Boat Image Classification

December 3, 2017

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1 Introduction

The goal of this project is to train a classifier using LeNet architecture in order to classify different categories of boats navigating in the City of Venice (Italy).

The dataset that is being used here is the MarDCT from the Sapienza University of Rome.

The training dataset contains 4.774 images and the test dataset contains 1.969 from 24 different categories.

2 Development

Below the development of the project is detailed, commenting each of the functions and steps given to achieve the desired goals for the project.

2.1 Import necessary libraries for the project

In the following block is listed all the necessary libraries for the project, the seed for the random numbers and the path for the folder containing.

```
In [1]: # Difine libraries
        from tqdm import tqdm
        from textwrap import wrap
        from sklearn.utils import shuffle
        from sklearn import preprocessing

        import os, os.path
        import random
        import matplotlib.pyplot as plt
        import numpy as np
        import pickle
        import cv2

        # Visualizations will be shown in the notebook.
        %matplotlib inline
```

```
# Set seed for random numbers
random.seed(1)

# Define folder where the log files are located
train_folder = 'training/'
test_folder = 'test/'

# Define the image size for the CNN
size_image = 90
```

2.2 Dictionary of classes

Because the dataset is too big and my computer cannot handle to keep in memory the whole dataset, the two dictionaries below are used to select which classes to be used from the training and test dataset.

```
In [2]: # Dictionary with classes
        dict_train = {
            #'Alilaguna':0,
            #'Ambulanza':1,
            #'Barchino':2,
            #'Cacciapesca':3,
            #'Caorlina':4,
            #'Gondola':5,
            #'Lanciafino10m':6,
            'Lanciafino10mBianca':7,
            'Lanciafino10mMarrone':8,
            #'Lanciamaggioredi10mBianca':9,
            #'Lanciamaggioredi10mMarrone':10,
            'Motobarca':11,
            #'Motopontonerettangolare':12,
            #'MotoscafoACTV':13,
            'Mototopo':14,
            'Patanella':15,
            #'Polizia':16,
            #'Raccoltarifiuti':17,
            #'Sandoloaremi':18,
            #'Sanpierota':19,
            #'Topa':20,
            'VaporettoACTV':21,
            #'VigilidelFuoco':22,
            'Water':23
            #'SnapshotBarcaParziale':24,
            #'SnapshotBarcaMultipla':25
        }

        dict_test = {
            #'Alilaguna':0,
            #'Ambulanza':1,
            #'Barchino':2,
            #'Cacciapesca':3,
            #'Caorlina':4,
            #'Gondola':5,
            #'Lancia: fino 10 m':6,
            'Lancia: fino 10 m Bianca':7,
            'Lancia: fino 10 m Marrone':8,
            #'Lancia: maggiore di 10 m Bianca':9,
            #'Lancia: maggiore di 10 m Marrone':10,
            'Motobarca':11,
            #'Motopontone rettangolare':12,
            #'Motoscafo ACTV':13,
            'Mototopo':14,
            #'Mototopo corto':14,
            'Patanella':15,
            #'Polizia':16,
            #'Raccolta rifiuti':17,
            #'Sandolo a remi':18,
            #'Sanpierota':19,
            #'Topa':20,
            'Vaporetto ACTV':21,
            #'Vigili del Fuoco':22,
            'Snapshot Acqua':23
            #'Snapshot Barca Parziale':24,
            #'Snapshot Barca Multipla':25
        }

        # Invert dictionary keys and values to be used in the plots
        dict_test_inverse = dict((v,k) for k, v in dict_test.items())
```

2.3 Save and load pick file

Functions used to save and load the vector of images to a pickle file. It facilitates the work because reading one single file is much faster than reading image by image to create the dataset.

```
In [3]: # Save data to file
        def save_data(X, y, name):
            with open(name + '.p', 'wb') as f:
                pickle.dump({'features':X, 'labels':y}, f, pickle.HIGHEST_PROTOCOL)

        # Load data from file
        def load_data(name):
            with open(name + '.p', 'rb') as f:
                return pickle.load(f)
```

