

# SRM INSTITUTE OF SCIENCE AND TECHNOLOGY, RAMAPURAM

## DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

### ANSWER KEY SUBMISSION

|  |                          |                                  |            |
|--|--------------------------|----------------------------------|------------|
| Date of Exam & Session                     | 05/05/2023 FN            | Category of Exam                 | CLA3       |
| Course Name                                | Applied Machine Learning | Course Code                      | 18CSE481T  |
| Name of the Faculty submitting             | Dr. M. Mahasree          | Date of submission of Answer Key | 08/05/2023 |
| Department to which the faculty belongs to | CSE                      | Total Marks                      | 50         |

#### PART A (10x1= 10)

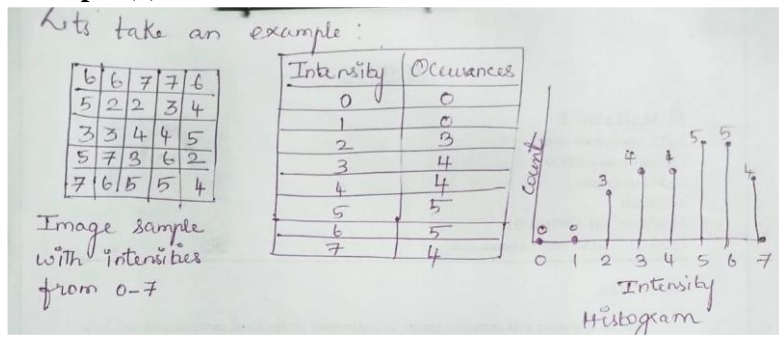
#### ANSWER ALL THE QUESTIONS

| Q.No. | Question  | Marks | CO | BL | PI    |
|-------|---|-------|----|----|-------|
| 1     | Which of the following is the pixel range for grayscale image?<br>a) 1 to 256 <b>b) 0 to 255</b> c) 1 to 255    d) 0 to 256   | 1     | 4  | 2  | 2.2.3 |
| 2     | Gradient computation equation is<br><b>a) <math> G_x + G_y </math></b> b) $ G_x - G_y $ c) $ G_x / G_y $ d) $ G_x \times  G_y $   | 1     | 4  | 1  | 2.1.2 |
| 3     | What is the expanded form of JPEG?<br>a) Joint Photographic Expansion Group<br><b>b) Joint Photographic Experts Group</b><br>c) Joint Photographs Expansion Group<br>d) Joint Photographic Expanded Group   | 1     | 4  | 2  | 2.1.2 |
| 4     | Zero crossing operator appears in which of the following<br>a) First derivative <b>b) Second derivative</b><br>c) Sobel operator    d) Gaussian operator  | 1     | 4  | 1  | 4.1.1 |
| 5     | Laplacian is a<br>a) First order derivative filter    b) Sobel operator<br>c) Canny operator <b>d) Second order derivative filter</b>   | 1     | 4  | 2  | 2.2.3 |
| 6     | Designing a biometric system accuracy with respect to?<br>a) FAR    b) FRR    c) FCR and FRR <b>d) FAR and FRR</b>  | 1     | 4  | 1  | 4.1.1 |
| 7     | Viola-Jones algorithm uses _____ to find the best features and to train a classifier.<br>a) Haar features    b) Integral image<br><b>c) AdaBoost</b> d) Edges and Lines   | 1     | 4  | 1  | 2.1.2 |
| 8     | Which method is used for face recognition?<br><b>a) Holistic matching</b> b) Segmentation<br>c) Canny operator    d) Sobel operator   | 1     | 4  | 1  | 2.1.2 |
| 9     | _____ is the separation of a set of source signals from a set of mixed signals, without the aid of information about the source signals or the mixing process<br>a) Segmentation    b) Acquisition<br><b>c) Blind Source Separation</b> d) Gaussian noise removal | 1     | 4  | 3  | 4.1.1 |

|    |   |   |   |   |       |
|----|---|---|---|---|-------|
| 10 | <p>What PCA does at the end?</p> <p>a) Give you the highest number of features possible, to maximize the efficiency of your Machine Learning algorithm</p> <p>b) Predicts your target with high efficiency</p> <p>c) <b>Reduce dimensionality of the data and create new features from features set given</b></p> <p>d) Create clusters in order to let you know what are the class</p> | 1 | 4 | 2 | 2.1.2 |
|----|---|---|---|---|-------|

