International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor (2018): 7.426

Hybrid Image Segmentation Using Mean Shift and Predicate Algorithms

Amit Patel[1,2], Roopesh Kumar Yadav[1], Kavitha Ambrelli[2]

[1]Lecturer, Government Polytechnic Jaunpur, Jagdishpur, Jaunpur, Uttar Pradesh, 222002, India

[2]Rajiv Gandhi University of Knowledge Technologies, APIIIT Nuzvid, Krishna, 500046, Andhra Pradesh, India

Abstract: ***This paper addresses the problem of image segmentation by combing different segmentation algorithms in such a way that the hybrid approach results in feasible segmentation of digital images. Segmentation is generally the first stage in any attempt to analyze or interpret an image automatically. Various segmentation algorithms like graph based, cluster based, mean shift based, intensity based, discontinuity based and predicate based are proposed so as to achieve image segmentation process. Each algorithm finds application in versatile real time problems. Although there are many segmentation algorithms, graph based, mean shift based and cluster based methods are efficient and easier to implement. As part of our work we considered hybrid combination of mean shift and predicate using algorithms. The results of mean shift segmentation are then processed by normal cuts and predicate using algorithm and the results are compared. Mean shift segmentation is robust feature space analysis algorithm capable of storing and saving the discontinuity, edge preservation of image features, it smoothens the image after segmentation. Predicate based algorithms use a function that can be again a segmentation method or a logical predicate based on the image features. Normalized cuts segmentation is the most widely used segmentation algorithm and is parameter sensitive. Cluster based algorithms clusters similar features of image to segment the image.***

Keywords: Hybrid segmentation, Mean shift, Normalized cuts, Predicate using Mean shift**.**

1. Introduction

An image can be divided into sub partitions based on some similar characteristics like intensity, texture and color is called image segmentation. The main objective of segmentation is to change or modify the representation of an image into something easier to analyze and more meaningful. Image segmentation is used to detect objects and boundaries that is lines, curves etc. in an images.

1.1 Introduction about Images

Broadly images are of three types. Binary, Gray and RGB. Binary Image is a black and white image which contains only zeros and ones in each pixel where zero represents black and one represents white [5]. Gray image contains values in between 0 to 255 in each pixel and those are called as gray levels. Every value corresponds to one gray level (gray shade). Each pixel of RGB Image contains three values namely (r,g,b) where $0 \leq r,g,b \leq 255$. Binary and Gray are two dimensional images and RGB is three dimensional image [1][4][6].

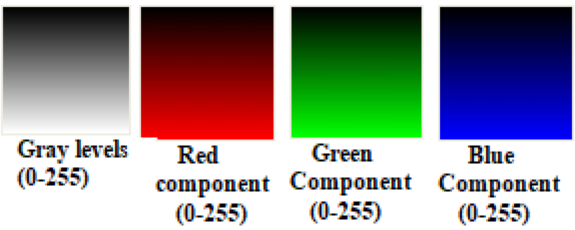


Figure 1.1: Components of color

Figure 1.2: Types of images

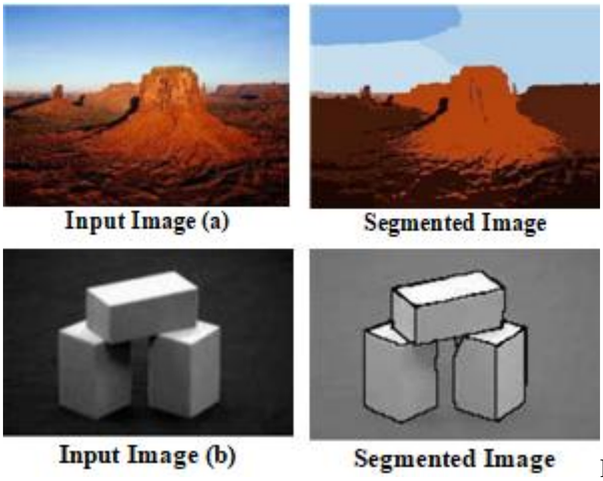
1.2 Introduction about Segmentation

In past years, a lot of efforts have been concentrating on the segmentation process. Segmentation process is an important and mandatory process used in making optical character recognition [7]. Many Numbers of various segmentation techniques are observed in the literature, but there is no method to be considered as prime method for various types of images, they are suitable for only one specific kind of images. Many methods have developed for image segmentation, many methods are relying on two basic properties i.e. Similarity based and Discontinuity based.