2.4 Training dataset

Try to find the pickle file in the folder, if the file is not found, the dataset need to be create. In order to create the dataset, first it reads image by image from the folders, resize (because the images are really big for a good classification and my graphic card) and append to the training vector.

```
In [4]: # List for files
        X_train = list()
        y_train = list()

        if os.path.isfile('training.p'):
            print('Training file found!')
            with open('training.p', mode='rb') as f:
                train = pickle.load(f)
            X_train, y_train = train['features'], train['labels']
        else:
            print('Training file not found!')

            for i in os.listdir(train_folder):
                subfolder = train_folder + i + "/"
                if os.path.isdir(subfolder):
                    files = os.listdir(subfolder)

                    # If file is in classes to be classified
                    if i in dict_train:
                        pbar = tqdm(range(len(files)))
                        pbar.set_description('Processing \'' + i + '\'')

                        # For each file
                        for j in pbar:
                            f = files[j]
                            image = cv2.resize(plt.imread(subfolder + f),
                                               (size_image,size_image),
                                               interpolation=cv2.INTER_LINEAR)
                            X_train.append(image)
                            y_train.append(dict_train[i])

            X_train = np.array(X_train)
            y_train = np.array(y_train)

            # Save dictionary
            save_data(X_train, y_train, 'training')
            print('\nTraining saved to file!')
```

```
Training file not found!


Processing 'Lanciafino10mBianca': 100%|| 484/484 [00:04<00:00, 107.66it/s]
Processing 'Lanciafino10mMarrone': 100%|| 355/355 [00:03<00:00, 115.21it/s]
Processing 'Motobarca': 100%|| 215/215 [00:02<00:00, 106.52it/s]
Processing 'Mototopo': 100%|| 878/878 [00:07<00:00, 115.91it/s]
Processing 'Patanella': 100%|| 279/279 [00:02<00:00, 124.93it/s]
Processing 'VaporettoACTV': 100%|| 949/949 [00:06<00:00, 143.78it/s]
Processing 'Water': 100%|| 907/907 [00:06<00:00, 147.67it/s]
```

```
Training saved to file!
```

2.5 Test dataset

The process to create the test dataset is basically the same as the training dataset, but here it is a little bit different because the files are all together, not divided by folders and the labels are in a txt file with names in different formats from the folders names used above.

```
In [5]: # List for files
        X_test = list()
        y_test = list()

        # load test files
        if os.path.isfile('test.p'):
            print('Test file found!')
            with open('test.p', mode='rb') as f:
                test = pickle.load(f)
            X_test, y_test = test['features'], test['labels']
        else:
            print('Test file not found!')

            test_label_dictionary = {}
            for l in open(test_folder + 'ground_truth.txt', 'r'):
                file, name = l.strip().split(';')
                if name in dict_test:
                    test_label_dictionary[file] = name

            pbar = tqdm(range(len(test_label_dictionary)))
            pbar.set_description('Processing test data')

            keys = list(test_label_dictionary)

            for f in pbar:
                image = cv2.resize(plt.imread(test_folder + keys[f]),
                                   (size_image,size_image),
                                   interpolation=cv2.INTER_LINEAR)
                X_test.append(image)
                y_test.append(dict_test[test_label_dictionary[keys[f]]])
            X_test = np.array(X_test)
            y_test = np.array(y_test)

            # Save dictionary
            save_data(X_test, y_test, 'test')
            print('\nTest saved to file!')
```

```
Test file not found!


Processing test data: 100%|| 1494/1494 [00:15<00:00, 96.80it/s]



Test saved to file!
```

The script below is used to print some basic information about the dataset, such as the number of files in each dataset, the shape of the images and the classes being classified.

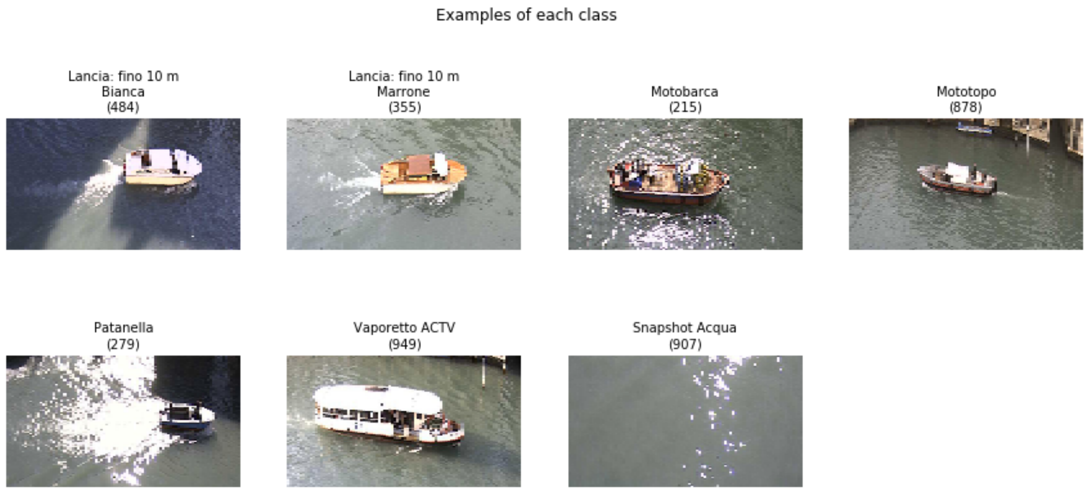
```
In [6]: # Number of training examples
        n_train = len(X_train)

        # Number of testing examples
        n_test = len(X_test)

        # Shape of the image
        image_shape = X_test[0].shape

        # Number of classes
        n_classes = len(dict_train)

        print("Number of training examples =", n_train)
        print("Number of testing examples =", n_test)
        print("Image data shape =", image_shape)
        print("Number of classes =", n_classes)
```

```
Number of training examples = 4067
Number of testing examples = 1494
Image data shape = (90, 90, 3)
Number of classes = 7
```