**PART B (4x4= 16)**

**ANSWER ANY FOUR OUT OF SIX QUESTIONS**

| Q.No.     | Question  | Marks     | CO          | BL | PI |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
|-----------|---|-----------|-------------|----|----|---|---|----|---|---|----|----|----|---|---|---|---|---|---|---|---|---|-------|
| 11        | <p><b>Define Histogram with an example</b></p> <p><b>Definition (2)</b></p> <p>A histogram of an image is the graphical interpretation of the image's pixel intensity values. It can be interpreted as the data structure that stores the frequencies of all the pixel intensity levels in the image.</p> <p><b>Example (2)</b></p>  <p>Let's take an example:</p> <table><thead><tr><th>Intensity</th><th>Occurrences</th></tr></thead><tbody><tr><td>0</td><td>0</td></tr><tr><td>1</td><td>0</td></tr><tr><td>2</td><td>3</td></tr><tr><td>3</td><td>4</td></tr><tr><td>4</td><td>4</td></tr><tr><td>5</td><td>5</td></tr><tr><td>6</td><td>5</td></tr><tr><td>7</td><td>4</td></tr></tbody></table> <p>Image sample with intensities from 0-7</p> <p>Histogram</p>   | Intensity | Occurrences | 0  | 0  | 1 | 0 | 2  | 3 | 3 | 4  | 4  | 4  | 5 | 5 | 6 | 5 | 7 | 4 | 4 | 4 | 1 | 4.1.2 |
| Intensity | Occurrences   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 0         | 0   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 1         | 0   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 2         | 3   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 3         | 4   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 4         | 4   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 5         | 5   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 6         | 5   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 7         | 4   |           |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 12.       | <p><b>Examine the importance of Sobel filter in edge detection</b></p> <p><b>Definition (2)</b></p> <ul style="list-style-type: none"><li>- The Sobel filter is used for edge detection.</li><li>- It works by calculating the gradient of image intensity at each pixel within the image.</li><li>- It finds the direction of the largest increase from light to dark and the rate of change in that direction.</li></ul> <div><div><p>X – Direction Kernel</p><table><tbody><tr><td>-1</td><td>0</td><td>1</td></tr><tr><td>-2</td><td>0</td><td>2</td></tr><tr><td>-1</td><td>0</td><td>1</td></tr></tbody></table></div><div><p>Y – Direction Kernel</p><table><tbody><tr><td>-1</td><td>-2</td><td>-1</td></tr><tr><td>0</td><td>0</td><td>0</td></tr><tr><td>1</td><td>2</td><td>1</td></tr></tbody></table></div></div> <p><b>Advantages (2)</b></p> <ul style="list-style-type: none"><li>- Simple and time efficient computation</li><li>- Very easy at searching for smooth edges</li></ul> | -1        | 0           | 1  | -2 | 0 | 2 | -1 | 0 | 1 | -1 | -2 | -1 | 0 | 0 | 0 | 1 | 2 | 1 | 4 | 4 | 2 | 2.2.3 |
| -1        | 0   | 1         |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| -2        | 0   | 2         |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| -1        | 0   | 1         |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| -1        | -2  | -1        |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 0         | 0   | 0         |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |
| 1         | 2   | 1         |             |    |    |   |   |    |   |   |    |    |    |   |   |   |   |   |   |   |   |   |       |