In similarity based property, we will group those pixels which are homogeneous in some sense, this includes approaches like region growing, clustering, and region merging and splitting.

In discontinuity based property, the sub division and partitions will be carried out on the bases of abrupt changes in grey levels or intensity levels of an image, in this method our main interest on the identification of isolated edges, lines and points.

Licensed Under Creative Commons Attribution CC BY



Fig

Figure 1.3: Segmentation Example

The paper is structured as follows. Excluding introduction, there are four sections in this paper. Section 2 highlights the overview of different image segmentation techniques. In Section 3 we discussed about the hybrid model segmentation technique, its advantages and disadvantages. Section 4 discusses the implementation and compared different hybrid segmentation technique with other techniques. We concluded with the section 5.

2. Related Work

This section discusses about the different segmentation technique.

2.1 Graph Based Segmentation

Graph Based Segmentation represents images as fully connected graphs. Each pixel is represented using a node and the similarity between each pair of vertices let (i, j) is the edge weigh $W_{i, j}$.

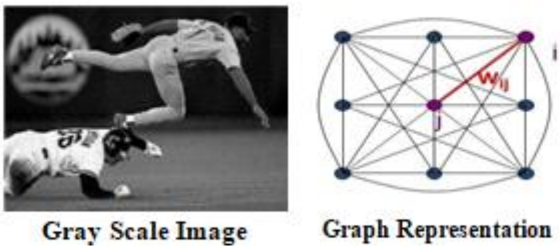


Figure 2.1: Graph Based Representation

Segmentation is done using graph cuts. A cut in a connected graph is a set of vertices those removals will make the graph disconnected. Finding a minimum cut gives us segmentation.

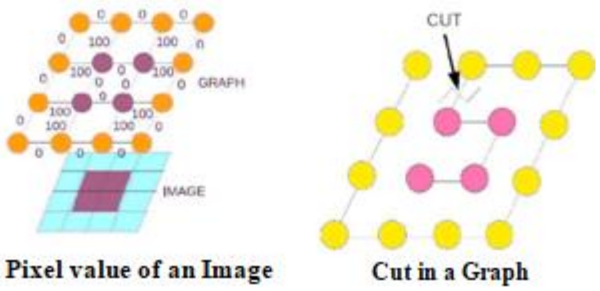


Figure 2.2: Graph Cut Representation

2.2 Normalized Cut Segmentation

Given a graph G = (E, V, W), where V represents the set of nodes, and E represents set of edges which connects the nodes. A pair of nodes v and u is connected by an edge which is weighted by w (v, u) = w (u, v) ≥ 0 to determine the dissimilarity between the pair of nodes. W is an edge affinity matrix with w (u, v) as its (u, v)th element. They can partition the graph into two disjoint sets A and B (V- A) by just removing the edges which are connecting the two parts. We can compute the degree of dissimilarity between the two sets as a total weight of the removed edges. This nearly related to a mathematical formulation of a cut [2].

$$\text{Cut}(A, B) = \sum_{p \in A, q \in B} Cp, q \qquad (1)$$

Where $C_{p,q}$ represents the cost of cut between vertex p and q.

The optimal bi-partitioning is the one which minimizes cut value in the graph. We have been well studied this problem of finding the minimum cut. However, the criteria of minimum cut favors grouping small sets of isolated nodes because above cut defined have not contained any intragroup information. Also, usually the minimum cut gives over clustered results when it will apply recursively. Several modified graph partition have been motivated from this which includes N_{cut} also [2].

Normalizing size of segments is defined mathematically as

$$N_{cut}(A, B) = \frac{Cut(A,B)}{Volume(A)} + \frac{Cut(A,B)}{Volume(B)} \qquad (2)$$

Where, volume (A) = sum of costs of all edges that touch A. We try to find a cut that penalizes the large segments Recursive normalized cuts procedure is as followed [2].

1) Given an image or image sequence, set up a weighted graph: G=(V, E) Vertex for each pixel Edge weight for nearby pairs of pixels
2) Solve for eigenvectors with the smallest eigenvalues: $(D - W)y = \lambda Dy$ Use the eigenvector with the second smallest eigenvalue to bipartition the graph Note: this is an approximation
3) Recursively repartition the segmented parts if necessary.

