Frans Fourie

fjf46

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Intelligent Autonomous Systems

Project 1

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Introduction

This report documents the creation of a model that can be trained to identify specific objects in pictures. To train the model one starts with training images of which the desired object is then extracted from each image. Once the object is extracted from an image all the RGB values of each pixel depicting the object is saved to one list while all the remaining pixels that did not depict the object is saved to another list. These lists are then given to the model for training. Once the model has been trained the model can be used to identify that specific object in new testing images. The model draws a rectangle around the found object and puts a dot on its center. The original image with the addition of the rectangle and dot is then displayed. The program also prints the coordinates of the objects center along with the distance to the object to the program console.

Problem Statement

For this project the objects the model is trained to identify are red barrels in images. A program needs to be written that can be trained to identify red barrels in unknown test images. A set of 50 pictures containing red barrels are provided as training data for the model. The first obstacle is to extract the necessary training data from these images in a usable format. The next problem is selecting the appropriate model/algorithm to effectively identifying the red barrels. Once a model is selected and it has been trained the probability of each pixel in an image being a red barrel needs to be calculated as well as the probability of the pixel being something else. With each pixel's probabilities calculated some post processing needs to be done in order to identify which of these pixels belong to an actual red barrel. Once the possible red barrels in the image have been identified they need to be highlighted by drawing a rectangle around them and indicating their center. With all the barrels in an image identified the distance to each barrel needs to be estimated. The final objective is to print the image with the barrel indicated to the user as well as informing the user of the coordinates of the barrel center and the distance to the barrel.

Description of Approach

General approach

The implemented model starts by loading the training lists of RGB values and initializing the distance lookup table. Next for each class the percentage of total training points belonging to this class is calculated followed by the calculation of the classes mean, covariance and norm of covariance. These values are then used to create the class regions. Now for every pixel in an image the probability of it being a red barrel is estimated. Next the probability of it not being a red barrel is calculated. The pixel is classified as belonging to the class where the largest estimator probability was calculated. Both estimators must be calculated as the probability estimator calculated is not the true probability. Thus, it cannot be assumed that belongs to a certain class as long as it has a probability larger than a certain value. Using the classification of each pixel a mask is made for the image indicating where barrel pixels are located. Using the generated mask with the 'regionprops' library regions of connected barrel pixels are created. Some post processing is then done on the identified regions in order to identify the regions truly holding a red barrel. Following the processing the remaining regions that possibly contain red barrels are plotted onto the image. The distance of these regions is then used to estimate the distance to these barrels. The center of each remaining region is then printed to the console with the distance to that barrel.

Post Processing

Multiple simple post processing checks are used to do a sanity check on the identified regions to try and eliminate false identified regions. The first check is to eliminate tiny regions that are unlikely to contain a red barrel. The second check checks the ratio of the regions height to its width which helps eliminate regions that don't have the correct barrel shape. The last check is for identifying the largest remaining region in the picture and then checking if any other remaining region has a size that makes sense considering the size of the largest barrel that was identified in the image.

Table 1: Post Processing Tests

Post Processing Tests	**Condition**	**Result**
Size check	Region area < 1000	Eliminate
Ratio check	Height/Width > 2.5	Eliminate
Logical check	Region area < (Largest region * 0.35)	Eliminate

Color space

The first color space that was tried was the RGB color space which was then kept as the color space to be used in the model. After researching different color spaces and discussing the effects of different color spaces on the performance of the model with fellow students. I determined that it would be wiser and beneficial to the performance of the model to rather spend more time on improving the rest of the model and keeping the color space as RGB then spending time on changing the color space and keeping the rest of the model as it was at that time.

Class models

In order to identify a red barrel in pictures the easiest method to use is to take the entire RGB color space and divide it into class regions that can be used to identify certain regions of the color space as certain objects. Using these class regions, it is then possible to see in which class every pixel is likely to be and this can then be used to classify the pixels. To create the class regions a simple naïve Bayes classifier was used.

In the creation of this model experiments where done with using different amounts classes. The best accuracy and highest performance where obtained when only using two classes namely 'Red Barrel' and 'Not Red Barrel'. When using multiple classes such as trying to distinguish chairs, robot arms, fire extinguishers and exit signs from red barrels it ended with classes overlapping a lot leading to false positives and false negatives. By having only two classes they were very distinguishable from each other. The advantage of the two-class approach is that it seldom led to false negatives with false negatives only occurring when the barrel was placed in bad lighting conditions which did not happen often. Considering the drawback of the two-class approach being that a lot of false positives occur this had to be addressed. The solution to this problem was found to be quite simply as it was found that all false positives detected on both the training and testing image sets could be eliminated simply using the above named three easy sanity checks in post processing.

