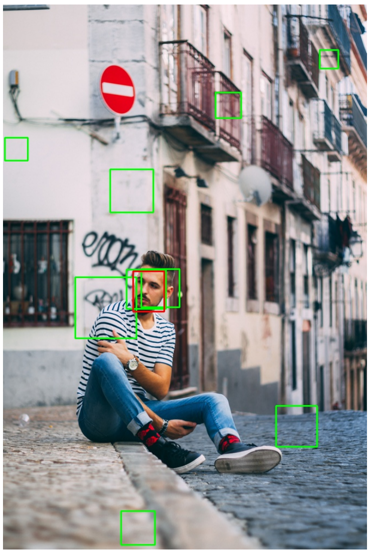
No Entry Sign Challenge Report

1 The Viola-Jones object detector

1.1 Ground truth and visualisation

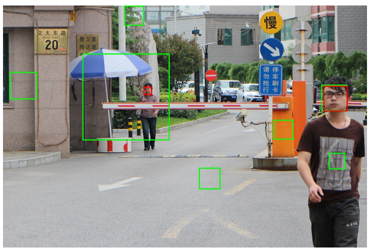


(a) `NoEntry1.jpg`

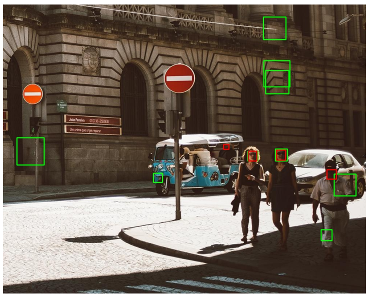
(b) `NoEntry2.jpg`

(c) `NoEntry4.jpg`

(d) `NoEntry5.jpg`



(e) `NoEntry7.jpg`



(f) `NoEntry11.jpg`

Figure 1: Six images with the bounding boxes of the ground truths (in red) and actually detected instances (in green) from the frontal face detector

In an object detection task, ground truth bounding boxes assist in determining the accuracy of the detection algorithm, and help to visualise how well it performs. Figure 1 displays six images, with their ground truth bounding boxes in red, and the frontal faces detected by `face.cpp`, which implements the Viola-Jones object detection framework, in green.

1.2 Intersection-over-union, true positve rate and F_1 score

True positive rate (TPR) is a popular metric used to assess the performance of an object detection algorithm. The TPR is the proportion of objects that an algorithm is attempting to detect that are actually detected, and is given by the formula:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

where TP is the number of true positives, and FN is the number of false negatives.

The first practical difficulty that arises in calculating the TPR is whether or not to define a predicted bounding box as a being a true positive or a false positive. I opted to define a detected bounding box as being a true positive if it had an intersection-over-union (IOU) value greater than 0.5 with a ground truth bounding box, as this is considered a good score [1]. For two bounding boxes A and B, the IOU is calculated as follows:

$$\mathrm{IOU}(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where $|A \cap B|$ is the area of intersection, and $|A \cup B|$ is the area of union. Moreover, for each ground truth bounding box, I only defined the detected bounding box with the largest IOU value as being a true positive if there was more than one intersecting detected bounding box.

In any detection task, TPR can be a flawed metric to use to define how well a given model performs. This is because, firstly, the TPR can be usually be artificially increased simply by lowering the IOU threshold, without the model actually performing any better in reality. Secondly, it is possible to achieve a TPR of 100% by detecting every possible pixel region as being the object being detected, despite having a large number of false positives.

As a result of this, the F_1 score is often used as a measure of a model's accuracy. F_1 score is the harmonic mean of recall (i.e. TPR) and precision (i.e. the proportion of predicted positives that are actually positive), and is calculated as follows:

$$\mathrm{F}_1 = \frac{\mathrm{TP}}{\mathrm{TP} + \frac{1}{2}(\mathrm{FP} + \mathrm{FN})}$$

where FP is the number of false positives.

Table 1: TPRs and F_1 scores of the frontal face detector

Image	TPR	F_1 Score
`NoEntry0.jpg`	Undefined	0.00
`NoEntry1.jpg`	1.00	0.20
`NoEntry2.jpg`	0.25	0.18
`NoEntry3.jpg`	Undefined	Undefined
`NoEntry4.jpg`	1.00	0.28
`NoEntry5.jpg`	Undefined	0.00
`NoEntry6.jpg`	Undefined	0.00
`NoEntry7.jpg`	0.50	0.22
`NoEntry8.jpg`	Undefined	0.00
`NoEntry9.jpg`	Undefined	0.00
`NoEntry10.jpg`	Undefined	0.00
`NoEntry11.jpg`	0.50	0.31
`NoEntry12.jpg`	0.00	0.00
`NoEntry13.jpg`	Undefined	0.00
`NoEntry14.jpg`	Undefined	0.00
`NoEntry15.jpg`	Undefined	0.00

Table 1 displays the TPR and F_1 score that `face.cpp` achieved on each of the `NoEntry*.jpg` images. Due to the definitions of TPR and F_1 score, many of the values are undefined since division by zero yields an undefined result.