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| 13 | <p><b>Analyze the role of vector quantization in image processing</b></p> <p><b>Definition (2)</b><br/>                     A vector quantizer maps <math>k</math>-dimensional vectors in the vector space <math>R^k</math> into a finite set of vectors <math>Y = \{y_i: i= 1, 2, \dots, N\}</math>. Each vector <math>y_i</math> is called a code vector or a <i>codeword</i>. and the set of all the codewords is called a <i>codebook</i>. Associated with each codeword, <math>y_i</math>, is a nearest neighbor region called <i>Voronoi</i> region, and it is defined by:</p> $V_i = \{x \in R^k : \ x - y_i\  \leq \ x - y_j\ , \text{ for all } j \neq i\}$ <p><b>Applications (2)</b><br/>                     Vector quantization is used in many applications such as image and voice compression, voice recognition (in general statistical pattern recognition)</p> | 4 | 4 | 3 | 4.1.2 |
| 14 | <p><b>Build the eye and nose detectors using python</b></p> <p><b>Eye descriptor code (2)</b><br/> <b>Nose descriptor code (2)</b></p> <pre>import numpy as np import cv2 face_cascade = cv2.CascadeClassifier("haarcascade_frontalface_default.xml") eye_cascade = cv2.CascadeClassifier("haarcascade_eye.xml") #save the image(i) in the same directory img = cv2.imread("friends.jpg") gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY) faces = face_cascade.detectMultiScale(gray, 1.3, 5) for (x,y,w,h) in faces:     img = cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)     roi_gray = gray[y:y+h, x:x+w]     roi_color = img[y:y+h, x:x+w]     eyes = eye_cascade.detectMultiScale(roi_gray) for (ex,ey,ew,eh) in eyes:     cv2.rectangle(roi_color,(ex,ey),(ex+ew,ey+eh),(0,255,0),2) cv2.imshow('img',img) cv2.waitKey(0) cv2.destroyAllWindows()</pre>                    | 4 | 4 | 3 | 4.1.2 |
| 15 | <p><b>Elaborate the conversion of dataset from a five- dimensional set to a two-dimensional set</b></p> <p><b>Definition (2)</b><br/>                     Dimensionality reduction, or dimension reduction, is the transformation of data from a high-dimensional space into a low-dimensional space so that the low-dimensional representation retains some meaningful properties of the original data, ideally close to its intrinsic dimension.</p> <p><b>Techniques (2)</b></p>   | 4 | 4 | 3 | 2.1.3 |

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|    |   |   |   |   |       |
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|    | t-SNE and Multidimensional scaling are probably two most popular techniques aimed specifically at dimension reduction for visualization. They have the property of preserving order of distances between data points, i.e. points close to each other in the original space remain close in the 2D representation, and the same applies to points which are far apart. t-SNE is particularly popular among machine learning practitioners, MDS is an older method but can work just fine on smaller datasets. PCA is a more general-purpose method, does not necessarily preserve the distances between points. |   |   |   |       |
| 16 | <b>Define Independent Components Analysis</b><br><b>Definition (4)</b><br>Independent Component Analysis (ICA) is a statistical and computational technique used in machine learning to separate a multivariate signal into its independent non-Gaussian components. ICA assumes that the observed data is a linear combination of independent, non-Gaussian signals. The goal of ICA is to find a linear transformation of the data that results in a set of independent components.   | 4 | 4 | 1 | 2.2.4 |

### PART C (2x12= 24)

#### ANSWER EITHER OR QUESTION IN EACH UNIT

| Q.No. | Question   | Marks | CO | BL | PI    |
|-------|--|-------|----|----|-------|
| 17.a) | <b>Demonstrate the steps involved in Canny edge detector</b><br><b>Definition (2)</b><br>The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. It was developed by John F. Canny in 1986.<br><b>Steps (4)</b><br>The Canny edge detection algorithm is composed of 5 steps:<br>o Noise reduction;<br>o Gradient calculation;<br>o Non-maximum suppression;<br>o Double threshold;<br>o Edge Tracking by Hysteresis.<br><b>Explanation with suitable diagrams and examples (6)</b><br><b>Noise reduction / Smoothing:</b> Blurring of the image to remove noise.<br>o One way to get rid of the noise on the image, is by applying Gaussian blur to smooth it. To do so, image convolution technique is applied with a Gaussian Kernel (3x3, 5x5, 7x7 etc...).<br>o The kernel size depends on the expected blurring effect. Basically, the smallest the kernel, the less visible is the blur. | 12    | 4  | 3  | 2.2.3 |

For example, we will use a 5 by 5 Gaussian kernel.

