model to checkpoints/every_epoch/checkpoint_014

Epoch 00014: val_accuracy did not improve from 0.92056

Epoch 00015: saving model to checkpoints/every_epoch/checkpoint_015

Epoch 00015: val_accuracy improved from 0.92056 to 0.92110, saving model to checkpoints/best_or

Epoch 00016: saving model to checkpoints/every_epoch/checkpoint_016

Epoch 00016: val_accuracy improved from 0.92110 to 0.92533, saving model to checkpoints/best_or

Epoch 00017: saving model to checkpoints/every_epoch/checkpoint_017

Epoch 00017: val_accuracy did not improve from 0.92533

Epoch 00018: saving model to checkpoints/every_epoch/checkpoint_018

Epoch 00018: val_accuracy did not improve from 0.92533

Epoch 00019: saving model to checkpoints/every_epoch/checkpoint_019

Epoch 00019: val_accuracy improved from 0.92533 to 0.92984, saving model to checkpoints/best_or

Epoch 00020: saving model to checkpoints/every_epoch/checkpoint_020

Epoch 00020: val_accuracy did not improve from 0.92984

Epoch 00021: saving model to checkpoints/every_epoch/checkpoint_021
```

```
Epoch 00021: val_accuracy improved from 0.92984 to 0.92998, saving model to checkpoints/best_or

Epoch 00022: saving model to checkpoints/every_epoch/checkpoint_022

Epoch 00022: val_accuracy improved from 0.92998 to 0.93079, saving model to checkpoints/best_or

Epoch 00023: saving model to checkpoints/every_epoch/checkpoint_023

Epoch 00023: val_accuracy did not improve from 0.93079

Epoch 00024: saving model to checkpoints/every_epoch/checkpoint_024

Epoch 00024: val_accuracy improved from 0.93079 to 0.93243, saving model to checkpoints/best_or

Epoch 00025: saving model to checkpoints/every_epoch/checkpoint_025

Epoch 00025: val_accuracy improved from 0.93243 to 0.93284, saving model to checkpoints/best_or

Epoch 00026: saving model to checkpoints/every_epoch/checkpoint_026

Epoch 00026: val_accuracy improved from 0.93284 to 0.93366, saving model to checkpoints/best_or

Epoch 00027: saving model to checkpoints/every_epoch/checkpoint_027

Epoch 00027: val_accuracy did not improve from 0.93366

Epoch 00028: saving model to checkpoints/every_epoch/checkpoint_028

Epoch 00028: val_accuracy improved from 0.93366 to 0.93434, saving model to checkpoints/best_or

Epoch 00029: saving model to checkpoints/every_epoch/checkpoint_029

Epoch 00029: val_accuracy did not improve from 0.93434

Epoch 00030: saving model to checkpoints/every_epoch/checkpoint_030

Epoch 00030: val_accuracy did not improve from 0.93434

Epoch 00031: saving model to checkpoints/every_epoch/checkpoint_031

Epoch 00031: val_accuracy did not improve from 0.93434

Epoch 00032: saving model to checkpoints/every_epoch/checkpoint_032

Epoch 00032: val_accuracy did not improve from 0.93434

Epoch 00033: saving model to checkpoints/every_epoch/checkpoint_033
```

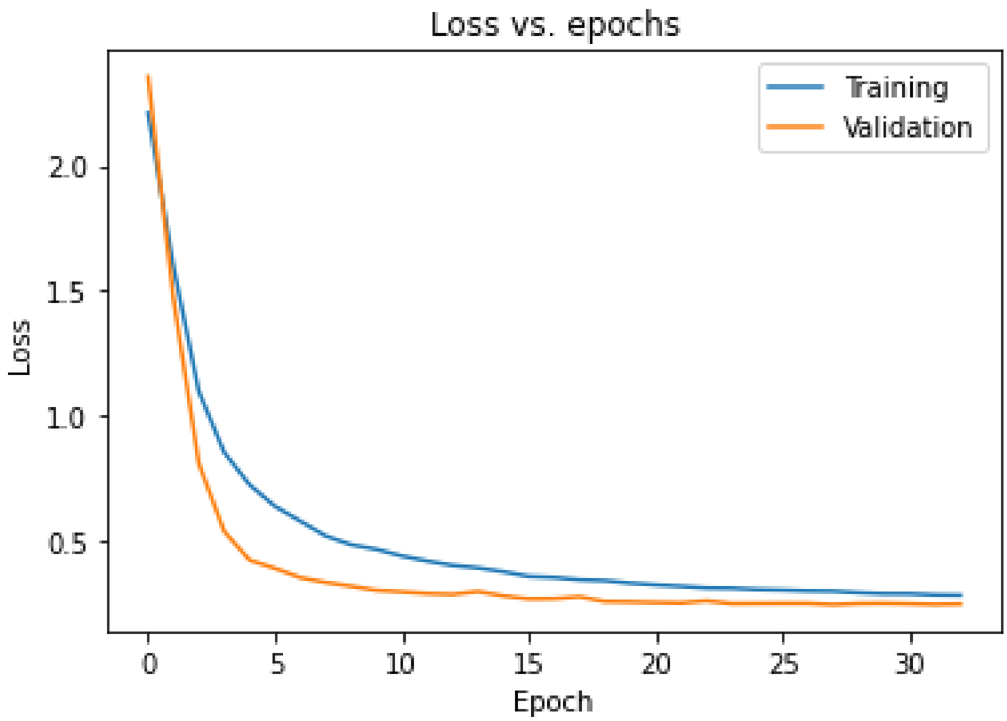
```
Epoch 00033: val_accuracy did not improve from 0.93434
```

Plotting Accuracy and Loss graphs from training history of CNN model