Table 2: Classes

List of Classes
Red Barrel
Not Red Barrel

Thus, the choice had to be made between using multiple classes and dealing with false negatives or using only two classes and dealing with false positives. The solution to solving the false positive problem was found to be easier and more efficient. This led to the two-class approach being selected as the one implemented in the model.

Distance estimation model

In order to estimate the distance to the barrel a lookup table was constructed using the barrels provided in the training data set. By looking at the size of each barrel in the training set and matching the sizes of the barrels to their provided true distances, it was possible to identify boundaries that could be used for classifying the distance of new testing barrels. Considering the barrels where all measured to be a precise meter value away estimating the distance of the barrels based on size to a precise meter gave more accurate results then estimating the distance using a distance equation.

Table 3: Barrel Distance Lookup Table

Lower Bound	Upper Bound	Meter Value
150000	1000000	1
50000	150000	2
19000	50000	3
13000	19000	4
9000	13000	5
6000	9000	6
5000	6000	7
3800	5000	8
2800	3800	9
2000	2800	10
1000	2000	14
0	1000	15+

This approach has advantages and disadvantages. Advantages of this approach is that it gives a precise meter result thus if a barrel size is in the range of expected values its distance would be accurately estimated. Another advantage is that it compensates for some minor flaws because it was calibrated using the training images. As some of the training images weren't precisely identified but the lookup table approach would still correctly estimate their distance. Therefore, taking into consideration the model will make the same minor errors on the testing images, the lookup table approach would correctly estimate their distances whereas an equation would not be able to. A disadvantage of this approach is that the model can only estimate the distance of a testing barrel to one of the training values thus if a barrel is further away than 14 meters then the method would not work.

In conclusion this method of distance estimation is rudimentary and a simple example of machine learning where the program was given the available training data points and a linear k means clustering classification method is used where each cluster is a specific distance (Given limited training data, clusters where manually created). This method outperformed the alternative tested analytical method when testing using cross validation and if given more training data this method would work even better.

Discussion of results

The following are the results obtained on the testing images using the implemented model.

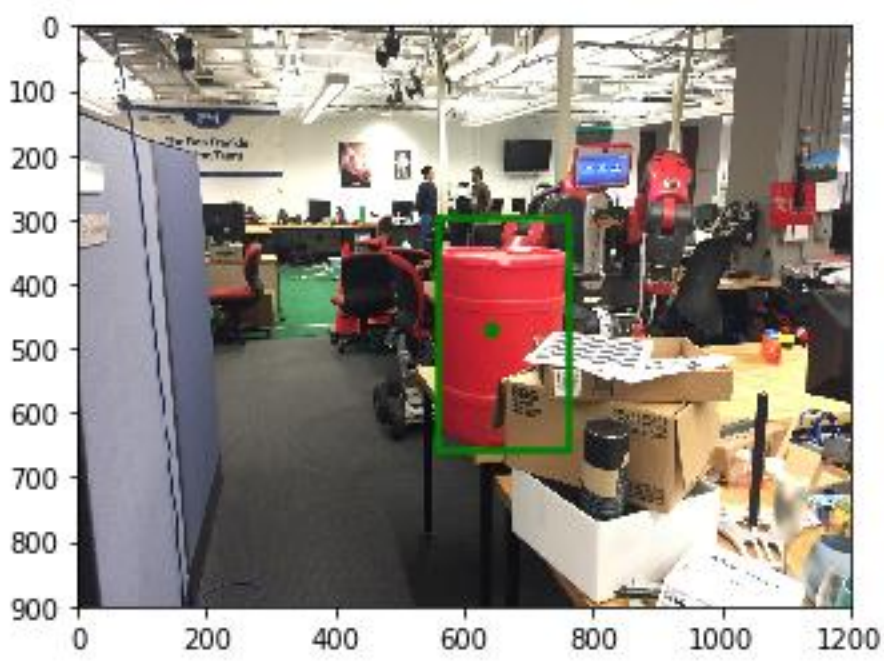

Figure 1: Image 001

As can be seen in the above figure the red barrel in image 1 has been correctly identified. The region just extends a small end higher than the actual barrel; this is due to the red robotic arm touching the barrel and the algorithm thinking it is part of the barrel.