**Gradient Calculation:** The edges should be marked where the gradients of the image has large magnitudes

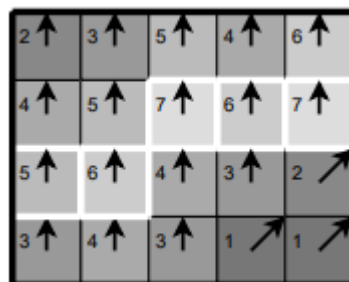
- The Gradient calculation step detects the edge intensity and direction by calculating the gradient of the image using edge detection operators.
- Edges correspond to a change of pixels' intensity. To detect it, the easiest way is to apply filters that highlight this intensity change in both directions: horizontal (x) and vertical (y)
- When the image is smoothed, the derivatives  $I_x$  and  $I_y$  w.r.t.  $x$  and  $y$  are calculated. It can be implemented by convolving  $I$  with Sobel kernels  $K_x$  and  $K_y$ , respectively:

$$K_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, K_y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}$$

Sobel filters for both direction (horizontal and vertical)

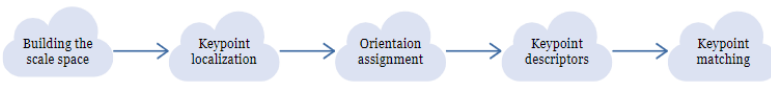
**Non-maximum suppression:** Only local maxima should be marked as edges

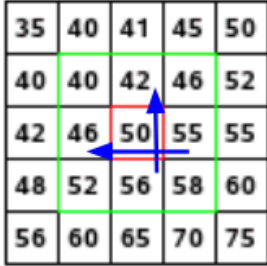
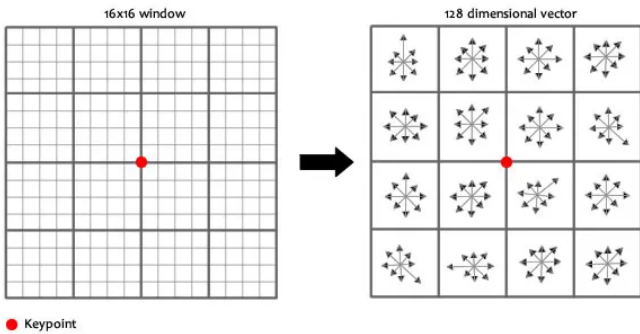
- The purpose of this step is to convert the “blurred” edges in the image of the gradient magnitudes to “sharp” edges.
- Basically this is done by preserving all local maxima in the gradient image, and deleting everything else.
- The algorithm is for each pixel in the gradient image:
  1. Round the gradient direction  $\theta$  to nearest  $45^\circ$  corresponding to the use of an 8-connected neighbourhood.
  2. Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. i.e. if the gradient direction is north ( $\theta = 90^\circ$ ), compare with the pixels to the north and south.
  3. If the edge strength of the current pixel is largest; preserve the value of the edge strength. If not, suppress (i.e. remove) the value.


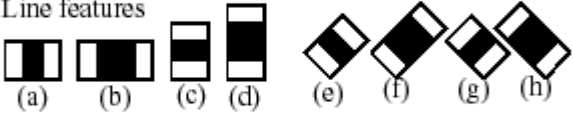
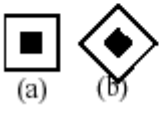