3 Visualize data

In order to give an overview of the images that will be classified, below a random example of each one is plotted with the number in each class.

```
In [7]: def visualize_data(X, y):
            rows = 4
            samples = list()

            fig = plt.figure(facecolor="white")
            fig.set_size_inches(15, 12)
            fig.subplots_adjust(hspace=.8)

            position = 0
            for i in dict_train:
                position += 1
                index_dic = dict_train[i]
                count = sum(y == index_dic)
                index = random.choice(np.where(y == index_dic)[0])

                ax=fig.add_subplot(rows,rows,position, aspect='equal')
                ax.imshow(X[index])
                ax.axis('off')
                ax.set_title("\n".join(wrap(dict_test_inverse[index_dic],20)) +
                             "\n(" + str(count) + ")", fontsize = 10)
                ax.axis('tight')
            plt.suptitle('Examples of each class')

        visualize_data(X_train, y_train)
```

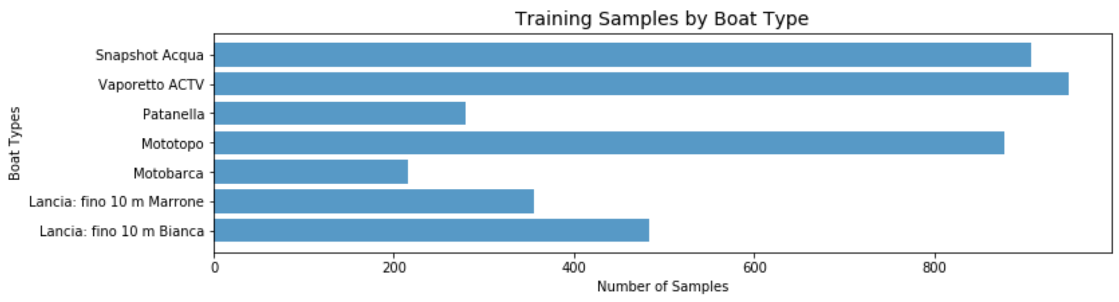


This function is used to plot the number of classes in each dataset. For the test dataset it does not make any difference, because the goal is only to classify the images. However, for the training dataset it is important to have approximately the same number of examples in each class, in order to avoid training a biased classifier.

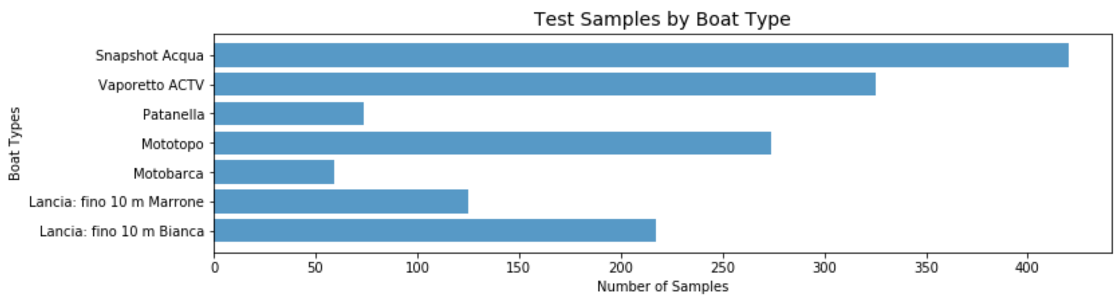
```
In [8]: ## Plot number of each examples in the test data
        def plot_sample_class_distributions(samples, title):
```

```
        label_count = list()
        for i in dict_train:
            index_dic = dict_train[i]
            label_count.append((samples == index_dic).sum())

        indexes = np.arange(len(dict_test))

        fig = plt.figure(facecolor="white")
        fig.set_size_inches(12, int(len(dict_train)/2))
        ax = fig.add_subplot(111)
        ax.barh(indexes, label_count, alpha=0.75)
        ax.set_yticks(indexes)
        ax.set_yticklabels(dict_test, fontsize = 10)
        ax.set_ylabel('Boat Types', fontsize = 10)
        ax.set_xlabel('Number of Samples', fontsize = 10)
        ax.set_title(title, fontsize = 14)
```

```
In [9]: plot_sample_class_distributions(samples=y_train,
                                        title='Training Samples by Boat Type')
```



```
In [10]: plot_sample_class_distributions(samples=y_test,
                                         title='Test Samples by Boat Type')
```



3.1 Data Augmentation

As shown above, the number of examples in each class is not the same, and to create a good classifier it is important to have balanced dataset.