2 Building and testing my own detector

2.1 Training performance

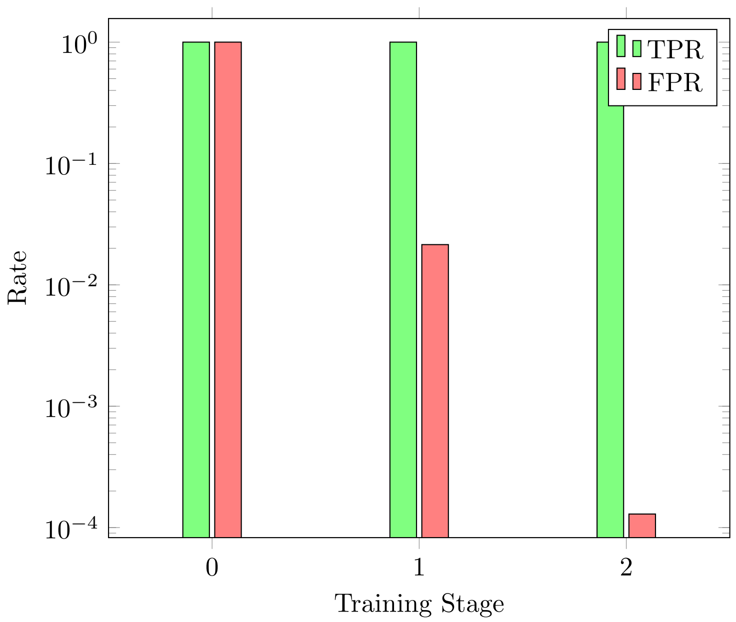


Figure 2: TPR and FPR of stages in Viola-Jones no entry sign training process

During the Viola-Jones no entry sign training process, the false positive rate (FPR) is the number of negatives incorrectly predicted as being a positive no entry sign. Figure 2 displays the TPR and FPR at each stage of the training process. Throughout each stage, the TPR remains to 100%, while the FPR exponentially decreases.

2.2 Testing performance

Table 2: TPRs and F_1 scores of Viola-Jones no entry sign detector

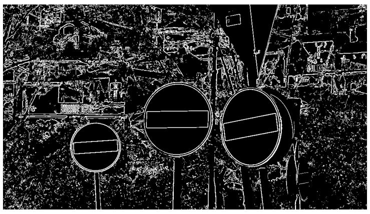
Image	TPR	F_1 Score
`NoEntry0.jpg`	1.00	0.67
`NoEntry1.jpg`	1.00	0.40
`NoEntry2.jpg`	1.00	0.40
`NoEntry3.jpg`	1.00	0.80
`NoEntry4.jpg`	0.50	0.67
`NoEntry5.jpg`	0.40	0.47
`NoEntry6.jpg`	0.00	0.00
`NoEntry7.jpg`	0.00	0.00
`NoEntry8.jpg`	0.57	0.72
`NoEntry9.jpg`	0.00	0.00
`NoEntry10.jpg`	0.67	0.67
`NoEntry11.jpg`	0.50	0.25
`NoEntry12.jpg`	0.25	0.40
`NoEntry13.jpg`	0.00	0.00
`NoEntry14.jpg`	1.00	1.00
`NoEntry15.jpg`	0.50	0.67
All images	0.44	0.48

3 Integration with shape detectors

3.1 Hough Details

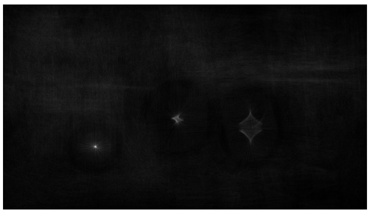
(a) `NoEntry6.jpg` with detected bounding boxes

(b) `NoEntry2.jpg` with detected bounding boxes



(c) `NoEntry6.jpg` gradient magnitude threshold

(d) `NoEntry2.jpg` gradient magnitude threshold



(e) `NoEntry6.jpg` 2D Hough space

(f) `NoEntry2.jpg` 2D Hough space

Figure 3: Two examples of no entry sign images

Figure 3 contains two examples of no entry sign images that best exhibit the merits and limitations of my integrated implementation.