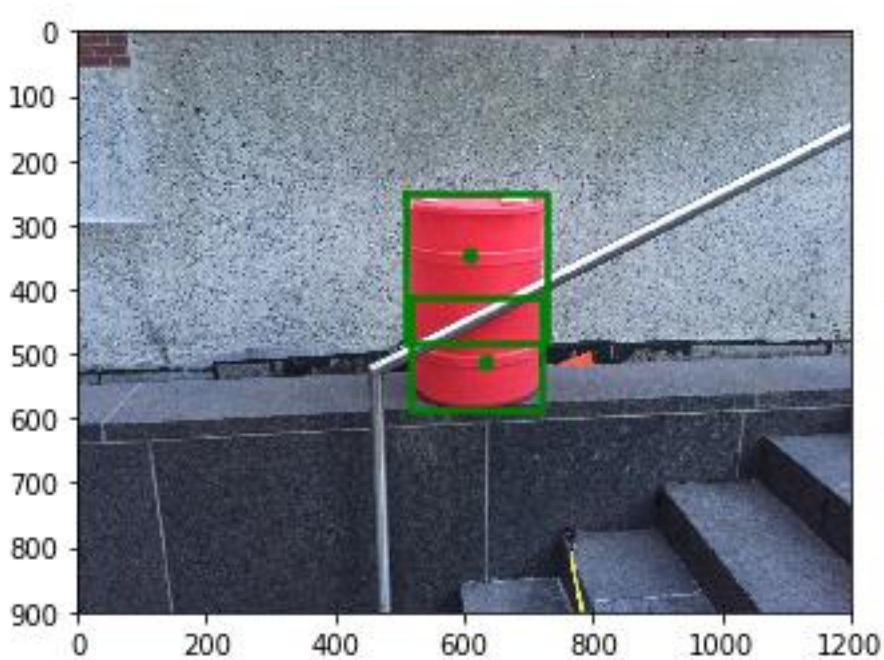

Figure 2: Image 002

As can be seen in the above figure the red barrel in image 2 have been identified as a red barrel with the only problem being that due to the bar cutting the barrel in two the barrel was identified as two separate overlapping barrels.

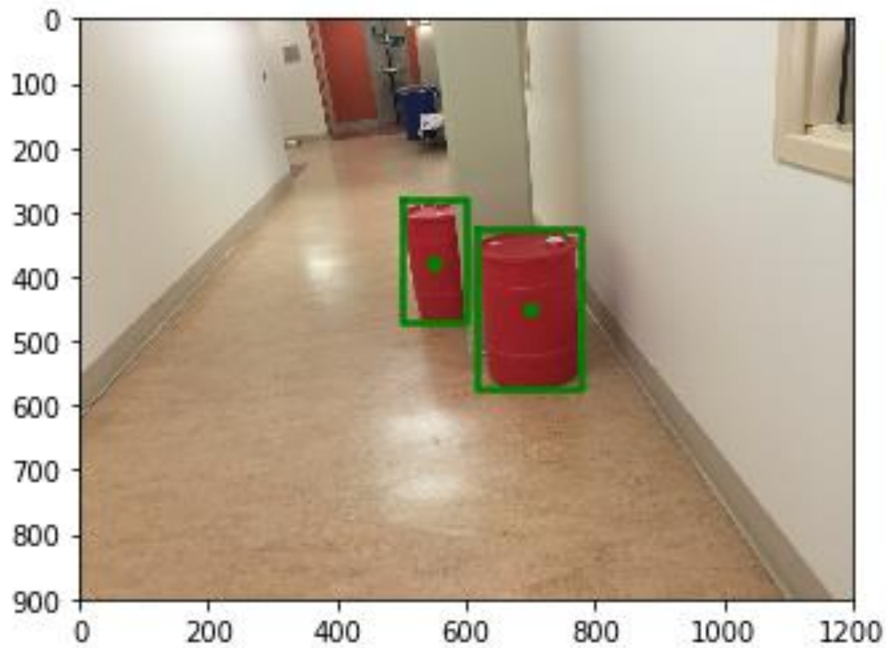

Figure 3: Image 003

As can be seen in the above figure the red barrels in image 3 have been correctly identified. A small corner that is not part of the one barrel was also included in the region. This is due to the region plotting tool plotting the smallest possible upright rectangle that included all the points identified as part of the barrel.