In order to to this, it is possible to apply some transformations to the images, such as flip, rotation, translation, zoom, shadow, and thus create new ones that can be used by the classifier.

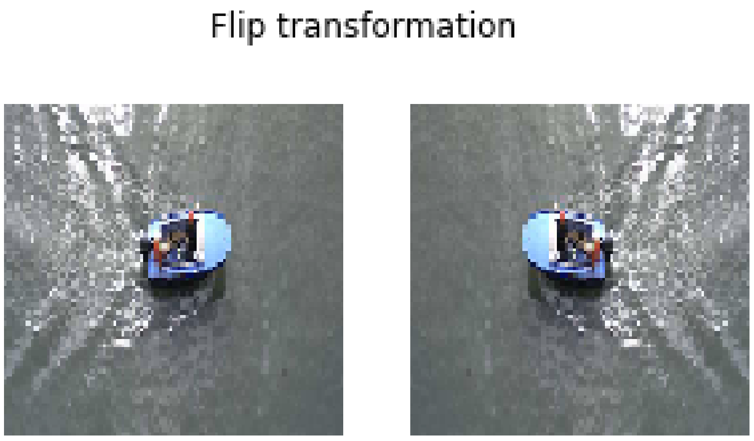
Although for us, seeing two slightly different images does not make any difference, for the classifier these augmentation cause a big impact and it can be really used as new dataset.

```
In [11]: def flip_image(img, flip = False):
             if random.randint(0, 1) or flip:
                 return cv2.flip(img, 1)
             else:
                 return img

         def brightness_image(img):
             hsv = cv2.cvtColor(img, cv2.COLOR_RGB2HSV)
             hsv[:,:,2] = hsv[:,:,2] * (1 + np.random.uniform(-0.6, 0.0))
             return cv2.cvtColor(hsv, cv2.COLOR_HSV2RGB)

         def rotate_image(img):
             rows,cols,channel = img.shape
             M = cv2.getRotationMatrix2D((cols/2,rows/2),
                             random.uniform(-int(rows/5), int(rows/5)), 1)
             return cv2.warpAffine(img,M,(cols,rows), borderMode=1)

         def translate_image(img):
             rows, cols, chs = img.shape
             horz_range=int(cols/10)
             vert_range=int(rows/10)
             tx = np.random.randint(-horz_range, horz_range+1)
             ty = np.random.randint(-vert_range, vert_range+1)
             tr_M = np.float32([[1,0,tx], [0,1,ty]])
             img = cv2.warpAffine(img, tr_M, (cols,rows), borderMode=1)
             return img

         def shadow_image(img):
             rows, cols, chs = img.shape

             # Generate a separate buffer
             shadows = np.copy(img)

             randomUp = int(random.random() * cols)
             randomDown = int(random.random() * cols)

             if random.randint(0, 1):
                 poly = [[randomUp,0],[cols,0],[cols,rows], [randomDown,rows]]
             else:
                 poly = [[randomUp,0],[0,0],[0,rows], [randomDown,0]]

             cv2.fillPoly(shadows, np.array([poly]), -1)

             alpha = np.random.uniform(0.6, 0.9)
             cv2.addWeighted(shadows, alpha, img, 1-alpha, 0, shadows)
             return shadows

         # Function to plot example data
         def plot_example(image1, image2, title):
             fig = plt.figure(facecolor="white")
             fig.set_size_inches(5, 5)
             ax=fig.add_subplot(221)
             ax.imshow(image1)
             ax.axis('off')
             ax.axis('tight')
             ax=fig.add_subplot(222)
             ax.imshow(image2)
             ax.axis('off')
             ax.axis('tight')
             plt.suptitle(title)

         img = np.copy(random.choice(X_train))
```

3.1.1 Data augmentation examples

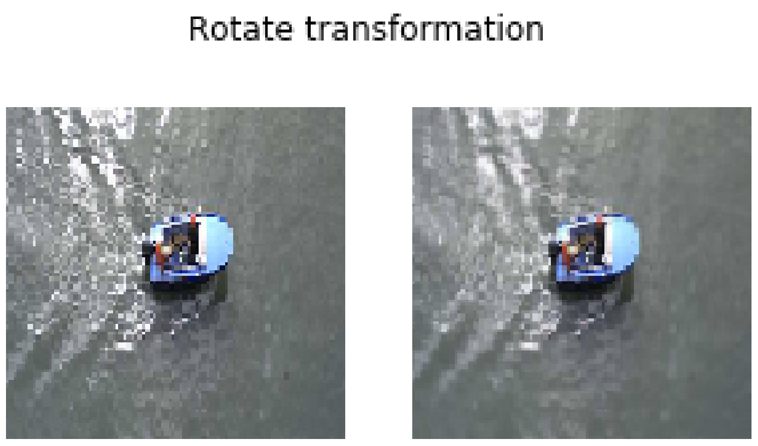
Below is presented an example of each transformation described above.

```
In [12]: plot_example(img, flip_image(img, True), 'Flip transformation')
```



