Question 1

a.

Implemented 1D Gaussian. See Fig. 2 for plot.

b.

Implemented 2D Gaussian blur filter.

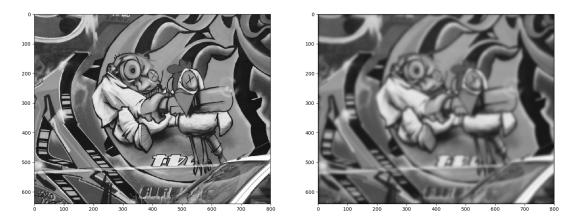


Figure 1: Effect of applying 2D Gaussian blur filter (right) on the example image (left).

c.

We implemented Gaussian function and its derivative. The plots of these functions are shown in Fig. 2. After that we applied them to an image that has only one non-zero pixel at the center. In case of first applying G and then G' we see that the image (with only one non-zero pixel in middle) is blurred in both X and Y directions with a Gaussian distribution (See Fig. 3 top-left). Applying first G and then D' (Fig. 3 top-middle) or first D' and then G (Fig. 3 top-right) has the same effect i.e the order in which G or D' is applied doesn't matter. Both operations compute Gaussian image derivative in Y direction. This also follows from properties of convolution. The effect of using first a Gaussian derivative D and the applying its transpose D' is shown in Fig. 3 bottom-left and allows the edge detection. Finally, we notice that the effect of applying first G' and then D is similar to that of first D' and then G i.e the order of application does not matter and both operations compute Gaussian image derivative in X direction .

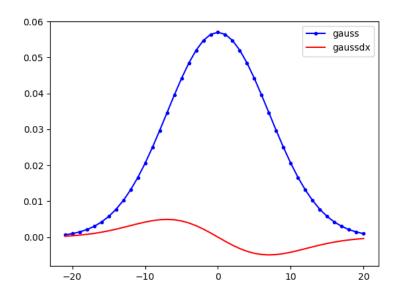


Figure 2: Gaussian blue kernel (blue) and its derivative (red)

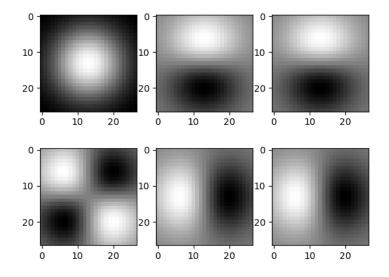


Figure 3: Effect of consecutive apply of G, D, G', and D' filter on image. First row, left: the effect of G followed by G', middle: first G and then D', right: D' followed by G. Second row, left: D followed by D', middle: D then G', right: G' and then D.

d.

Using 2D Gaussian derivatives, we are able to perform edges detection in the images (Fig. 4). This is possible considering the fact that at edges rapid changes in the image intensity function happen. And this can be detected by calculating the Gaussian derivatives of

image.

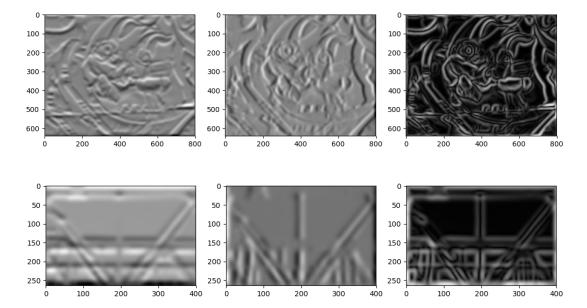


Figure 4: Top: The 2D Gaussian derivatives of graffiti image in x direction (left), y direction (middle), and the output of combining both directional derivatives. Bottom: The 2D Gaussian derivatives of crane image in x direction (left), y direction (middle), and the output of combining both directional derivatives.

Question 2

a.

Comparison of implemented and numpy histogram diagram of an example gray-scale image (Fig. 5). Numpy outputs a histogram which is not normalized, in contrast to the implemented version that at the end normalizes the diagram so that the sum (area under the curve) becomes one.

