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Image Classification

DSC650: Big Data

Spring 2023

```
# mounting drive to assignment06 folder
import os
from google.colab import drive
drive.mount('/content/drive', force_remount = True)
os.chdir('/content/drive/My Drive/Colab Notebooks/DSC650/assignments/assignment06')
!pwd
```

Mounted at /content/drive /content/drive/My Drive/Colab Notebooks/DSC650/assignments/assignment06

CNN - MNIST Dataset Classification

Model

```
In [2]:
         !pip install keras
        Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
        ic/simple/
        Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (2.12.0)
In [3]:
         # Libraries
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import keras
         import tensorflow
         from keras import layers
         from keras import models
         from keras.datasets import mnist
         from keras.datasets import cifar10
         from keras.utils import to categorical
In [4]:
         # import data
         (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
        Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.
        11490434/11490434 [============== ] - Os Ous/step
In [5]:
         # reshape and reformat data
         train images = train images.reshape((train images.shape[0], 28, 28, 1))
```

```
test_images = test_images.reshape((test_images.shape[0], 28, 28, 1))
        test_images = test_images.astype('float32')/255
        train labels = to categorical(train labels)
        test labels = to categorical(test labels)
In [6]:
        # generate instance of sequential model
        model = models.Sequential()
        model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)))
        model.add(layers.MaxPooling2D((2,2)))
        model.add(layers.Conv2D(64, (3,3), activation='relu'))
        model.add(layers.MaxPooling2D((2,2)))
        model.add(layers.Conv2D(64, (3,3), activation='relu'))
        model.add(layers.Flatten())
        model.add(layers.Dense(64, activation='relu'))
        model.add(layers.Dense(10, activation='softmax'))
In [7]:
        # compile
        model.compile(optimizer='rmsprop', loss='categorical crossentropy', metrics=['accuracy'
In [8]:
        # holdout validation
        validation images = train images[:10000]
        partial train images = train images[10000:]
        validation_labels = train_labels[:10000]
        partial train labels = train labels[10000:]
In [9]:
        # csvlogger
        from keras.callbacks import CSVLogger
        csv_logger = CSVLogger('results/CNN_mnist_training.log')
In [10]:
        # train model
        history = model.fit(partial_train_images,
                        partial_train_labels,
                        epochs=10,
                        batch size=64,
                        validation data=(validation images, validation labels),
                        callbacks=[csv_logger])
       Epoch 1/10
       89 - val_loss: 0.1178 - val_accuracy: 0.9668
       Epoch 2/10
       - val loss: 0.0478 - val accuracy: 0.9860
       Epoch 3/10
       - val loss: 0.0421 - val accuracy: 0.9882
       Epoch 4/10
```

train images = train images.astype('float32')/255

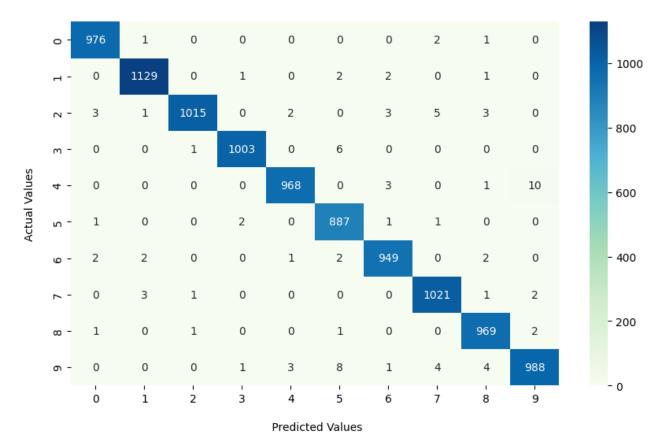
```
- val loss: 0.0450 - val accuracy: 0.9874
    Epoch 5/10
    - val_loss: 0.0383 - val_accuracy: 0.9903
    Epoch 6/10
    - val loss: 0.0493 - val accuracy: 0.9871
    Epoch 7/10
    - val loss: 0.0407 - val accuracy: 0.9896
    Epoch 8/10
    - val_loss: 0.0399 - val_accuracy: 0.9909
    Epoch 9/10
    - val loss: 0.0420 - val accuracy: 0.9899
    Epoch 10/10
    - val loss: 0.0493 - val accuracy: 0.9908
In [11]:
    # save the model
    model.save('results/CNN_mnist_model')
    model.save('results/CNN_mnist_model.h5')
```

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compile d_convolution_op, _jit_compiled_convolution_op while saving (showing 3 of 3). These functions will not be directly callable after loading.