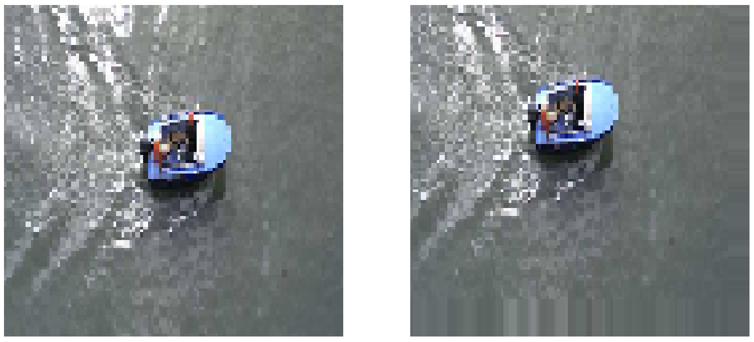
```
In [13]: plot_example(img, brightness_image(img), 'Brightness transformation')
```

```
In [14]: plot_example(img, rotate_image(img), 'Rotate transformation')
```



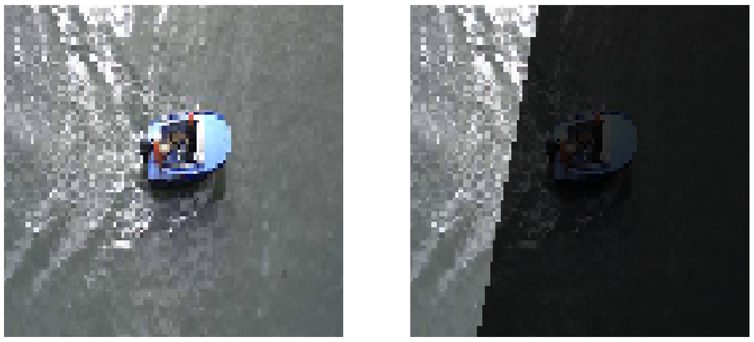
```
In [15]: plot_example(img, translate_image(img), 'Translade transformation')
```

Translade transformation



```
In [16]: plot_example(img, shadow_image(img), 'Shadow transformation')
```

Shadow transformation



The function below selects randomly samples from the samples vector and applies the transformations above in order to match the number of examples of the biggest class. After the transformation is applied it also saves it as a pickle file, so it is not necessary to redo this in the future.

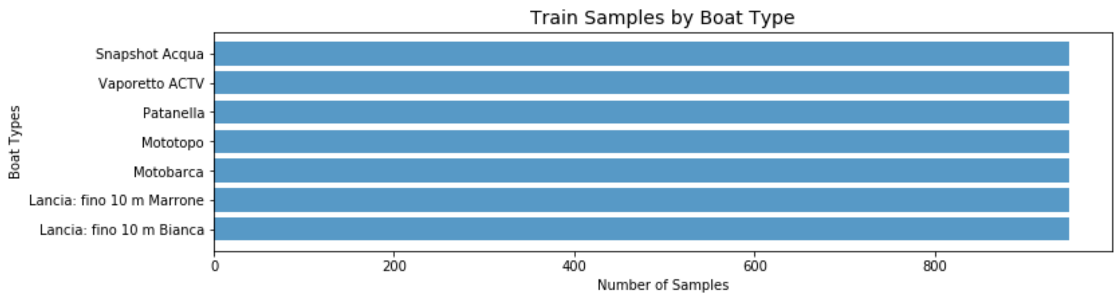
```
In [17]: def augment_image(X, y):

             # Class with more samples
             n_max = 0
             for i in dict_train:
                 index_dic = dict_train[i]
                 n_max = max(n_max, (y == index_dic).sum())
```

```
        # Generate new random images
        for i in dict_train:
            index_dic = dict_train[i]
            n_actual = (y == index_dic).sum()
            n_class = n_max - n_actual

            if n_class != 0:
                index = [j for j,v in enumerate(y == index_dic) if v]

                indexes = [random.choice(index) for _ in range(n_class)]

                pbar = tqdm(range(n_class))
                pbar.set_description('Processing \'' +
                                     dict_test_inverse[index_dic] + '\'')

                for j in pbar:

                    img = np.copy(X[indexes[j]])

                    # Apply transformations
                    img = flip_image(img)
                    img = brightness_image(img)
                    img = rotate_image(img)
                    img = translate_image(img)
                    img = shadow_image(img)

                    X = np.vstack([X, np.reshape(img,
                                   [1, size_image, size_image, 3])])
                    y = np.append(y, y[indexes[j]])

        return X, y

    # load training files
    if os.path.isfile('training_augmented.p'):
        print('Training augmented file found!')
        with open('training_augmented.p', mode='rb') as f:
            train = pickle.load(f)
        X_train, y_train = train['features'], train['labels']
    else:
        X_train, y_train = augment_image(X_train, y_train)

        # Save augmented data
        save_data(X_train, y_train, 'training_augmented')
        print('Training augmented saved to file!')
```

```
Processing 'Lancia: fino 10 m Bianca': 100%|| 465/465 [00:23<00:00, 19.64it/s]
Processing 'Lancia: fino 10 m Marrone': 100%|| 594/594 [00:35<00:00, 16.51it/s]
Processing 'Motobarca': 100%|| 734/734 [00:49<00:00, 14.81it/s]
Processing 'Mototopo': 100%|| 71/71 [00:05<00:00, 13.84it/s]
Processing 'Patanella': 100%|| 670/670 [00:51<00:00, 13.01it/s]
Processing 'Snapshot Acqua': 100%|| 42/42 [00:03<00:00, 12.28it/s]


Training augmented saved to file!
```