**Double thresholding:** Potential edges are determined by thresholding.

- The Canny edge detection algorithm uses double

|       |   |    |   |   |       |
|-------|---|----|---|---|-------|
|       | <p>thresholding. Edge pixels stronger than the high threshold are marked as strong; edge pixels weaker than the low threshold are suppressed and edge pixels between the two thresholds are marked as weak.</p> <p><b>Edge tracking by hysteresis:</b> Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.</p>  |    |   |   |       |
|       | <b>OR</b>   |    |   |   |       |
| 17.b) | <p><b>Explain SIFT feature detection</b></p> <p><b>Definition (2)</b></p> <ul style="list-style-type: none"> <li>– <b>Scale Invariant Feature Transform (SIFT)</b> was introduced by D. Lowe, a former professor at the University of British Columbia, in the year 2004.</li> <li>– It is a technique for detecting salient, stable feature points in an image.</li> <li>– For every such point, it also provides a set of “features” that “characterize/describe” a small image region around the point.</li> <li>– These features are invariant to rotation and scale.</li> </ul> <p><b>Steps (4)</b></p>  <p align="center">Overview of the SIFT Algorithm</p> <p><b>Explanation with diagram and examples (6)</b></p> <p><b>1. Building the scale space:</b></p> <ul style="list-style-type: none"> <li>– We need to identify the most distinct features in a given input image while ignoring any noise. Additionally, we need to ensure that the features are not scale-dependent.</li> <li>– For every pixel in an image, <b>the Gaussian Blur</b> calculates a value based on its neighboring pixels with a certain sigma value.</li> <li>– After applying the Gaussian blur, the texture and minor details are removed from the image, and only the relevant information, like the shape and edges, remain.</li> </ul> <p><b>2. Key point localization:</b></p> <ul style="list-style-type: none"> <li>– Once the images have been created, the next step is to find the important keypoints from the image that can be used for feature matching.</li> <li>– The idea is to find the local maxima and minima for the images. This part is divided into two steps: <ul style="list-style-type: none"> <li>○ Find the local maxima and minima</li> <li>○ Remove low contrast keypoints (keypoint selection)</li> </ul> </li> </ul> <p><b>3. Orientation Assignment:</b></p> <ul style="list-style-type: none"> <li>– At this stage, we have a set of stable keypoints for the images. The next step is to assign an orientation to each of</li> </ul> | 12 | 4 | 1 | 4.2.2 |

|       |   |    |   |   |       |
|-------|---|----|---|---|-------|
|       | <p>these keypoints so that they are invariant to rotation. It is again divided into two smaller steps:</p> <ul style="list-style-type: none"> <li>○ Calculate the magnitude and orientation</li> <li>○ Create a histogram for magnitude and orientation</li> </ul>  <p><b>4. Keypoint descriptor:</b></p> <ul style="list-style-type: none"> <li>– At this point, each keypoint has a location, scale, orientation. Next is to compute a descriptor for the local image region about each keypoint that is highly distinctive and invariant as possible to variations such as changes in viewpoint and illumination.</li> <li>– To do this, a 16x16 window around the keypoint is taken. It is divided into 16 sub-blocks of 4x4 size.</li> </ul>  <p><b>5. Keypoint Matching:</b></p> <ul style="list-style-type: none"> <li>– Keypoints between two images are matched by identifying their nearest neighbors.</li> <li>– But in some cases, the second closest-match may be very near to the first. It may happen due to noise or some other reasons. In that case, the ratio of closest-distance to second-closest distance is taken. If it is greater than 0.8, they are rejected.</li> <li>– It eliminates around 90% of false matches while discards only 5% correct matches</li> </ul> |    |   |   |       |
| 18.a) | <p><b>Discuss about building of face detector using Haar cascades</b></p> <p><b>Definition (2)</b></p> <p>Viola-Jones Face Detection Technique, popularly known as Haar Cascades, is an Object Detection Algorithm used to identify faces in an image or a real time video. The algorithm uses edge or line detection features proposed by Viola and Jones in their research paper “Rapid Object Detection using a</p>  | 12 | 4 | 2 | 4.3.3 |