```
In [40]: plot_accuracy_graph(cnn_history)
```




```
In [41]: plot_loss_graph(cnn_history)
```




```
In [42]: # Testing CNN model accuracy and loss after training

         test_model(cnn_model, test_imgs, test_labels)
```

```
Test Accuracy: 0.926
Test Loss : 0.270
```

```
In [0]: # Deleting the model to clear RAM

        del cnn_model
```

1.5 4. Get model predictions

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

Checking the location of checkpoint files

```
In [44]: ! ls -lh checkpoints
```

```
total 8.0K
drwxr-xr-x 4 root root 4.0K May 12 03:06 best_only
drwxr-xr-x 2 root root 4.0K May 12 03:07 every_epoch
```

Creating a new MLP model

```
In [45]: new_mlp_model = get_mlp_model(train_imgs[0].shape)
         new_mlp_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_2 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_6 (Dense)              (None, 128)               131200
_________________________________________________________________
dense_7 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_8 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_9 (Dense)              (None, 10)                650
=================================================================
Total params: 156,618
Trainable params: 156,618
Non-trainable params: 0
_________________________________________________________________
```

```
In [46]: # Testing model's accuarcy and loss before loading weights

         test_model(new_mlp_model, test_imgs, test_labels)
```

```
Test Accuracy: 0.074
Test Loss : 2.478
```

Loading best weights for MLP model and then testing it's accuarcy and loss after loading weights

```
In [47]: new_mlp_model.load_weights(mlp_best_path)
         test_model(new_mlp_model, test_imgs, test_labels)
```

```
Test Accuracy: 0.814
Test Loss : 0.710
```

Creating new CNN model

In [48]:
```
new_cnn_model = get_cnn_model(train_imgs[0].shape)
new_cnn_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 32, 32, 32)        320
_________________________________________________________________
batch_normalization_4 (Batch (None, 32, 32, 32)        128
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 32, 32, 32)        9248
_________________________________________________________________
batch_normalization_5 (Batch (None, 32, 32, 32)        128
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 32)        0
_________________________________________________________________
dropout_3 (Dropout)          (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 16, 16, 32)        9248
_________________________________________________________________
batch_normalization_6 (Batch (None, 16, 16, 32)        128
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 16, 16, 32)        9248
_________________________________________________________________
batch_normalization_7 (Batch (None, 16, 16, 32)        128
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 8, 8, 32)          0
_________________________________________________________________
dropout_4 (Dropout)          (None, 8, 8, 32)          0
_________________________________________________________________
flatten_3 (Flatten)          (None, 2048)              0
_________________________________________________________________
dense_10 (Dense)             (None, 32)                65568
_________________________________________________________________
dropout_5 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_11 (Dense)             (None, 10)                330
=================================================================
Total params: 94,474
Trainable params: 94,218
Non-trainable params: 256
_________________________________________________________________
```

In [49]:
```
# Testing CNN model's accuarcy and loss before loading weights

test_model(new_cnn_model, test_imgs, test_labels)
```

```
Test Accuracy: 0.083
Test Loss : 2.320
```

Loading best weights for CNN model and then testing it's accuarcy and loss after loading weights

```
In [50]: new_cnn_model.load_weights(cnn_best_path)
         test_model(new_cnn_model, test_imgs, test_labels)
```