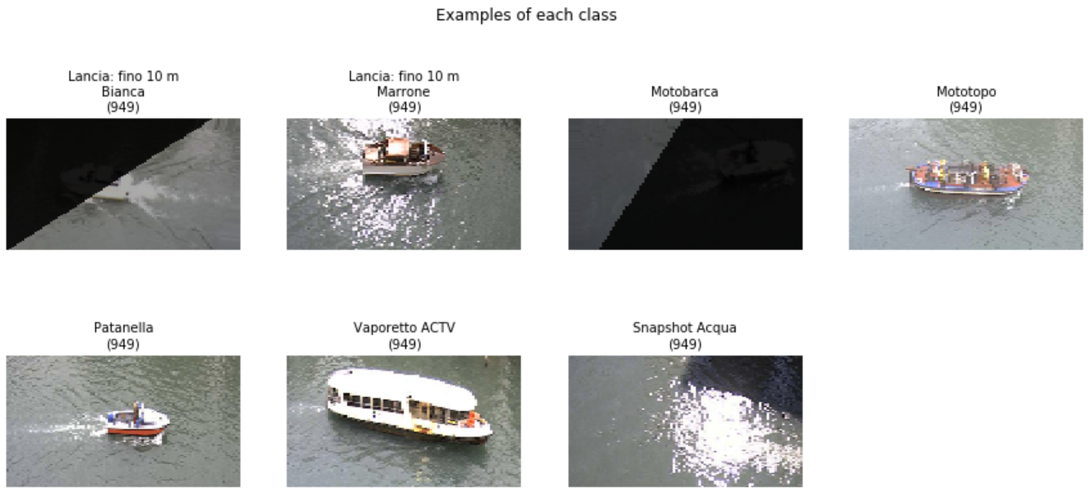
And now, it is possible to check that each class has the same number of examples, what will impact in the classifier training.

```
In [18]: plot_sample_class_distributions(samples=y_train,
                                         title='Train Samples by Boat Type')
```



Also, it is important to show again random examples of the new dataset with the augmented images.

```
In [19]: visualize_data(X_train, y_train)
```



3.2 Preprocess data

The data has already being preprocessed in the last few lines of code, however, before, the process was to create the dataset. Now the preprocess that need to be done is to feed this data to the Convolutional Neural Network.

There are three important preprocess in this step:

- Shuffle - used to avoid mini batches during training
- Normalization - used to improve convergence in gradient descent (this is not implemented here, will be implemented in the model)
- One-hot encode labels - used to represent the classes where each bit is one class and not an int number

```
In [20]: # One Hot encode the labels to the variable y_one_hot
         label_binarizer = preprocessing.LabelBinarizer()
         label_binarizer.fit(y_train)

         # Shuffle the data
         X_train, y_train = shuffle(X_train, y_train)

         # Encode labels
         y_train = label_binarizer.transform(y_train)
         y_test = label_binarizer.transform(y_test)

         # Change to float32, so it can be multiplied
         # against the features in TensorFlow, which are float32
         X_train = X_train.astype(np.float32)
         y_train = y_train.astype(np.float32)
         X_test = X_test.astype(np.float32)
         y_test = y_test.astype(np.float32)
```

3.3 Architecture

Below is described the architecture to train the classifier. The classifier chosen was the LeNet, which is a straightforward and small classifier that can be trained in a not very good graphic card and even a CPU.

The LeNet architecture was first introduced by LeCun et al. in their 1998 paper, Gradient-Based Learning Applied to Document Recognition. As the name of the paper suggests, the authors' implementation of LeNet was used primarily for OCR and character recognition in documents.