2.2.1. Advantages

a) Generic framework, can be used with many different features and affinity formulations.
b) Provides regular segments.

2.2.2. Drawbacks

a) Need to choose number of segments
b) High storage requirement and time complexity
c) Edges of the images are not preserved
d) Parameter sensitive so calculation becomes difficult.

2.3 Mean Shift Image Segmentation

Mean shift (MS) algorithm is a nonparametric statistical method for seeking the main mode of a point sample distribution [3].

Licensed Under Creative Commons Attribution CC BY

Given n points data set $\{X_i\}$ i = 1…n in the d - dimensional space R_d , the multivariate kernel density estimator with kernel $K(x)$ and window radius (bandwidth) h is given by

$$f(x) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \quad (3)$$

The *modes* of this density, where density $f(x)$ takes local maxima, are located among the zeroes of the gradient

$$\nabla f(x) = 0 \quad (4)$$

We denote $g(x) = -k'(x)$

Where $k(x)$ is the profile of the kernel function $K(x)$

If $g(x)$ is some profile of a kernel function $G(x)$, G is called the shadow of kernel K.

An image is typically represented as a 2-dimensional lattice of r -dimensional vectors (pixels), where r is 1 in the grey-level case, 3 for color images. The space of the lattice is known as the *spatial domain* while the grey level or the color is represented in the *range domain*. However, after a proper normalization with h_s and h_r , global parameters in the spatial and range domains, the location and range vectors can be concatenated to obtain a spatial range domain of dimension $d = r + 2$. The mean shift segmentation in the spatial-range domain is implemented on the mean shift filtered images.

2.3.1. Advantages

a) Storing and saving discontinuity.
b) Smoothing of image followed by image segmentation.
c) The features present in the whole image are restored due to its edge storing and saving property.

2.4. Predicate Algorithm Using K-Means Clustering

K-means clustering is an algorithm to classify or to group your objects based on attributes/features into K number of group. K is positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. The basic step of k-means clustering is simple. In the beginning, we determine number of cluster K and we assume the centroid or center of these clusters. We can take any random objects as the initial centroids or the first K objects can also serve as the initial centroids.

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1) Pick K cluster centers, either randomly or based on some heuristic.
2) Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center.
3) Re-compute the cluster centers by averaging all of the pixels in the cluster.
4) Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters).

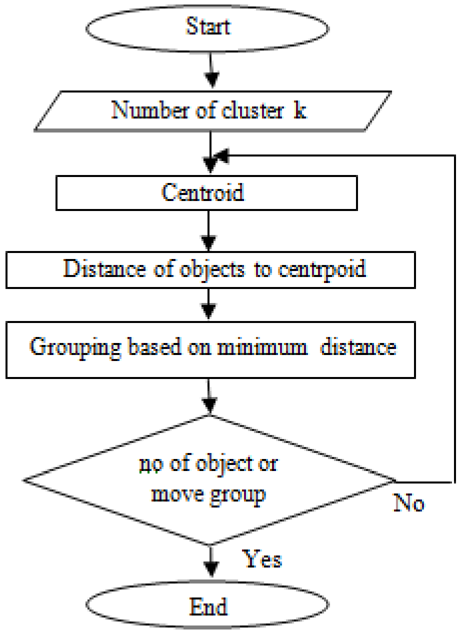


Figure 2.3: Iterative steps of K-Means Cluster

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, Intensity, texture, and location, or a weighted combination of these factors. It can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

3. Proposed Hybrid Model of Segmentation

There are some hybrid image segmentation models available based on the integration of edge and region-based techniques through the morphological watershed transform. The foremost step of any hybrid segmentation approach is to reduce the noise corruption present in the image. There exist some considerable drawbacks which makes the approaches quite complex. The problem with watershed algorithm is over-segmentation, this is due to the high sensitivity of the watershed algorithm to the gradient image intensity variations, and, consequently, depends on the performance of the noise reduction algorithm.