Predictions

```
In [12]:
          predictions = model.predict(test images)
          predictions.tofile('results/CNN mnist predictions.csv', sep = ',')
         313/313 [========== ] - 1s 2ms/step
In [13]:
          max test labels = np.argmax(test labels, axis=1)
          max_predictions = np.argmax(predictions, axis=1)
In [14]:
          import seaborn as sns
          from sklearn.metrics import confusion matrix
          confusion = confusion matrix(max test labels, max predictions)
          plt.figure(figsize=(10,6))
          fx=sns.heatmap(confusion, annot=True, fmt=".0f",cmap="GnBu")
          fx.set title('Confusion Matrix \n');
          fx.set_xlabel('\n Predicted Values\n')
          fx.set ylabel('Actual Values\n');
          plt.savefig("results/CNN_mnist_confusionmatrix.png")
          plt.show()
```

Confusion Matrix



Metrics

2

3

4

5

6

1.00

1.00

0.99

0.98

0.99

0.98

0.99

0.99

0.99

0.99

```
In [15]:
        results = model.evaluate(test_images, test_labels)
        In [16]:
        from sklearn.metrics import classification_report
         class_report = classification_report(max_test_labels, max_predictions)
        print(class_report)
        #open text file
        text file = open("results/CNN mnist metrics.txt", "w")
        #write string to file
        text_file.write(class_report)
        #close file
        text_file.close()
                               recall f1-score
                    precision
                                               support
                 0
                        0.99
                                1.00
                                         0.99
                                                  980
                 1
                                0.99
                        0.99
                                         0.99
                                                 1135
```

0.99

0.99

0.99

0.99

0.99

1032

1010

982

892

958

7	0.99	0.99	0.99	1028
8	0.99	0.99	0.99	974
9	0.99	0.98	0.98	1009
accuracy			0.99	10000
macro avg	0.99	0.99	0.99	10000
weighted avg	0.99	0.99	0.99	10000

Validation Plots

```
In [17]: # plot loss

loss = history.history['loss']
val_loss = history.history['val_loss']

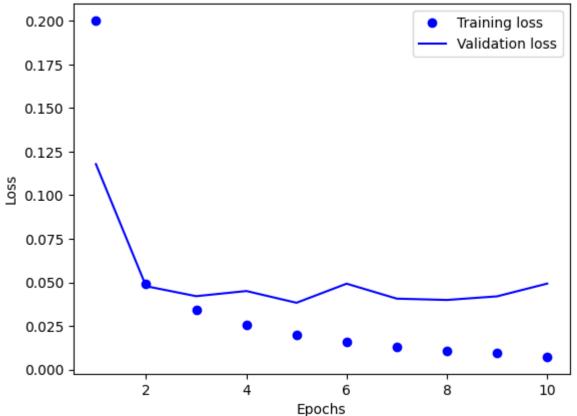
epochs = range(1, len(loss)+1)

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.ylabel('Loss')
plt.legend()

plt.savefig("results/CNN_mnist_loss.png")

plt.show()
```

Training and Validation Loss



```
In [18]: # plot accuracy

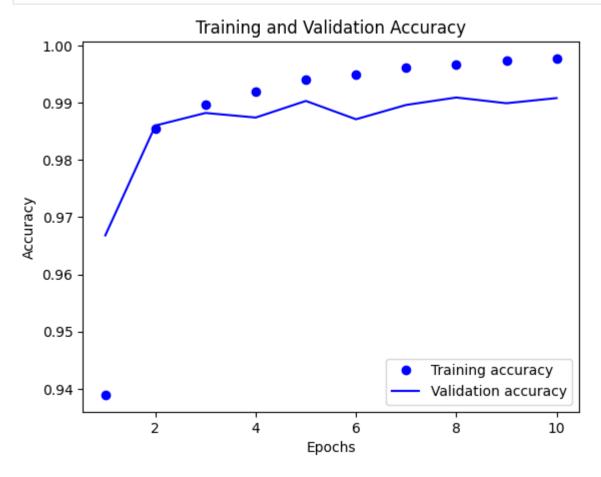
plt.clf()

acc = history.history['accuracy']
  val_acc = history.history['val_accuracy']

plt.plot(epochs, acc, 'bo', label='Training accuracy')
  plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
  plt.title('Training and Validation Accuracy')
  plt.xlabel('Epochs')
  plt.ylabel('Accuracy')
  plt.legend()

plt.savefig("results/CNN_mnist_accuracy.png")

plt.show()
```



