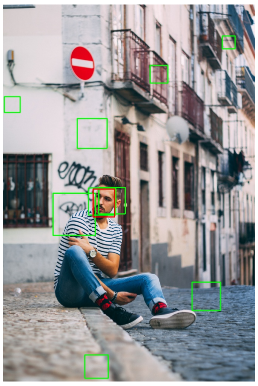
No Entry Sign Challenge Report

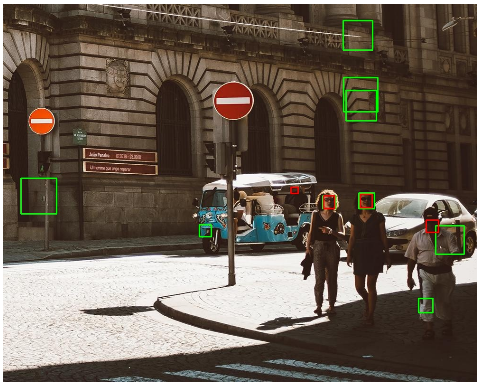
1 The Viola-Jones object detector

1.1 Ground truth and visualisation



(a) NoEntry1.jpg

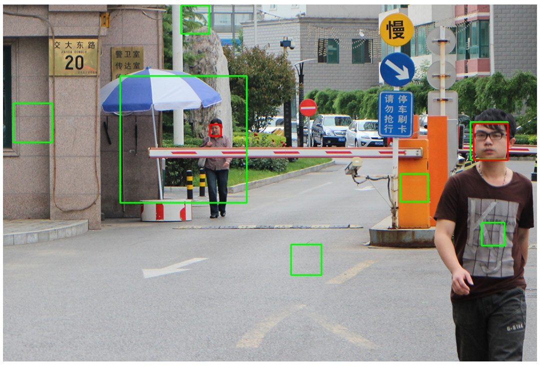
(b) NoEntry5.jpg



(c) NoEntry11.jpg

(d) NoEntry2.jpg

(e) NoEntry4.jpg



(f) NoEntry7.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

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

In an object detection task, the true positive rate (TPR) is the probability that an object will be positively detected. However, 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]. 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, 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 sensitivity (i.e. TPR) and precision. Table 1 displays the F_1 score and TPR that 'face.cpp' achieved on each of the NoEntry∗.jpg images

Table 1: TPR and F_1 score 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

2 Building and testing my own detector

2.1 Training performance

ROC graph

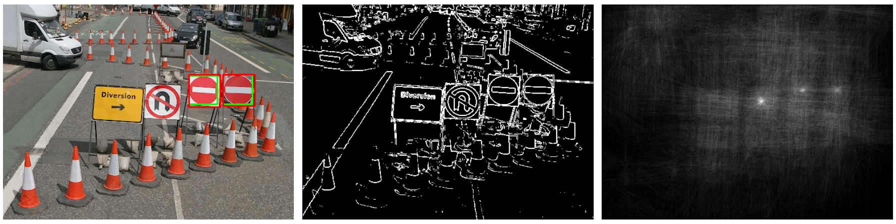
2.2 Testing performance

Table 2: TPR and F_1 score of Viola-Jones no entry sign detector

Image	TPR	F_1 score
NoEntry0.jpg	0.00	0.00
NoEntry1.jpg	1.00	0.13
NoEntry2.jpg	1.00	0.08
NoEntry3.jpg	0.50	0.15
NoEntry4.jpg	1.00	0.16
NoEntry5.jpg	0.30	0.17
NoEntry6.jpg	0.00	0.00
NoEntry7.jpg	0.00	0.00
NoEntry8.jpg	0.57	0.62
NoEntry9.jpg	0.00	0.00
NoEntry10.jpg	0.67	0.33
NoEntry11.jpg	0.50	0.11
NoEntry12.jpg	0.38	0.21
NoEntry13.jpg	0.00	0.00
NoEntry14.jpg	0.00	0.00
NoEntry15.jpg	0.50	0.40
All images	0.40	0.12

3 Integration with shape detectors

(a) NoEntry5.jpg



(b) NoEntry15.jpg

Figure 2: Two examples of no entry sign images which exhibit the merit and limitations of my implementation, and their corresponding gradient magnitude threshold and 2D Hough space images