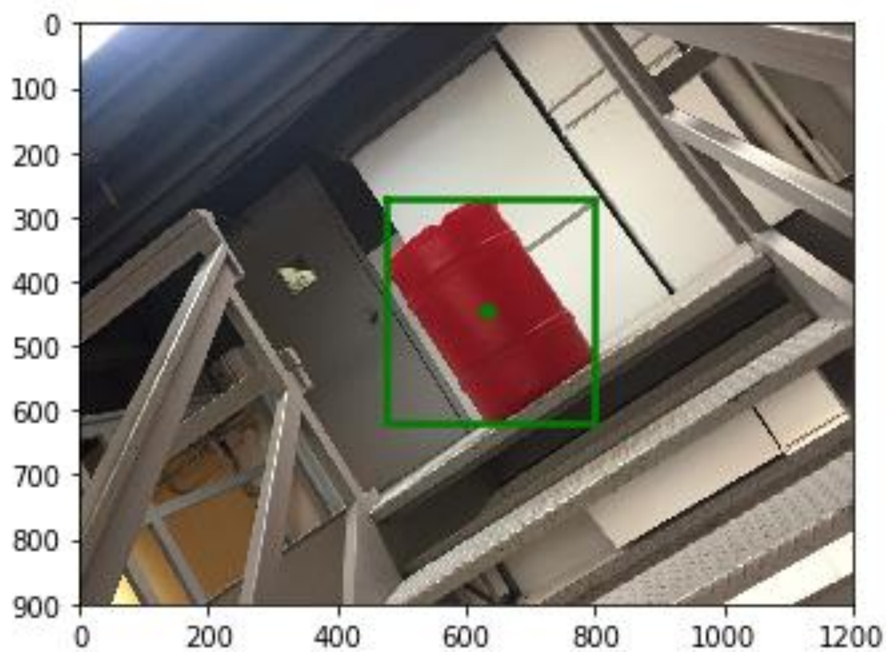

Figure 4: Image 004

As can be seen in the above figure the red barrel in image 4 has been correctly identified. The center of the barrel seems to be correct but the region of the barrel includes corners that does not contain the barrel this is due to the orientation of the barrel and the fact that the model did not make preparations incase the barrel was tilted when drawing the region. The correct area was thus identified, and the corners was not identified as part of the barrel, rather the region plotting tool just plotted the smallest possible upright rectangle possible that would contain all of the points identified as part of the barrel.

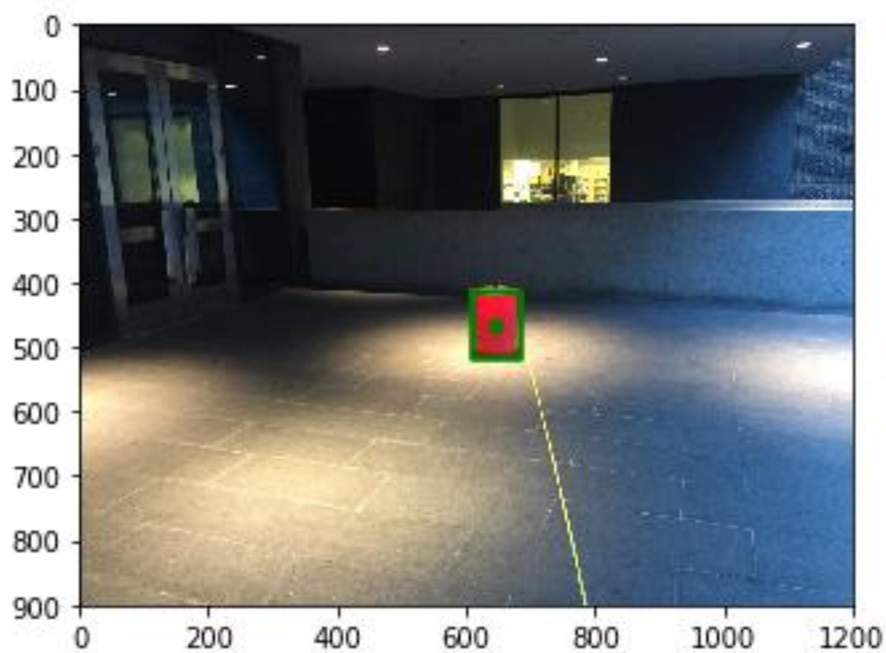

Figure 5: Image 005

As can be seen in the above figure the red barrel in image 5 has been correctly identified.