CNN - CIFAR10 Small Image Classification Dataset

Model

```
In [19]: # Load data
```

```
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
          assert x_train.shape == (50000, 32, 32, 3)
          assert x_test.shape == (10000, 32, 32, 3)
          assert y_train.shape == (50000, 1)
          assert y test.shape == (10000, 1)
         Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
         170498071/170498071 [=============] - 2s Ous/step
In [20]:
          y_train = to_categorical(y_train)
          y_test = to_categorical(y_test)
In [21]:
          # holdout validation
          x \text{ val} = x \text{ train}[:10000]
          partial_x_train = x_train[10000:]
          y val = y train[:10000]
          partial_y_train = y_train[10000:]
In [22]:
          from keras.preprocessing.image import ImageDataGenerator
In [23]:
          train datagen = ImageDataGenerator(rescale=1./255)
          test datagen = ImageDataGenerator(rescale=1./255)
          # train_datagen.fit(x_train)
          batch_size = 32
          train_generator = train_datagen.flow(x_train,
                                                y train,
                                                batch size=batch size,
                                                shuffle=False)
          validation_generator = test_datagen.flow(x_val,
                                                    y val,
                                                    batch size=batch size,
                                                    shuffle=False)
          test_generator = test_datagen.flow(
              x_test,
              y_test,
              batch_size=batch_size,
              shuffle=False)
In [24]:
          # model
          model = models.Sequential()
          model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3))) # output
          model.add(layers.MaxPooling2D((2,2))) # output shape (15, 15, 32)
          model.add(layers.Conv2D(64, (3,3), activation='relu')) # output shape (13, 13, 64)
          model.add(layers.MaxPooling2D((2,2))) # output shape (6, 6, 64)
```

model.add(layers.Flatten())

```
model.add(layers.Dense(512, activation='relu'))
     model.add(layers.Dense(10, activation='softmax'))
In [25]:
     # compile
     model.compile(optimizer='rmsprop',
             loss='categorical crossentropy',
             metrics=['accuracy'])
In [26]:
     # csvlogger
     from keras.callbacks import CSVLogger
     csv logger = CSVLogger('results/CNN cifar10 training.log')
In [27]:
     # train model
     train_generator.reset()
     validation generator.reset()
     history = model.fit(train generator,
                      steps_per_epoch=len(x_train) // batch_size,
                      epochs=30,
                      validation_data=validation_generator,
                      validation steps=50,
                      callbacks=[csv logger])
     Epoch 1/30
     003 - val loss: 0.9945 - val accuracy: 0.6369
     Epoch 2/30
     28 - val loss: 0.7725 - val accuracy: 0.7344
     Epoch 3/30
     13 - val loss: 0.6642 - val accuracy: 0.7688
     Epoch 4/30
     26 - val_loss: 0.5261 - val_accuracy: 0.8263
     Epoch 5/30
     67 - val loss: 0.3989 - val accuracy: 0.8562
     Epoch 6/30
     43 - val_loss: 0.2688 - val_accuracy: 0.9187
     Epoch 7/30
     69 - val_loss: 0.2933 - val_accuracy: 0.8913
     Epoch 8/30
     29 - val_loss: 0.1402 - val_accuracy: 0.9556
     Epoch 9/30
     22 - val_loss: 0.0839 - val_accuracy: 0.9694
     Epoch 10/30
     63 - val_loss: 0.1001 - val_accuracy: 0.9694
     Epoch 11/30
     62 - val_loss: 0.0648 - val_accuracy: 0.9781
     Epoch 12/30
```

```
26 - val loss: 0.0417 - val accuracy: 0.9862
Epoch 13/30
80 - val loss: 0.0757 - val accuracy: 0.9737
Epoch 14/30
14 - val_loss: 0.0328 - val_accuracy: 0.9894
Epoch 15/30
39 - val loss: 0.0479 - val accuracy: 0.9844
Epoch 16/30
74 - val_loss: 0.0211 - val_accuracy: 0.9937
90 - val_loss: 0.0346 - val_accuracy: 0.9862
Epoch 18/30
01 - val loss: 0.1002 - val accuracy: 0.9750
Epoch 19/30
19 - val_loss: 0.0274 - val_accuracy: 0.9900
Epoch 20/30
18 - val loss: 0.0527 - val accuracy: 0.9844
Epoch 21/30
1562/1562 [=============== ] - 8s 5ms/step - loss: 0.0598 - accuracy: 0.98
31 - val loss: 0.0269 - val accuracy: 0.9894
Epoch 22/30
52 - val_loss: 0.0741 - val_accuracy: 0.9775
Epoch 23/30
856 - val_loss: 0.0410 - val_accuracy: 0.9875
Epoch 24/30
60 - val_loss: 0.0366 - val_accuracy: 0.9906
Epoch 25/30
73 - val_loss: 0.0575 - val_accuracy: 0.9875
Epoch 26/30
78 - val_loss: 0.0217 - val_accuracy: 0.9931
Epoch 27/30
885 - val loss: 0.0152 - val accuracy: 0.9956
Epoch 28/30
85 - val_loss: 0.0320 - val_accuracy: 0.9919
Epoch 29/30
890 - val loss: 0.0386 - val accuracy: 0.9875
Epoch 30/30
90 - val_loss: 0.0556 - val_accuracy: 0.9881
```

```
model.save('results/CNN_cifar10_model.h5')
```