|  |   |  |  |  |  |
|--|---|--|--|--|--|
|  | <p>Boosted Cascade of Simple Features” published in 2001. The algorithm is given a lot of positive images consisting of faces, and a lot of negative images not consisting of any face to train on them</p> <p><b>Steps (4)</b></p> <p>The algorithm can be explained in four stages:</p> <ul style="list-style-type: none"> <li>- Haar Feature Selection</li> <li>- Integral Image Representation</li> <li>- Adaboost Training</li> <li>- Implementing Cascading Classifiers</li> </ul> <p><b>Explanation with diagram and examples (6)</b></p> <p><b>Calculating Haar Features</b></p> <p>The first step is to collect the Haar features. A Haar feature is essentially calculations that are performed on adjacent rectangular regions at a specific location in a detection window. The calculation involves summing the pixel intensities in each region and calculating the differences between the sums. Here are some examples of Haar features below.</p> <div style="text-align: center;"> <p>1. Edge features</p>  <p>(a) (b) (c) (d)</p> <p>2. Line features</p>  <p>(a) (b) (c) (d) (e) (f) (g) (h)</p> <p>3. Center-surround features</p>  <p>(a) (b)</p> <p style="color: #4F81BD;">Haar Features</p> </div> <p><b>Creating Integral Images</b></p> <p>Integral images essentially speed up the calculation of these Haar features. Instead of computing at every pixel, it instead creates sub-rectangles and creates array references for each of those sub-rectangles. These are then used to compute the Haar features.</p> |  |  |  |  |
|--|---|--|--|--|--|



|        |  |        |    |    |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
|--------|--|--------|----|----|-------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|----|---|---|----|----|----|----|---|---|----|----|----|----|---|----|----|----|----|----|---|----|----|----|----|----|--|--|--|--|
|        | <div><table><tr><td>1</td><td>2</td><td>2</td><td>4</td><td>1</td></tr><tr><td>3</td><td>4</td><td>1</td><td>5</td><td>2</td></tr><tr><td>2</td><td>3</td><td>3</td><td>2</td><td>4</td></tr><tr><td>4</td><td>1</td><td>5</td><td>4</td><td>6</td></tr><tr><td>6</td><td>3</td><td>2</td><td>1</td><td>3</td></tr></table><p>Input Image</p><table><tr><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td></tr><tr><td>0</td><td>1</td><td>3</td><td>5</td><td>9</td><td>10</td></tr><tr><td>0</td><td>4</td><td>10</td><td>13</td><td>22</td><td>25</td></tr><tr><td>0</td><td>6</td><td>15</td><td>21</td><td>32</td><td>39</td></tr><tr><td>0</td><td>10</td><td>20</td><td>31</td><td>46</td><td>59</td></tr><tr><td>0</td><td>16</td><td>29</td><td>42</td><td>58</td><td>74</td></tr></table><p>Integral Image</p></div>   | 1      | 2  | 2  | 4     | 1 | 3 | 4 | 1 | 5 | 2 | 2 | 3 | 3 | 2 | 4 | 4 | 1 | 5 | 4 | 6 | 6 | 3 | 2 | 1 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 3 | 5 | 9 | 10 | 0 | 4 | 10 | 13 | 22 | 25 | 0 | 6 | 15 | 21 | 32 | 39 | 0 | 10 | 20 | 31 | 46 | 59 | 0 | 16 | 29 | 42 | 58 | 74 |  |  |  |  |
| 1      | 2  | 2      | 4  | 1  |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 3      | 4  | 1      | 5  | 2  |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 2      | 3  | 3      | 2  | 4  |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 4      | 1  | 5      | 4  | 6  |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 6      | 3  | 2      | 1  | 3  |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 0      | 0  | 0      | 0  | 0  | 0     |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 0      | 1  | 3      | 5  | 9  | 10    |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 0      | 4  | 10     | 13 | 22 | 25    |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 0      | 6  | 15     | 21 | 32 | 39    |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 0      | 10   | 20     | 31 | 46 | 59    |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 0      | 16   | 29     | 42 | 58 | 74    |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
|        | <p><b>Cascade Classifier Architecture</b></p> <p>A cascade classifier refers to the concatenation of several classifiers arranged in successive order. It makes large numbers of small decisions as to whether its the object or not.</p> <div><p>Architecture</p></div>   |        |    |    |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
|        | <p align="center"><b>OR</b></p>  |        |    |    |       |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |
| 18. b) | <p><b>Describe the following</b></p> <p><b>i) Kernel PCA</b></p> <p><b>Definition (2)</b></p> <p>Kernel Principal Component Analysis (KPCA) is a technique used in machine learning for nonlinear dimensionality reduction. It is an extension of the classical Principal Component Analysis (PCA) algorithm, which is a linear method that identifies the most significant features or components of a dataset. KPCA applies a nonlinear mapping function to the data before applying PCA, allowing it to capture more complex and nonlinear relationships between the data points.</p> <p><b>Steps (2)</b></p> <ol style="list-style-type: none"><li>1. First we will choose a kernel functions <math>k(x_i, x_j)</math> and let <math>T</math> be any transformation to a higher dimension.</li><li>2. And like PCA, we will find the covariance matrix of our data. But here, we will use kernel function to calculate this matrix. So will compute kernel matrix, which is the matrix that results from applying kernel function to all pairs of data.</li><li>3. We will choose what number of dimensions that we want our</li></ol> | 6<br>6 | 4  | 2  | 4.3.3 |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |    |   |   |    |    |    |    |   |   |    |    |    |    |   |    |    |    |    |    |   |    |    |    |    |    |  |  |  |  |