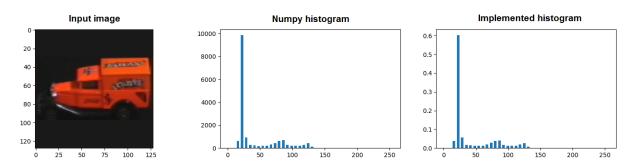


Figure 5: Histogram diagram for pixel's intensities for a gray-scale image. Left: Original input image. Middle: Numpy Histogram, Right: Histogram resulted from our implementation.

b.

Sole implementation task. No explanation required.

c.

Sole implementation task. No explanation required.

Question 3

a.

No explanation required.

b.

The output of show_neighbours is shown in Fig. 6. We can observe that in the selected examples the top match is that of the similar image with a slightly different orientation. The other top-4 images are also very similar in color characteristics and hence histograms features.

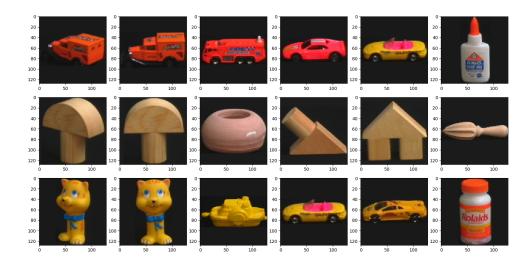


Figure 6: Top-5 neighbours of query images. The query image is in the first column. Nearest 5-neighbours are shown in adjacent 5 columns

c.

The results of our evaluation for all possible combinations of distance measures and histogram types are listed in Tables 1–4 for bin sizes of 10 to 30. We found that the 'RGB' and 'RG' histograms have better performances. This is specially the case, when the 'intersect' and 'chi2' distance measures are employed. On the other hand, the poorest performance is that of 'dxdy' histogram. The performance of 'l2' distance measure is always less than those of 'intersect' and 'chi2', except in the case of 'dxdy' for which have almost similar values. Regarding the number of bins, the best results in average could be archived for 15 and 25 bins (excluding the case of 'dxdy' histogram).

Table 1: Summary of Recognition Rates for gray-value histogram

Histogram	Distance Measure	Bins	Recognition Rate
grayvalue	12	10	43.82%
grayvalue	12	15	40.45%
grayvalue	12	20	38.2%
grayvalue	12	25	40.45%
grayvalue	12	30	40.45%
grayvalue	intersect	10	50.56%
grayvalue	intersect	15	44.94%
grayvalue	intersect	20	51.69%
grayvalue	intersect	25	48.31%
grayvalue	intersect	30	50.56%
grayvalue	chi2	10	52.81%
grayvalue	chi2	15	57.3%
grayvalue	chi2	20	53.93%
grayvalue	chi2	25	57.3%
grayvalue	chi2	30	53.93%

Table 2: Summary of Recognition Rates for RGB-histogram

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Histogram	Distance Measure	Bins	Recognition Rate
$\phantom{aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa$	12	10	60.67%
rgb	12	15	59.55%
rgb	12	20	48.31%
rgb	12	25	50.56%
rgb	12	30	39.33%
$\operatorname{\mathbf{rgb}}$	intersect	10	78.65 %
$\operatorname{\mathbf{rgb}}$	intersect	15	88.76 %
$\operatorname{\mathbf{rgb}}$	intersect	20	79.78 %
$\operatorname{\mathbf{rgb}}$	intersect	25	$\boldsymbol{91.01\%}$
$\operatorname{\mathbf{rgb}}$	intersect	30	82.02 %
$\operatorname{\mathbf{rgb}}$	${ m chi2}$	10	78.65 %
$\operatorname{\mathbf{rgb}}$	${ m chi2}$	15	88.76 %
$\operatorname{\mathbf{rgb}}$	${ m chi}{f 2}$	20	79.78%
$\operatorname{\mathbf{rgb}}$	${ m chi}{f 2}$	25	88.76%
$\operatorname{\mathbf{rgb}}$	${ m chi2}$	30	79.78%

Table 3: Summary of Recognition Rates for RG-histogram

Histogram	Distance Measure	Bins	Recognition Rate
rg	12	10	58.43%
rg	12	15	58.43%
rg	12	20	48.31%
rg	12	25	52.81%
rg	12	30	43.82%
rg	intersect	10	69.66%
rg	intersect	15	83.15%
rg	intersect	20	73.03%
rg	intersect	25	84.27%
rg	intersect	30	73.03%
rg	chi2	10	73.03%
rg	chi2	15	82.02%
rg	chi2	20	73.03%
rg	chi2	25	84.27%
rg	chi2	30	74.16%