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compile d_convolution_op while saving (showing 2 of 2). These functions will not be directly cal lable after loading.

Predictions

```
In [29]:
          test generator.reset()
          predictions = model.predict(test_generator,steps = len(x_test) // batch_size)
          predictions.tofile('results/CNN cifar10 predictions.csv', sep = ',')
         312/312 [========= ] - 1s 3ms/step
In [30]:
          predictions.shape
         (9984, 10)
Out[30]:
In [31]:
          max_y_test = np.argmax(y_test[:9984], axis=1)
          max predictions = np.argmax(predictions, axis=1)
In [32]:
          import seaborn as sns
          from sklearn.metrics import confusion matrix
          confusion = confusion_matrix(max_y_test, max_predictions)
          plt.figure(figsize=(10,6))
          fx=sns.heatmap(confusion, annot=True, fmt=".0f",cmap="GnBu")
          fx.set title('Confusion Matrix \n');
          fx.set_xlabel('\n Predicted Values\n')
          fx.set_ylabel('Actual Values\n');
          plt.savefig("results/CNN_cifar10_confusionmatrix.png")
          plt.show()
```

Confusion Matrix



Metrics

4

0.65

0.66

```
In [33]:
        test_generator.reset()
        results = model.evaluate(test_generator)
        In [34]:
        from sklearn.metrics import classification_report
         class_report = classification_report(max_y_test, max_predictions)
         print(class_report)
        #open text file
        text_file = open("results/CNN_cifar10_metrics.txt", "w")
         #write string to file
        text_file.write(class_report)
        #close file
        text_file.close()
                    precision
                               recall f1-score
                                                support
                 0
                                 0.81
                                         0.74
                                                   998
                        0.68
                 1
                        0.81
                                 0.82
                                         0.82
                                                   999
                 2
                                 0.58
                                         0.60
                                                   999
                        0.61
                 3
                        0.49
                                 0.56
                                         0.52
                                                   997
```

0.66

1000

```
5
                  0.64
                            0.52
                                      0.58
                                                 997
          6
                            0.80
                                      0.77
                  0.74
                                                 1000
          7
                  0.77
                            0.72
                                      0.74
                                                 997
          8
                  0.89
                            0.70
                                      0.78
                                                 997
          9
                  0.74
                            0.78
                                      0.76
                                                 1000
    accuracy
                                      0.70
                                                 9984
                  0.70
                            0.70
                                      0.70
                                                 9984
  macro avg
weighted avg
                  0.70
                             0.70
                                      0.70
                                                 9984
```