Below is also plotted the model, with the sizes of the input and output of each layer of the LeNet architecture.

```
In [21]: from keras.models import Sequential
         from keras.layers import Lambda, Activation, Conv2D
         from keras.layers.core import Flatten, Dense, Dropout
         from keras.layers.convolutional import MaxPooling2D, ZeroPadding2D
         from keras import optimizers
         from keras.utils.vis_utils import plot_model
```

```python
height, width, depth = X_train[0].shape

def lenet(width, height, depth, classes, weightsPath=None):
    model = Sequential()

    model.add(Lambda(lambda x: x/127.5 - 1.,
        input_shape=(width,height,depth),
        output_shape=(width,height,depth)))

    # first set of CONV => RELU => POOL
    model.add(Conv2D(20, (5, 5), padding="same",
                     input_shape=(depth, height, width)))
    model.add(Activation("relu"))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

    # second set of CONV => RELU => POOL
    model.add(Conv2D(50, (5, 5), padding="same"))
    model.add(Activation("relu"))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

    # set of FC => RELU layers
    model.add(Flatten())
    model.add(Dense(500))
    model.add(Activation("relu"))

    # softmax classifier
    model.add(Dense(classes))
    model.add(Activation("softmax"))

    # if a weights path is supplied (inicating that the model was
    # pre-trained), then load the weights
    if weightsPath is not None:
        model.load_weights(weightsPath)

    # return the constructed network architecture
    return model

model = lenet(width, height, depth, n_classes, weightsPath=None)

model.summary()
```

```
Using TensorFlow backend.


_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_1 (Lambda)            (None, 90, 90, 3)         0
```

```
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 90, 90, 20)        1520
_________________________________________________________________
activation_1 (Activation)    (None, 90, 90, 20)        0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 45, 45, 20)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 45, 45, 50)        25050
_________________________________________________________________
activation_2 (Activation)    (None, 45, 45, 50)        0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 50)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 24200)             0
_________________________________________________________________
dense_1 (Dense)              (None, 500)               12100500
_________________________________________________________________
activation_3 (Activation)    (None, 500)               0
_________________________________________________________________
dense_2 (Dense)              (None, 7)                 3507
_________________________________________________________________
activation_4 (Activation)    (None, 7)                 0
=================================================================
Total params: 12,130,577
Trainable params: 12,130,577
Non-trainable params: 0
_________________________________________________________________
```

3.4 Training

After defining the architecture, it is necessary to really train the classifier. This classifier is using the Adam Optimizer, 10 epochs and a batch size of 20 images.

Below is printed the time, loss and accuracy of each epoch.

```
In [22]: # Initialize the optimizer and model
         print("Training model...")
         opt = optimizers.Adam(lr=0.001)
         model.compile(loss="categorical_crossentropy",
                       optimizer=opt, metrics=["accuracy"])

         # Train model if there is no pre-existing one
         history = model.fit(X_train, y_train, batch_size=20, epochs=10, verbose=2)
```

```
Training model...
Epoch 1/10
 - 96s - loss: 1.0272 - acc: 0.6071
Epoch 2/10
```

```
 - 94s - loss: 0.6912 - acc: 0.7352
Epoch 3/10
 - 93s - loss: 0.5593 - acc: 0.7834
Epoch 4/10
 - 106s - loss: 0.3962 - acc: 0.8457
Epoch 5/10
 - 98s - loss: 0.2730 - acc: 0.8973
Epoch 6/10
 - 93s - loss: 0.1905 - acc: 0.9305
Epoch 7/10
 - 93s - loss: 0.1166 - acc: 0.9583
Epoch 8/10
 - 93s - loss: 0.1347 - acc: 0.9551
Epoch 9/10
 - 94s - loss: 0.0952 - acc: 0.9699
Epoch 10/10
 - 93s - loss: 0.0525 - acc: 0.9828
```

This is the function used to plot the results of the classifier training.

```
In [23]: def plot_iteration_graph(data, title, xlabel, ylabel):
             fig = plt.figure(facecolor="white")
             fig.set_size_inches(9, 4)
             ax = fig.add_subplot(111)

             dim = np.arange(1,len(data)+1,1);
             ax.plot(dim,data)
             ax.axis([1, len(data), min(data) - 0.05, max(data) + 0.05])

             ax.set_ylabel(ylabel, fontsize = 10)
             ax.set_xlabel(xlabel, fontsize = 10)
             ax.set_title(title, fontsize = 14)
```