3.1 Proposed Model

Proposed model is a simple variant of mean shift algorithm. We considered hybrid combination of mean shift and predicate using algorithms. Mean shift segmentation is popular for its edge preserving property giving better segmentation results. The results of mean shift segmentation are then processed by normal cuts and predicate using algorithm. As we know mean shift segmentation is simple, efficient and non-parametric feature space analysis algorithm. There exit much scope of smoothening of segmented regions and edge separation which makes us to go for feature extraction also.

Licensed Under Creative Commons Attribution CC BY

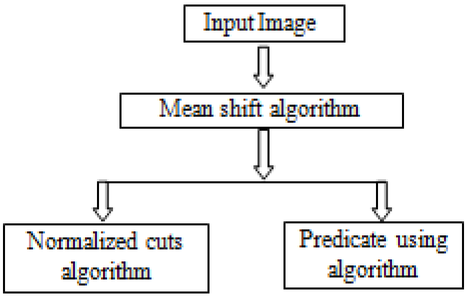


Figure 3.1: Hybrid Segmentation Model

4. Implementation

We applied existing segmentation technique but on preprocessed images.

The image is passed by two phases:
Phase 1. Preprocessing
Phase 2. Segmentation

In phase 1 we used mean shift algorithm, by using the mean shift algorithm we form segmented regions that preserve the desirable discontinuity characteristics of the image. The mean shift algorithm is a robust feature-space analysis approach which can be applied to discontinuity preserving smoothing and image segmentation problems. It can significantly reduce the number of basic image entities, and due to the good discontinuity preserving filtering characteristic, the salient features of the overall image are retained. Image Region Segmentation Based on Mean Shift

The computational module based on the mean shift procedure is an extremely versatile tool for feature-space analysis. In [3], two applications of the feature-space analysis technique are discussed based on the mean shift procedure: discontinuity preserving filtering and the segmentation of gray level or color images.

In this section, we present a brief review of the image segmentation method based on the mean shift procedure [3].

We consider radially symmetric kernels satisfying $K(x) = c_{k,d}\, k(\|x\|^2)$, R where constant $c_{k,d} > 0$ is chosen such that $\int_0^\infty K(x)dx = \int_0^\infty c_{k,d}\, k(\|x\|^2)dx = 1$ [note that $k(x)$ is defined only for $x \geq 0$]. $k(x)$ is a monotonically decreasing function and is referred to as the profile of the kernel. Given the function $g(x) = -k'(x)$ for profile, the kernel $G(x)$ is defined as $G(x) = c_{g,d}\, g(\|x\|^2)$.

For n data points x_i, $i = 1,\ldots,n$; in the d-dimensional space Rd, the mean shift is defined as [3].

$$a = \sum_{i=1}^{n} x_i\, g\left(\left\|\frac{x - x_i}{h}\right\|^2\right) \quad (5)$$

$$b = \sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right) \quad (6)$$

$$m_{h,G(x)} = \frac{a}{b} - x \quad (7)$$

Where x is the center of the kernel (window), and h is a bandwidth parameter. Therefore, the mean shift is the difference between the weighted mean, using kernel G as the weights and x as the center of the kernel (window). The mean shift method is guaranteed to converge to a nearby point where the estimate has zero gradient. Regions of low-density values are of no interest for the feature-space analysis, and in such regions, the mean shift steps are large. On the other hand, near local maxima, the steps are small, and the analysis is more refined.

The mean shift procedure, thus, is an adaptive gradient ascent method. The center position of kernel G can be updated iteratively by

$$c = \sum_{i=1}^{n} x_i\, g\left(\left\|\frac{y_j - x_i}{h}\right\|^2\right) \quad (8)$$

$$d = \sum_{i=1}^{n} g\left(\left\|\frac{y_j - x_i}{h}\right\|^2\right) \quad (9)$$

$$y_{j+1} = \frac{c}{d}, j = 1,2 \ldots \ldots \quad (10)$$

Where y_1 is the center of the initial position of the kernel. Based on the above analysis, the mean shift image filtering algorithm can be obtained. First, an image is represented as a 2-D lattice of p- dimensional vectors (pixels), where p = 1 for gray-level images, p = 3 for color images, and $p \geq 3$ for multispectral images. The space of the lattice is known as the spatial domain, while the graph level and the color of spectral information are represented in the range domain.