Validation Plots

```
In [35]: # plot loss

loss = history.history['loss']
val_loss = history.history['val_loss']

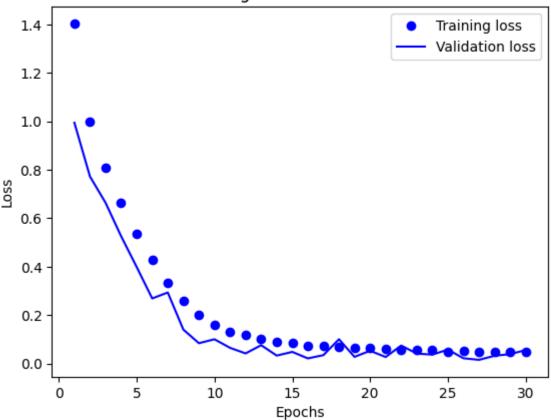
epochs = range(1, len(loss)+1)

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.ylabel('Loss')
plt.legend()

plt.savefig("results/CNN_cifar10_loss.png")

plt.show()
```

Training and Validation Loss



```
In [36]: # plot accuracy

plt.clf()

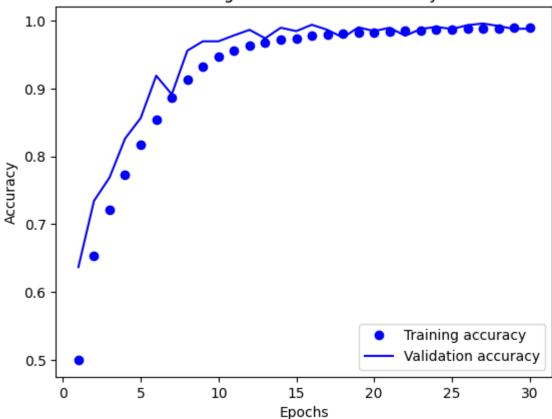
acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']

plt.plot(epochs, acc, 'bo', label='Training accuracy')
    plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

plt.savefig("results/CNN_cifar10_accuracy.png")

plt.show()
```

Training and Validation Accuracy



CNN - CIFAR10 Small Image Classification Dataset with dropout and data augmentation