3.2 Evaluation

Table 3 displays the TPR and F_1 score of the integrated implementation, as well as the differences compared with the Viola-Jones implementation. The key merits and shortcomings include:

- A significantly larger F_1 score, primarily as a result of increasing the precision; achieved by only defining an object detected by the Viola-Jones detector as positive if it has an IOU value with a bounding box from the circle Hough transform greater than 50%
- A small improvement to the TPR score, by reducing the minimum number of neighbours allowing for more true positives to be identified (the extra false positives were 'filtered out' by utilising the circle Hough transform)
- If a no entry sign is positively detected by one of the detectors, but not the other, it is not positively detected by the integrated implementation
- A significantly slower implementation, since the circle Hough transform takes longer to calculate

3.3 Detection pipeline

Figure 4 outlines the way I combined evidence in my algorithm. The rationale behind this was as follows:

- The Viola-Jones detector detected 44% of no entry signs, but had a low level of precision
- Upon inspection of the detected bounding boxes, it became clear the Viola-Jones detector appeared to be detecting regions with a light bar horizontally between two dark bars
- Since no entry signs are circles, we could choose to detect the circles from the circle Hough transform that have an IOU with a Viola-Jones bounding box of greater than 50% (i.e. they are likely detecting the same object)

Table 3: TPRs and F_1 scores of the integrated implementation

	Result		Difference	
Image	TPR	F_1 Score	TPR	F_1 Score
`NoEntry0.jpg`	1.00	1.00	±0.00	+0.33
`NoEntry1.jpg`	1.00	1.00	±0.00	+0.60
`NoEntry2.jpg`	1.00	1.00	±0.00	+0.60
`NoEntry3.jpg`	1.00	1.00	±0.00	+0.20
`NoEntry4.jpg`	1.00	1.00	+0.50	+0.33
`NoEntry5.jpg`	0.20	0.31	−0.20	−0.16
`NoEntry6.jpg`	0.00	0.00	±0.00	±0.00
`NoEntry7.jpg`	0.00	0.00	±0.00	±0.00
`NoEntry8.jpg`	0.43	0.60	−0.14	−0.13
`NoEntry9.jpg`	1.00	1.00	+1.00	+1.00
`NoEntry10.jpg`	1.00	1.00	+0.33	+0.33
`NoEntry11.jpg`	0.50	0.67	±0.00	+0.42
`NoEntry12.jpg`	0.38	0.55	+0.13	+0.16
`NoEntry13.jpg`	0.00	0.00	±0.00	±0.00
`NoEntry14.jpg`	1.00	1.00	±0.00	±0.00
`NoEntry15.jpg`	1.00	1.00	+0.50	+0.33
All images	0.50	0.66	+0.04	+0.17

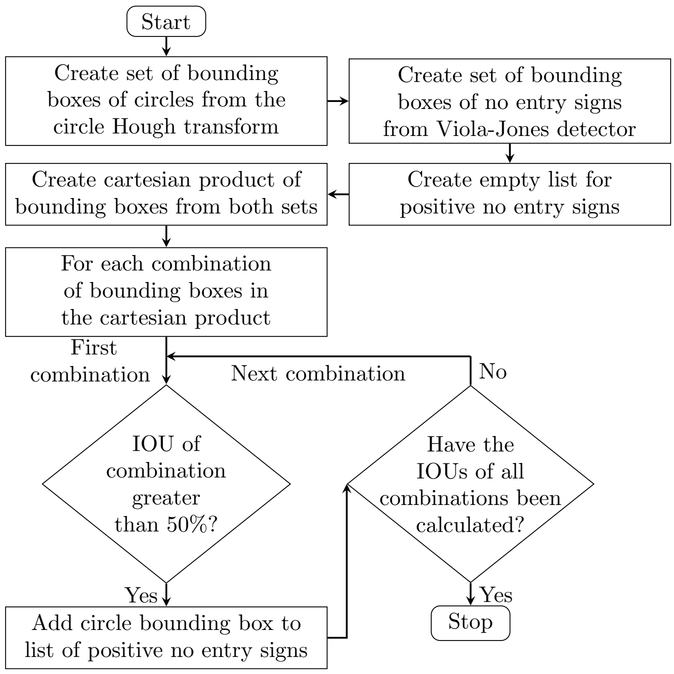


Figure 4: Flow chart detailing my algorithm that integrates Viola-Jones with the circle Hough transform

4 Improving my detector

References

[1] Adrian Rosebrock. *Intersection over Union (IoU) for object detection.* URL: https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/.