For both domains, the Euclidean metric is assumed. Let xi and z_i, I = 1,..,n, respectively, be the d-dimensional (d = p + 2) input and the filtered image pixels in the joint spatial-range domain. The segmentation is actually a merging process performed on a region that is produced by the mean shift filtering. The use of the mean shift segmentation algorithm requires the selection of the bandwidth parameter h = (h_r, h_s), which, by controlling the size of the kernel, determines the resolution of the mode detection. In phase 2 we have used predicate using segmenting algorithm. The input images may be of different sizes and resolutions as well, for considering any input as generalized one we resized input image to rows of 256 and columns will automatically adjust, The Mat Lab resize function works as follows.

I = imresize(input,[256 NaN]); (11)

4.1 Mean shift image segmentation

As we discussed earlier the input image is treated initially using Mean Shift Segmentation algorithm. This step smoothens the segmented regions and edges are preserved as well. The bandwidth parameter for mean shift.

Bandwidth = 0.2

Licensed Under Creative Commons Attribution CC BY

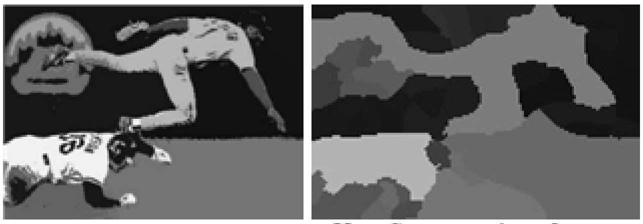
Input Image Mean Shift Segmented

Figure 4.1: Mean shift segmentation

4.2 Applying Hybrid Segmentation model

The results of mean shift segmentation are available and the later part is comparative application of normal cuts segmentation and predicate using K-Means clustering algorithms on output of Mean Shift Algorithms. We start with processing the output image using Ncut segmentation and the same output is processed applying predicate using K-Means clustering algorithm. We recorded the results comparatively

4.3 Processing with Normalized cuts segmentation

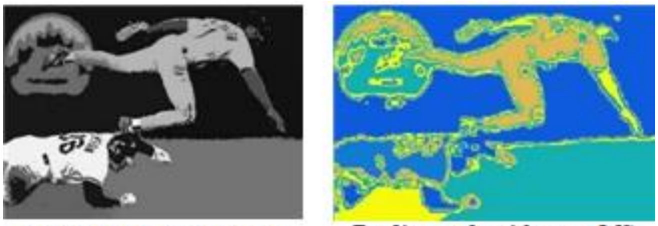


Mean Shift Segmented Ncut Segmentation of mean MS

Figure 4.2: Ncut Segmentation of Mean Shift

4.4 Processing using K-Means Cluster

Next out procedure continues by the application of predicate using K-Means Cluster Algorithm on output of mean shift Algorithm. The results are as follows



Mean Shift Segmented Predicate algorithm on MS

Figure 4.3: Predicate using algorithm of Mean Shift

4.5 Example of hybrid model

Figure 4.4 and Figure 4.5 shows another example of Mean Shift, Predicate Using Algorithm and combination of mean shift and predicate using algorithm outputs.

Input Image (a) Mean Shift Segmented

Figure 4.4: Predicate using algorithm of Mean Shift

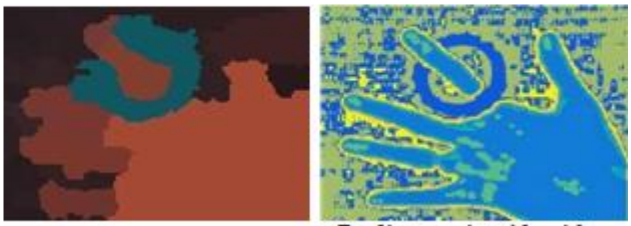
Predicate Using Algorithm Predicate using algorithm on Mean Shift

Figure 4.5: Predicate using algorithm on Mean Shift

5. Results

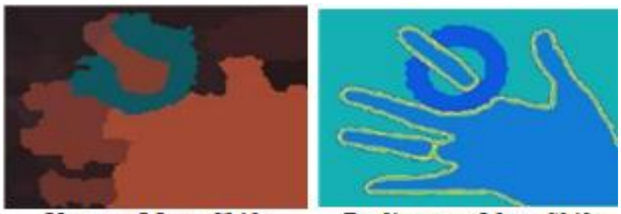
The model tested against various images of different sizes and resolutions, and the results are considered along with CPU execution time taken by each segmentation algorithm to process the image.