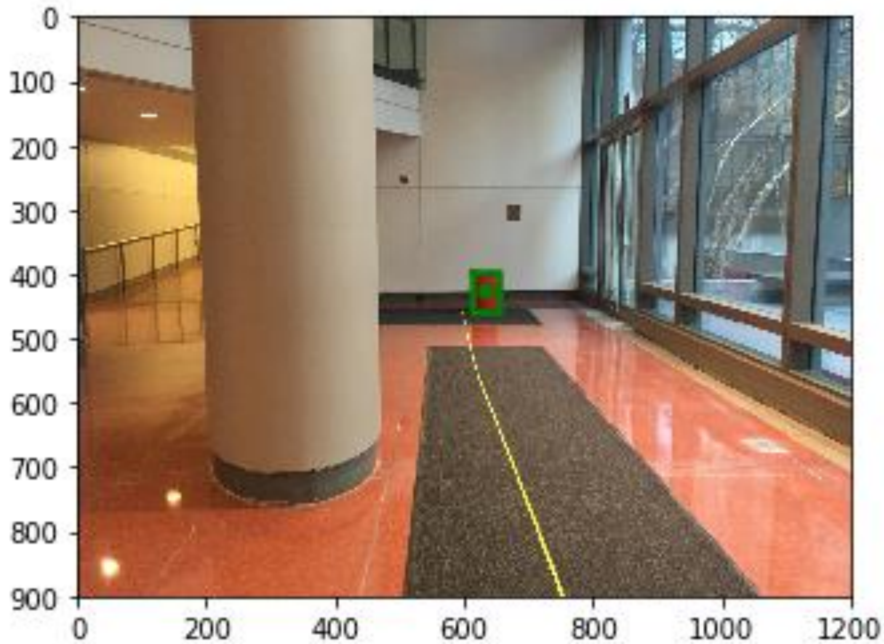

Figure 6: Image 006

As can be seen in the above figure the red barrel in image 6 has been correctly identified.

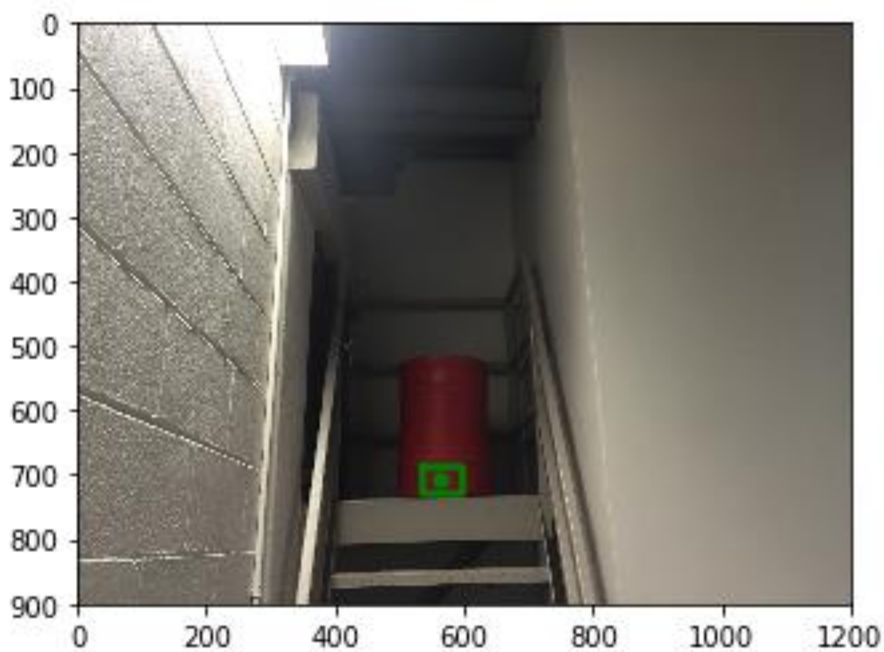

Figure 7: Image 007

As can be seen in the above figure the red barrel in image 7 was found but the model was only able to identify a small part of the barrel and not the entire barrel. This is due to the barrel being so dark that the implemented model has trouble identifying the red barrel in dark environments.

Figure 8: Image 008

As can be seen in the above figure the red barrel in image 8 has been correctly identified.