Model

```
In [37]:
          # Load data
          (x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
          assert x train.shape == (50000, 32, 32, 3)
          assert x_test.shape == (10000, 32, 32, 3)
          assert y train.shape == (50000, 1)
          assert y_test.shape == (10000, 1)
In [38]:
          y_train = to_categorical(y_train)
          y_test = to_categorical(y_test)
In [39]:
          # holdout validation
          x_val = x_train[:10000]
          partial_x_train = x_train[10000:]
          y_val = y_train[:10000]
          partial_y_train = y_train[10000:]
```

```
In [40]:
          from keras.preprocessing.image import ImageDataGenerator
In [41]:
          train datagen = ImageDataGenerator(
              rescale=1./255,
              rotation_range=40,
              width shift range=0.2,
              height_shift_range=0.2,
              shear_range=0.2,
              zoom range=0.2,
              horizontal_flip=True)
          test datagen = ImageDataGenerator(rescale=1./255)
          # train datagen.fit(x train)
          batch size = 32
          train_generator = train_datagen.flow(x_train,
                                                batch_size=batch_size,
                                                shuffle=False)
          validation_generator = test_datagen.flow(x_val,
                                                    batch_size=batch_size,
                                                    shuffle=False)
          test_generator = test_datagen.flow(
              x_test,
              y test,
              batch_size=batch_size,
              shuffle=False)
In [42]:
          # modeL
          model = models.Sequential()
          model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3))) # output
          model.add(layers.MaxPooling2D((2,2))) # output shape (15, 15, 32)
          model.add(layers.Conv2D(64, (3,3), activation='relu')) # output shape (13, 13, 64)
          model.add(layers.MaxPooling2D((2,2))) # output shape (6, 6, 64)
          model.add(layers.Flatten())
          model.add(layers.Dropout(0.5))
          model.add(layers.Dense(512, activation='relu'))
          model.add(layers.Dense(10, activation='softmax'))
In [43]:
          # compile
          model.compile(optimizer='rmsprop',
                        loss='categorical_crossentropy',
                        metrics=['accuracy'])
In [44]:
          # csvlogger
          from keras.callbacks import CSVLogger
          csv_logger = CSVLogger('results/CNN_cifar10_augmented_training.log')
```

```
In [45]:
```

```
Epoch 1/30
3386 - val_loss: 1.5423 - val_accuracy: 0.4394
Epoch 2/30
4214 - val_loss: 1.3397 - val_accuracy: 0.5219
Epoch 3/30
4499 - val loss: 1.2386 - val accuracy: 0.5688
Epoch 4/30
1562/1562 [=============== ] - 47s 30ms/step - loss: 1.4870 - accuracy: 0.
4679 - val loss: 1.1367 - val accuracy: 0.6200
Epoch 5/30
4819 - val_loss: 1.0925 - val_accuracy: 0.6306
Epoch 6/30
1562/1562 [============== ] - 53s 34ms/step - loss: 1.4384 - accuracy: 0.
4918 - val_loss: 1.2544 - val_accuracy: 0.5531
Epoch 7/30
1562/1562 [================ ] - 57s 37ms/step - loss: 1.4211 - accuracy: 0.
4967 - val loss: 1.1450 - val accuracy: 0.5950
1562/1562 [=============== ] - 41s 26ms/step - loss: 1.4119 - accuracy: 0.
5021 - val_loss: 1.1287 - val_accuracy: 0.6062
Epoch 9/30
5036 - val loss: 1.2648 - val accuracy: 0.5519
Epoch 10/30
5081 - val loss: 1.1723 - val accuracy: 0.5863
Epoch 11/30
1562/1562 [=============== ] - 41s 26ms/step - loss: 1.3946 - accuracy: 0.
5123 - val_loss: 1.0680 - val_accuracy: 0.6319
Epoch 12/30
5132 - val_loss: 1.0410 - val_accuracy: 0.6331
Epoch 13/30
5165 - val_loss: 1.1202 - val_accuracy: 0.6338
Epoch 14/30
5144 - val_loss: 1.0727 - val_accuracy: 0.6144
Epoch 15/30
1562/1562 [============== ] - 37s 23ms/step - loss: 1.3792 - accuracy: 0.
5178 - val_loss: 1.0434 - val_accuracy: 0.6313
Epoch 16/30
5193 - val_loss: 1.0193 - val_accuracy: 0.6562
```

```
Epoch 17/30
      1562/1562 [=============== ] - 37s 24ms/step - loss: 1.3898 - accuracy: 0.
      5169 - val_loss: 1.0996 - val_accuracy: 0.6319
      Epoch 18/30
      5209 - val_loss: 1.2364 - val_accuracy: 0.5806
      Epoch 19/30
      1562/1562 [=============== ] - 37s 24ms/step - loss: 1.3877 - accuracy: 0.
      5225 - val_loss: 1.0319 - val_accuracy: 0.6637
      Epoch 20/30
      5199 - val_loss: 1.0921 - val_accuracy: 0.6250
      Epoch 21/30
      5196 - val_loss: 1.0536 - val_accuracy: 0.6325
      Epoch 22/30
      5201 - val_loss: 1.1315 - val_accuracy: 0.6338
      Epoch 23/30
      1562/1562 [=============== ] - 38s 25ms/step - loss: 1.3874 - accuracy: 0.
      5198 - val loss: 1.0197 - val accuracy: 0.6544
      1562/1562 [=============== ] - 37s 24ms/step - loss: 1.3940 - accuracy: 0.
      5174 - val_loss: 1.2417 - val_accuracy: 0.6388
      Epoch 25/30
      5217 - val_loss: 1.0952 - val_accuracy: 0.6325
      Epoch 26/30
      5214 - val loss: 1.1270 - val accuracy: 0.6306
      Epoch 27/30
      1562/1562 [=============== ] - 38s 24ms/step - loss: 1.3926 - accuracy: 0.
      5193 - val loss: 1.0787 - val accuracy: 0.6488
      Epoch 28/30
      5158 - val_loss: 1.1407 - val_accuracy: 0.5994
      Epoch 29/30
      1562/1562 [=============== ] - 39s 25ms/step - loss: 1.4010 - accuracy: 0.
      5137 - val loss: 1.0905 - val accuracy: 0.6300
      Epoch 30/30
      5188 - val loss: 1.0220 - val accuracy: 0.6475
In [46]:
      # save the model
      model.save('results/CNN_cifar10_augmented_model')
      model.save('results/CNN_cifar10_augmented_model.h5')
```

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compile d_convolution_op while saving (showing 2 of 2). These functions will not be directly cal lable after loading.