Table 4: Summary of Recognition Rates for Gaussian dxdy (derivatives) histogram

Histogram	Distance Measure	Bins	Recognition Rate
dxdy	12	10	22.47%
dxdy	12	15	22.47%
dxdy	12	20	22.47%
dxdy	12	25	23.6%
dxdy	12	30	23.6%
dxdy	intersect	10	21.35%
dxdy	intersect	15	21.35%
dxdy	intersect	20	21.35%
dxdy	intersect	25	22.47%
dxdy	intersect	30	23.6%
dxdy	chi2	10	23.6%
dxdy	chi2	15	23.6%
dxdy	chi2	20	23.6%
dxdy	chi2	25	28.09%
dxdy	chi2	30	34.83%

We include the recognition rates vs. number of histogram bins in Fig. 7. This helps to visualize the comparison between different histogram types for the 3 different distance measures, as it is shown and discussed in Tables 1–4.

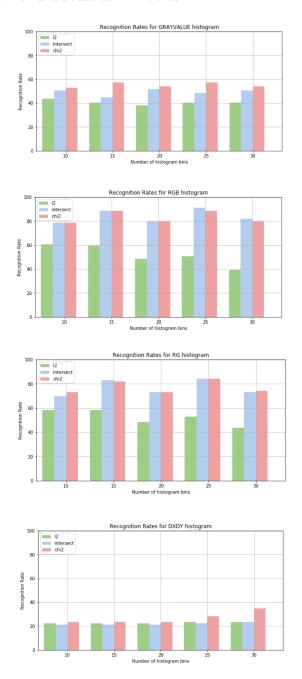


Figure 7: Recognition rates vs number of bins using gray-value (first panel from top), 'RGB' (second panel), 'RG' (third panel), and 'dxdy' (bottom panel) histograms for three 'l2', intersect, and chi2 distance measures. 'l2' distance measure is shown in green, while 'intersect' and 'chi2' measures are in blue and pink, respectively.

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Question 4

a.

No explanation required.

b.

Precision-Recall curves are shown in 8. Depending on the user requirement, an appropriate algorithm can be chosen. However high precision has the cost of recall, while high recall lowers precision. In almost all histogram models, we notice that 'intersect' and 'chi2' has better performance levels than the other models. With similar precision values they show greater recall values. However, 12 delivers a comparable performance in the case of 'dx/dy'.

At lower precision, we see that 'RGB' histogram can deliver higher recall values in comparison to the other histogram. It is followed by 'RG' histogram.

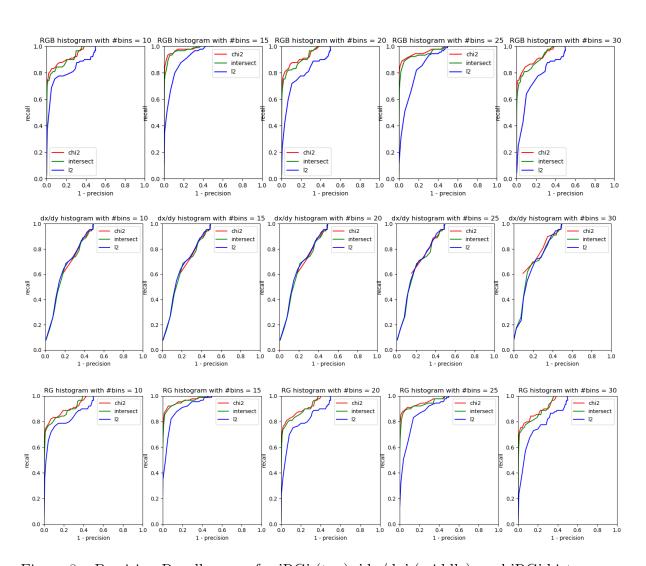


Figure 8: Precision-Recall curves for 'RG' (top), 'dx/dy' (middle), and 'RG' histograms.