Figure 9: Image 009

As can be seen in the above figure the red barrel in image 9 has been correctly identified.

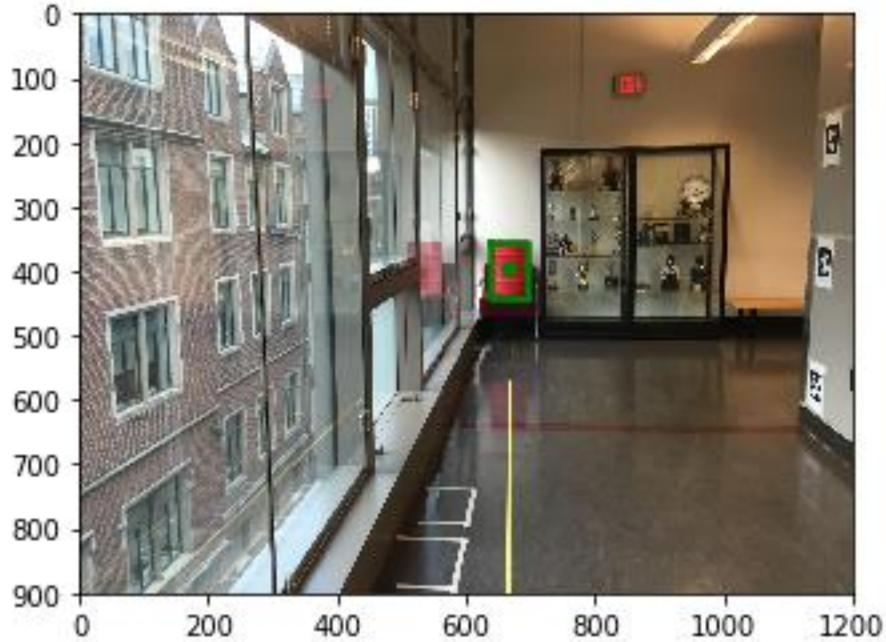

Figure 10: Image 010

As can be seen in the above figure the red barrel in image 10 has been correctly identified.

Table 4: Test images numerical results

Image Name	Centroid X	Centroid Y	Distance (m)
001	643.1580988177083	472.33208839831576	2
002	607.6393270821842	347.7867346938776	2
002	632.1813153310104	513.7909407665505	3
003	552.1161790678032	378.3158258465791	4
003	698.8692360428031	448.3541089153179	3
004	634.143375055365	443.96031759051164	2
005	645.3535005738646	464.7507788161994	6
006	632.4128440366973	426.49410222804715	10
007	564.0851254480286	706.8252688172043	10
008	737.2208624708625	477.5215617715618	10
009	673.543918918919	426.34572072072075	10
010	664.4532537067545	395.5796952224053	7

In the above table the numerical results gotten when running the model on the test images are shown. It includes the coordinates to the center of each barrel as well as the estimated distance to each barrel.

From the results above it can be seen that the model worked quite well but does have a few weak points. The model has some weak points namely difficulty in identifying the red barrel when it is situated in a dark environment and splitting the barrel into multiple parts if an object is obstructing the re red barrel such as the stairway railing in the test data. The region plotting tool implementation also has some weak points such as that it always draws an upright rectangle even when the identified barrel is not upright.

These weak points could be fixed by implementing a normalization method for the light in a room to try and better identify barrels in dark rooms. The problem with barrels being cut into multiple barrels could be fixed by having the model not just group touching barrel pixels together but also grouping nearby non touching barrel pixels together. The region plotting weakness could be fixed by analyzing the orientation of the barrel and rotating the rectangle accordingly.

Conclusion

A model was created to identify red barrels in images, draw an outline around, determine the distance and give the center coordinates of the barrel. The model was trained using the provided training data. The pixels where defined into two classes namely ‘red barrel’ and ‘not red barrel’ as it proved to be the best solution with only false positives that could be eliminated with simple sanity checks.

The model used in the classification was a simple naïve Bayes classifier to classify the pixels into a certain class. This left us with some false positives that where then eliminated using post processing such as checking the object size and ratios.

All the barrels were identified in the test data, with only some minor difficulty. Namely identification in a dark environment, the orientation of the plotting rectangle and determining how many barrels there are when barrels are divided by objects. The distance estimations found also looked to be close to correct. Thus, the simple model in combination with simple post processing delivered reasonably accurate results.