```
Test Accuracy: 0.928
Test Loss : 0.268
```

```
In [0]: # Selecting random images and their labels from testing dataset

        num_rows = 5
        num_cols = 5

        random_slices = np.random.choice(test_imgs.shape[0], num_rows*num_cols)
        random_images = test_imgs[random_slices]
        random_labels = test_labels[random_slices]
```

```
In [0]: # Converting numpy array to normal list

        random_labels = [[x][0][0] for x in np.ndarray.tolist(random_labels)]
```

Predicting labels of random images using new CNN model

```
In [0]: random_MLP_predictions = new_mlp_model.predict(random_images)
        random_CNN_predictions = new_cnn_model.predict(random_images)
```

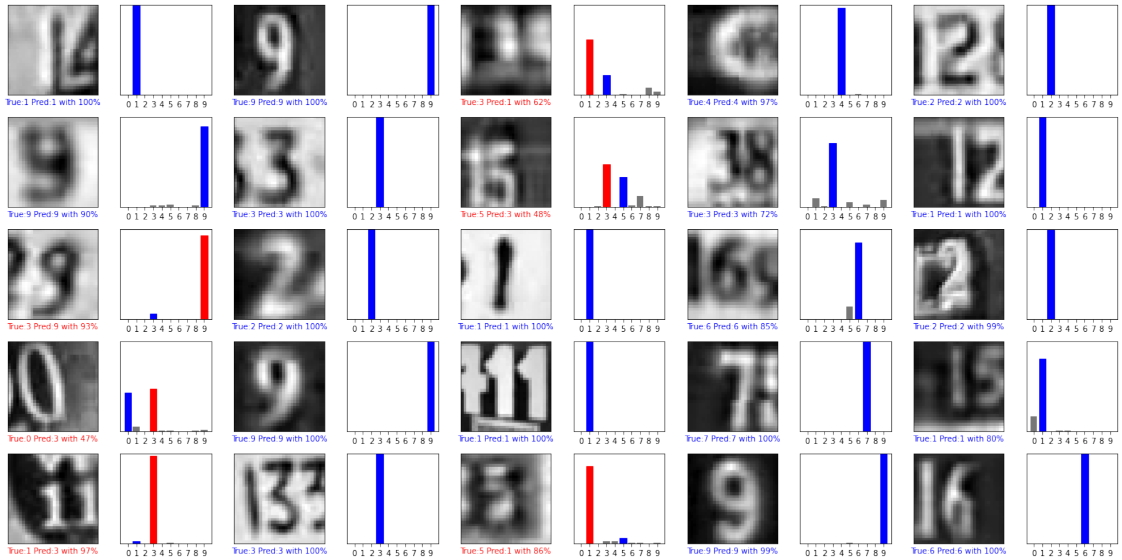
Functions to plot predictions with bar graph

```
In [0]: def plot_prediction_images(i, predictions_array, true_label, img):

            predictions_array, true_label, img = predictions_array, true_label[i], img[i]
            plt.grid(False)
            plt.xticks([])
            plt.yticks([])

            plt.imshow(img[:,:,0], cmap=plt.cm.binary)

            predicted_label = np.argmax(predictions_array)
            if predicted_label == true_label:
                color = 'blue'
            else:
                color = 'red'
```

```python
    plt.xlabel(f"True:{true_label} Pred:{predicted_label} with {100*np.max(predictions_

def plot_value_array(i, predictions_array, true_label):
    predictions_array, true_label = predictions_array, true_label[i]
    plt.grid(False)
    plt.xticks(range(10))
    plt.yticks([])
    thisplot = plt.bar(range(10), predictions_array, color="#777777")
    plt.ylim([0, 1])
    predicted_label = np.argmax(predictions_array)

    thisplot[predicted_label].set_color('red')
    thisplot[true_label].set_color('blue')
```

In [0]:
```python
# Plotting random images from test dataset, their predicted labels, and the true label
# Correct predictions are in blue and incorrect predictions are in red.

def plot_predictions(predictions):
    num_images = num_rows*num_cols

    plt.figure(figsize=(2*2*num_cols, 2*num_rows))
    for i in range(num_images):
        plt.subplot(num_rows, 2*num_cols, 2*i+1)
        plot_prediction_images(i, predictions[i], random_labels, random_images)
        plt.subplot(num_rows, 2*num_cols, 2*i+2)
        plot_value_array(i, predictions[i], random_labels)

    plt.tight_layout()
    plt.show()
```

In [56]:
```python
# Plotting MLP predictions

plot_predictions(random_MLP_predictions)
```



```
In [57]: # Plotting CNN predictions

         plot_predictions(random_CNN_predictions)
```