4 Results

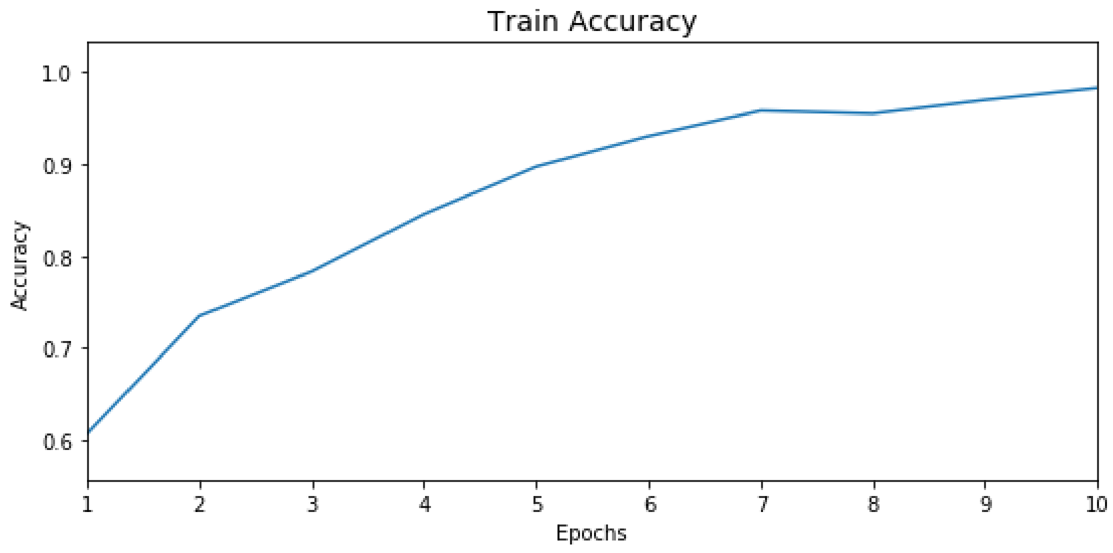
For the training set it is possible to obtain a higher accuracy, however, it is necessary to test in images never seen before to get the real accuracy of the model.

So, running the classifier with the test set it is possible to obtain the following accuracy presented below.

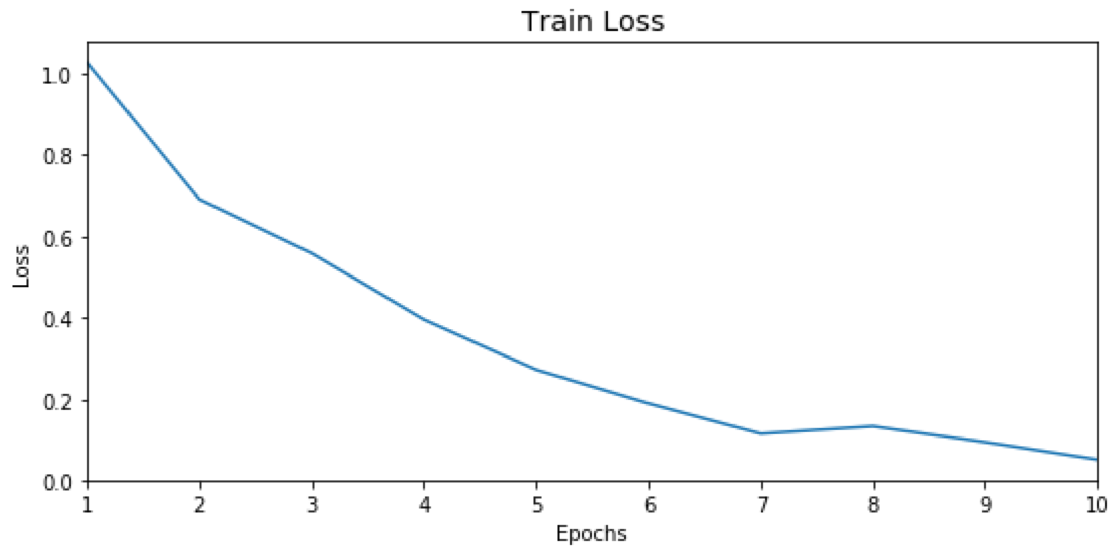
```
In [24]: # show the accuracy on the testing set
         (loss, accuracy) = model.evaluate(X_test, y_test, batch_size=100, verbose=2)
         print("Test Accuracy:\t{:.2f}%".format(accuracy * 100))

Test Accuracy:        86.01%
```

It is also interesting to plot the accuracy and loss over time to see the evolution of the training. In the images below it is possible to see how the accuracy improves over the epochs, towards 100% and the loss decreases to almost 0.

```
In [25]: plot_iteration_graph(history.history['acc'],
                              'Train Accuracy','Epochs', 'Accuracy')
```



```
In [26]: plot_iteration_graph(history.history['loss'],
                              'Train Loss', 'Epochs', 'Loss')
```



5 Further improvements

In this project it was possible to have good results using the simplest classifier known, however it can be improved and achieve much better results. Also, this training was most limited by the hardware being used, which do not allow to train with higher image sizes and more classes.

Another test that I would like to do is to use a pre-trained classifier, as the VGG-16, and retrain only the last layers in order to learn how to classify the boats in this dataset.

Besides this, it is also possible to improve the augmentation of the images (zoom, other transformations) and train each epoch with new augmented generated images.