Figure 5.1: Predicate using algorithm of Mean Shift



Normal Cut Image Predicate using Algorithm

Figure 5.2: Predicate using algorithm of Mean Shift



Ncut on Mean Shift Predicate on Mean Shift

Figure 5.3: Hybrid Segmentation model on a colored Image

Licensed Under Creative Commons Attribution CC BY

5.2 Comparative Results

Segmentation Algorithm	*CPU Execution Time(t) in seconds*			
	Fig. 1.3 (a)	Fig 4.4 (a)	Fig 4.1	Fig 5.1
Mean shift	24.91	33.38	25.68	17.8
Normalized cuts	8.72	10.74	7.2	6.35
Predicate	1.74	1.92	1.59	1.44
Ncut on mean shift	9.69	12.63	7.86	6.35
Predicate on MS	1.44	1.8	1.15	1.6

6. Conclusion

We implemented hybrid variant of Mean Shift Segmentation which has practical application in satellite image processing and video surveillance. By this process we can easily extract boundaries of images which can be useful in many areas of image processing. Boundaries extraction can be useful in recognition and segmentation tasks. Boundary Extraction has used in many wide range of fields like defense, health care, image retrieval and data mining, human-computer interaction, scientific image analysis, surveillance and security, industrial and personal robotics, manufacturing, and transportation.

References

[1] Amit Patel, "Enhanced Multi Secret Image Sharing Scheme for Gray and RGB Images", International Journal of Science and Research (IJSR), ijsr.net, Volume 5 Issue 2, February 2016, 1867 – 1871.

[2] J. Shi and J. Malik, Normalized cuts and image segmentation, IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 8, pp. 888905, Aug. 2000.

[3] D. Comaniciu and P. Meer, Mean shift: A robust approach toward feature space analysis, IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 5, pp. 603619, May 2002.

[4] Patel, Amit, Lakshmi Pras0anna Mutyala. "Secure way of sharing secret images using LSB and MSIS," International Journal of Advanced Research in Computer Science [Online], 8.1 (2017): 53-56. (Web. 6 Mar. 2019).

[5] Patel, Amit, and Sai Sudha Melapu. "New Secret Message Sharing scheme using MSIS scheme and LSB algorithm." 2016 International Conference on Computer Communication and Informatics (ICCCI). IEEE, 2016.

[6] Amit Patel, Sai Prasad Kousika VNH, "More Secure Way of Sharing Secret Text Message", International Journal of Science and Research (IJSR), https://www.ijsr.net/archive /v5i12/v5i12.php, Volume 5 Issue 12, December 2016, 1563 - 1568.

[7] Patel A., Sukumar B., Bhagvati C. (2018) SVM with Inverse Fringe as Feature for Improving Accuracy of Telugu OCR Systems. In: Sa P., Sahoo M., Murugappan M., Wu Y., Majhi B. (eds) Progress in Intelligent Computing Techniques: Theory, Practice, and Applications. Advances in Intelligent Systems and Computing, vol 518. Springer, Singapore.

Author Profile

Amit Patel received his B.Tech degree in Computer Science from Dr. K N Modi Institute of Engineering and Technology in 2012 and M.Tech degree in Artificial Intelligence from School of Computer and Information Sciences, University of Hyderabad in 2014. He worked as Assistant Professor in Department of Computer Science in Rajiv Gandhi University of knowledge Technologies, Nuzvid. Currently working as Lecturer, Government Polytechnic Jaunpur, Jaunpur, Uttar Pradesh.

Roopesh Kumar Yadav received his B.Tech degree in Computer Science from Institute of Engineering And Technology, CSJM University, Kanpur in 2006 and M.E degree in Software Systems from Birla Institute of Technology And Science, Pilani Rajasthan in 2009. He worked in Intel Bangalore and Aricent Technologies Gurgaon, currently working as Lecturer, Government Polytechnic Jaunpur, Jaunpur, Uttar Pradesh.

Kavitha Ambrelli received her B.Tech degree in Computer Science and Engineering from Rajiv Gandhi University of Knowledge and Technologies, IIIT Nuzvid, Nuzvid, Andhra Pradesh in 2018.

Licensed Under Creative Commons Attribution CC BY