3.1 Evaluation

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

- A vastly improved F_1 score, as a result of only defining no entry signs detected by the Viola-Jones detector as positive if accompanied by a corresponding circle in the circle Hough transform
- No real improvement to the TPR score, as essentially no extra no entry signs can be detected due to the algorithm used to integrate the two detectors

Table 3: TPR and F_1 score of the Viola-Jones integrated with circle Hough transform no entry sign detector and difference with Viola-Jones no entry sign detector results

	Result		Difference	
Image	TPR	F_1 score	TPR	F_1 score
NoEntry0.jpg	0.50	0.67	+0.50	+0.67
NoEntry1.jpg	1.00	1.00	+0.00	+0.87
NoEntry2.jpg	1.00	1.00	+0.00	+0.92
NoEntry3.jpg	1.00	0.80	+0.50	+0.65
NoEntry4.jpg	1.00	1.00	+0.00	+0.84
NoEntry5.jpg	0.10	0.15	−0.20	−0.02
NoEntry6.jpg	0.50	0.67	+0.50	+0.67
NoEntry7.jpg	0.00	0.00	+0.00	+0.00
NoEntry8.jpg	0.43	0.60	−0.14	−0.02
NoEntry9.jpg	1.00	1.00	+1.00	+1.00
NoEntry10.jpg	0.67	0.80	+0.00	+0.47
NoEntry11.jpg	0.50	0.67	+0.00	+0.56
NoEntry12.jpg	0.13	0.22	−0.25	+0.01
NoEntry13.jpg	0.00	0.00	+0.00	+0.00
NoEntry14.jpg	0.00	0.00	+0.00	+0.00
NoEntry15.jpg	1.00	1.00	+0.50	+0.60
All images	0.42	0.56	+0.02	+0.45

3.2 Detection pipeline

Figure 3 outlines the way I combined evidence in my algorithm. The rationale behind this was as follows:

- The Viola-Jones detector detected approximately 50% of no entry signs, but had a large number of false positives
- 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%

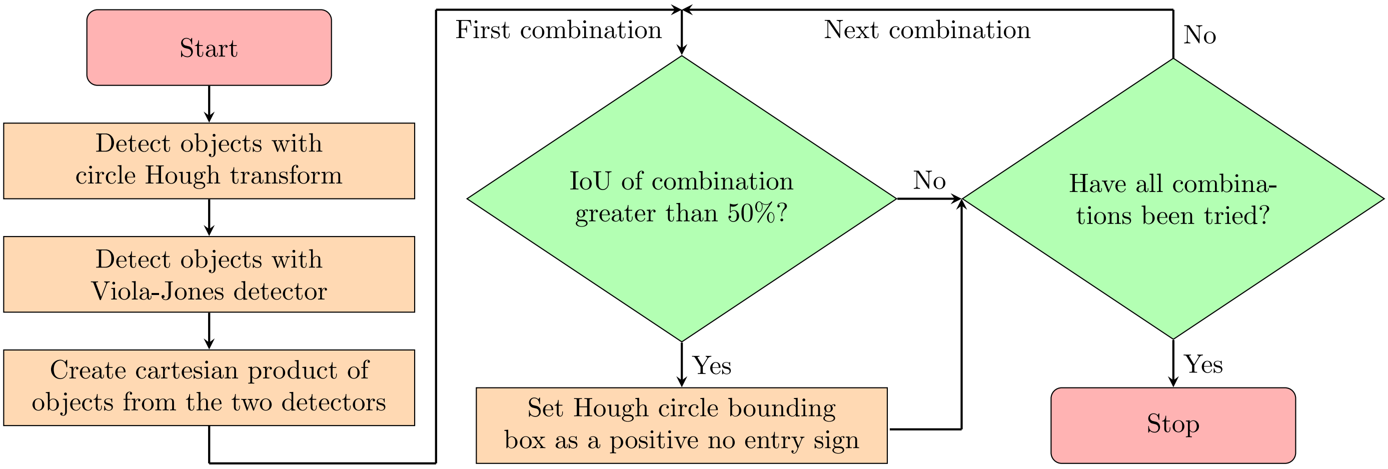


Figure 3: Flow chart detailing my algorithm that integrates Viola-Jones with the circle Hough transform

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/.