Predictions

```
test_generator.reset()
predictions = model.predict(test_generator, steps = len(x_test) // batch_size)
predictions.tofile('results/CNN_cifar10_augmented_predictions.csv', sep = ',')
```

```
312/312 [========= ] - 1s 4ms/step
In [48]:
          predictions.shape
         (9984, 10)
Out[48]:
In [49]:
          max_y_test = np.argmax(y_test[:9984], axis=1)
          max predictions = np.argmax(predictions, axis=1)
In [50]:
          import seaborn as sns
          from sklearn.metrics import confusion_matrix
          confusion = confusion_matrix(max_y_test, max_predictions)
          plt.figure(figsize=(10,6))
          fx=sns.heatmap(confusion, annot=True, fmt=".0f",cmap="GnBu")
          fx.set_title('Confusion Matrix \n');
          fx.set xlabel('\n Predicted Values\n')
          fx.set_ylabel('Actual Values\n');
          plt.savefig("results/CNN_cifar10_augmented_confusionmatrix.png")
          plt.show()
```

Confusion Matrix



Metrics

	precision	recall	f1-score	support
0	0.76	0.60	0.67	998
1	0.73	0.84	0.78	999
2	0.57	0.54	0.55	999
3	0.53	0.32	0.40	997
4	0.67	0.48	0.56	1000
5	0.56	0.61	0.58	997
6	0.68	0.72	0.70	1000
7	0.61	0.74	0.67	997
8	0.66	0.81	0.73	997
9	0.64	0.80	0.71	1000
accuracy			0.64	9984
macro avg	0.64	0.64	0.64	9984
weighted avg	0.64	0.64	0.64	9984

Validation Plots

```
In [52]:

In [53]: # plot loss

loss = history.history['loss']
    val_loss = history.history['val_loss']

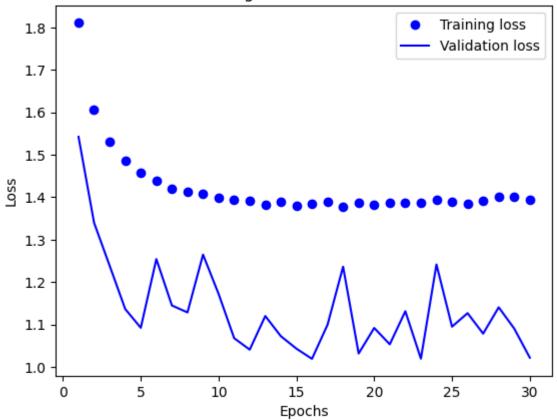
epochs = range(1, len(loss)+1)

plt.plot(epochs, loss, 'bo', label='Training loss')
    plt.plot(epochs, val_loss, 'b', label='Validation loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

plt.savefig("results/CNN_cifar10_augmented_loss.png")
```

plt.show()

Training and Validation Loss



```
In [54]: # plot accuracy

plt.clf()

acc = history.history['accuracy']

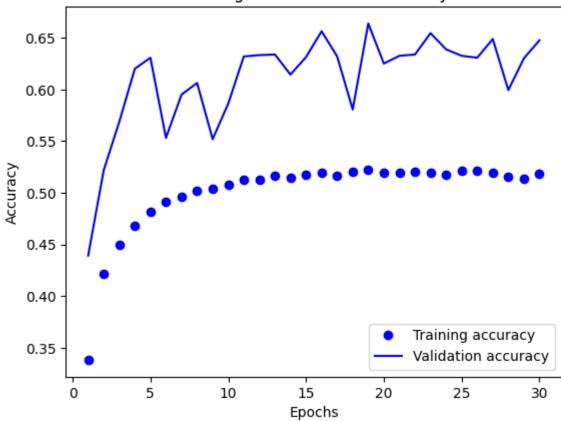
val_acc = history.history['val_accuracy']

plt.plot(epochs, acc, 'bo', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.ylabel('Accuracy')
plt.legend()

plt.savefig("results/CNN_cifar10_augmented_accuracy.png")

plt.show()
```

Training and Validation Accuracy



In [54]: # I expected the model with augmentation and dropout to perform better than the model w