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|  | <p>reduced dataset to be, let's call it <math>m</math>. Then we will choose our first <math>m</math> eigenvectors and concatenate them in one matrix.</p> <p>4. Finally, Calculate the product of that matrix with your data. The result will be your new reduced dataset.</p> <p><b>Advantages and disadvantages (2)</b></p> <p>One of the advantages of KPCA over traditional PCA is that it can handle nonlinear relationships between the input features, which can be useful for tasks such as image or speech recognition. KPCA can also handle high-dimensional datasets with many features by reducing the dimensionality of the data while preserving the most important information.</p> <p>However, KPCA has some limitations, such as the need to choose an appropriate kernel function and its corresponding parameters, which can be difficult and time-consuming. KPCA can also be computationally expensive for large datasets, as it requires the computation of the kernel matrix for all pairs of data points.</p> <p><b>ii) Blind source separation</b></p> <p><b>Definition (2)</b></p> <p>Blind Signal Separation or Blind Source Separation is the separation of a set of signals from a set of mixed signals without the aid of information (or with very little information) about the signal source or the mixing process. Blind source separation relies on the assumption that the source signals do not correlate with each other. For example, a set of signals may be statistically independent or decorrelated. Because of this independence, the set can be separated into another signal set, such that the regularity of each resulting signal is maximized, and the regularity between the different signals is minimized (i.e. statistical independence is maximized).</p> <p><b>BSS Methods (2)</b></p> <p>Typical methods for blind source separation include:</p> <ul style="list-style-type: none"> <li>Principal components analysis (PCA)</li> <li>Singular value decomposition (SVD)</li> <li>Independent component analysis (ICA)</li> <li>Dependent component analysis (DCA)</li> <li>Short-time Fourier transform (STFT)</li> <li>Degenerate unmixing estimation technique (DUET)</li> <li>W-disjoint orthogonality</li> <li>Joint approximate diagonalization eigen-matrices (JADE)</li> <li>Computational auditory scene analysis (CASA)</li> <li>Constant modulus algorithm (CMA)</li> </ul> <p><b>Applications of BSS (2)</b></p> <p>Signal separation using these blind techniques has found many applications in acoustics, where different sound sources are</p> |  |  |  |  |
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|  | <p>recorded simultaneously either with individual microphones or microphone arrays. These sources may be speech or music, or an underwater signal recorded with passive sonar. In these cases it can be especially useful for noise reduction processing where the signals of interest are isolated from interferes and other noise sources.</p> <p>Other applications for blind source separation include radio communications, where it is used to differentiate the mixtures of communication signals received by antenna arrays. The method has also been applied to image processing as well as used in the processing of biomedical markers like electrocardiogram (EKG/ECG), electromyogram (EMG) and other bio-potentials.</p> |  |  |  |  |
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