Resnet50 Pretrained Model Predictions

```
img_path = 'images/river.jpg'
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)

preds = model.predict(x)
print('Predicted:', decode_predictions(preds, top=3)[0])
```

```
1/1 [=======] - 3s 3s/step
        Downloading data from https://storage.googleapis.com/download.tensorflow.org/data/imagen
         et class index.json
         35363/35363 [============ ] - Os Ous/step
         Predicted: [('n09468604', 'valley', 0.38834167), ('n09246464', 'cliff', 0.09706052), ('n
        09332890', 'lakeside', 0.094666556)]
In [58]:
         img_path = 'images/tree.jpg'
         img = image.load_img(img_path, target_size=(224, 224))
         x = image.img_to_array(img)
         x = np.expand_dims(x, axis=0)
         x = preprocess_input(x)
         preds = model.predict(x)
         print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [======] - 0s 27ms/step
         Predicted: [('n02793495', 'barn', 0.11131605), ('n04604644', 'worm_fence', 0.10649704),
         ('n11879895', 'rapeseed', 0.10641846)]
In [59]:
         img_path = 'images/chicken.jpg'
         img = image.load_img(img_path, target_size=(224, 224))
         x = image.img_to_array(img)
         x = np.expand_dims(x, axis=0)
         x = preprocess_input(x)
         preds = model.predict(x)
         print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [=======] - 0s 36ms/step
         Predicted: [('n01514859', 'hen', 0.8507484), ('n01514668', 'cock', 0.14899172), ('n01855
         672', 'goose', 0.00017138451)]
In [60]:
         img_path = 'images/donkey.jpg'
         img = image.load_img(img_path, target_size=(224, 224))
         x = image.img_to_array(img)
         x = np.expand_dims(x, axis=0)
         x = preprocess_input(x)
         preds = model.predict(x)
         print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [=======] - 0s 43ms/step
         Predicted: [('n02423022', 'gazelle', 0.24799536), ('n02437616', 'llama', 0.23290879),
         ('n02410509', 'bison', 0.13938038)]
In [64]:
         img_path = 'images/boat.jpg'
         img = image.load_img(img_path, target_size=(224, 224))
         x = image.img_to_array(img)
         x = np.expand_dims(x, axis=0)
         x = preprocess_input(x)
         preds = model.predict(x)
         print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [======= ] - 0s 24ms/step
         Predicted: [('n04273569', 'speedboat', 0.50600773), ('n03344393', 'fireboat', 0.1657924
```

```
5), ('n09332890', 'lakeside', 0.10772088)]
In [65]:
          img_path = 'images/crosswalk.jpg'
          img = image.load_img(img_path, target_size=(224, 224))
          x = image.img_to_array(img)
          x = np.expand_dims(x, axis=0)
          x = preprocess_input(x)
          preds = model.predict(x)
          print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [=======] - 0s 77ms/step
         Predicted: [('n03733281', 'maze', 0.7480029), ('n03717622', 'manhole_cover', 0.0728127
         7), ('n04355338', 'sundial', 0.030221142)]
In [66]:
          img_path = 'images/traffic_light.jpg'
          img = image.load_img(img_path, target_size=(224, 224))
          x = image.img_to_array(img)
          x = np.expand_dims(x, axis=0)
          x = preprocess_input(x)
          preds = model.predict(x)
          print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [======= ] - 0s 81ms/step
         Predicted: [('n06874185', 'traffic_light', 0.9994947), ('n03126707', 'crane', 0.00018885
         13), ('n04371774', 'swing', 0.00016358876)]
In [67]:
          img path = 'images/dog.jpg'
          img = image.load_img(img_path, target_size=(224, 224))
          x = image.img_to_array(img)
          x = np.expand_dims(x, axis=0)
          x = preprocess_input(x)
          preds = model.predict(x)
          print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [======= ] - 0s 46ms/step
         Predicted: [('n02099712', 'Labrador_retriever', 0.7671822), ('n02099601', 'golden_retrie
         ver', 0.21572998), ('n02113799', 'standard_poodle', 0.005650355)]
In [68]:
          img_path = 'images/cat.jpg'
          img = image.load_img(img_path, target_size=(224, 224))
          x = image.img_to_array(img)
          x = np.expand_dims(x, axis=0)
          x = preprocess_input(x)
          preds = model.predict(x)
          print('Predicted:', decode_predictions(preds, top=3)[0])
         1/1 [======] - 0s 46ms/step
         Predicted: [('n02123394', 'Persian_cat', 0.9989759), ('n02123045', 'tabby', 0.000451667
         8), ('n02127052', 'lynx', 0.00016683698)]
In [69]:
          img_path = 'images/bird.jpg'
          img = image.load_img(img_path, target_size=(224, 224))
          x = image.img_to_array(img)
```

```
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)

preds = model.predict(x)
print('Predicted:', decode_predictions(preds, top=3)[0])
```