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A comprehensive study on image segmentation

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Abstract

With the evolution of computing, there is an acceleration in the use of image processing techniques in various applications, image segmentation, a procedure in which images are divided into many segments and with this, it's possible to identify the region of interest from an image. The main idea of this comprehensive study is to present various existing segmentation techniques.

Keywords: *Image Segmentation; Thresholding; Clustering; Soft Computing Approaches; Region-Based Segmentation.*

1. Introduction

The main objective of the image processing is to fetch information which is important from the specified image in such a manner that it doesn't make any changes in the other image features. Preprocessing of the image is the foremost and important step [1], [2] after performing preprocessing you can do any kind of operation on that resultant image. One of the most important stage in image processing is image segmentation. Radiology can be defined as a series of tests used to create images of the body parts which helps us to diagnose, screen and monitor the health condition.
There are various types of radiology such as X-rays, CT scan (computed tomography scan), MRI (magnetic resonance imaging) and ultrasound. Health professionals use these radiology imaging types for learning what is happening inside your body.

2. Common types of imaging include:

CT Images also referred as CAT scan which is responsible for generating images by combining multiple X-ray projections taken from different angles. CT images give an accurate view of certain body parts like lungs, heart, bones and blood vessels. Health professionals also consider this imaging method for diagnosing many cancers. Magnetic Resonance Imaging (MRI) is used to create detailed images of organs and tissues which is generated using radio waves and a magnetic field. By differentiating normal and diseased images of the body it is proven to effectively diagnose a number of conditions. Positron Emission Tomography (PET): Positron Emission Tomography (PET) is a nuclear imaging technique which generates images by making use of scanner and a small amount of radiopharmaceuticals is injected into the veins of patients. These images provide information to health professionals about the functioning of the various tissues and organs. PET-CT, to take more accurate decisions health professionals combine PET and CT which generates a superposed image. Ultrasound, it is also referred as sonography and it's working will be like, it sends sound waves into the body and based on the echoes coming from the body it creates an image.

3. Image segmentation

Image Segmentation, it's a process where an image is fragmented into multiple segments, each segment denotes some useful information in terms of color, intensity, texture to the user. Color, intensity, and texture are very important properties of an image with which each segment can be differentiated by assigning different color, intensity and texture values to every pixel.
Image segmentation and their types and the, applications of image segmentation are medical image processing to diagnose the presence of tumors and for classification of cancer cells etc. Image segmentation technique selection is done based on the application like noise removal in the bio-medical images, image retrievalssatellite image, machine vision, military, computer vision [3], [4], feature extraction and object recognition.
There are Humpty number of image segmentation techniques and among various techniques, there is no one method that can be used with all types of images, for this reason segmentation techniques are categorized into three types they are classical, AI and Hybrid techniques the following figure shows various image segmentation techniques.

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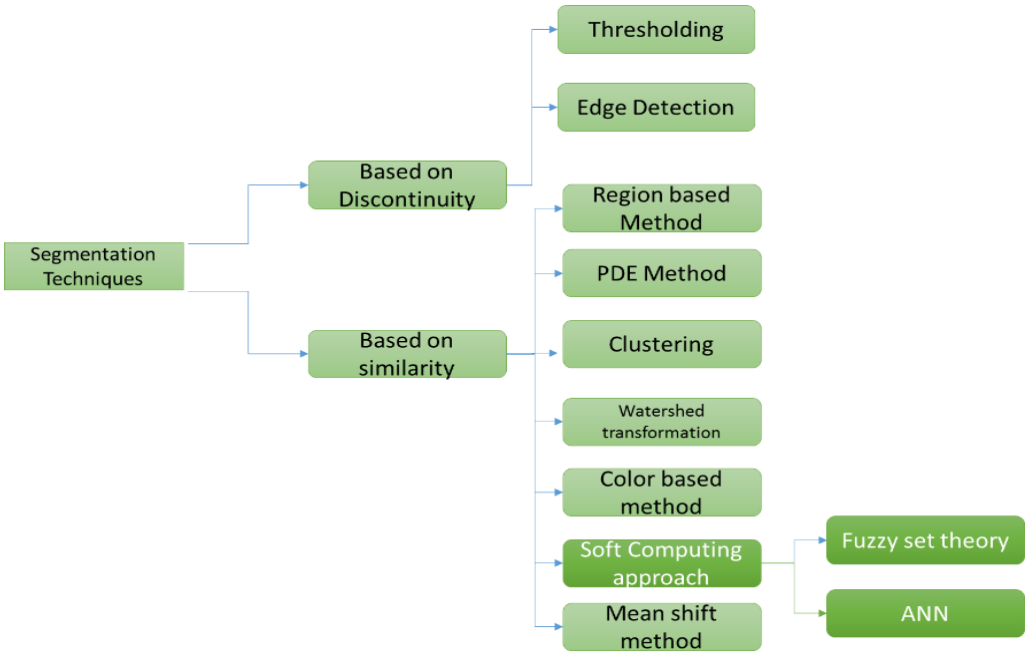


Fig. 1: Segmentation Techniques.

4. Segmentation techniques

4.1. Based on Discontinuity

- Thresholding based image segmentation

In [5] author Proposes an image segmentation model which will be performed in a two stage manner, in the first stage Mumford-shah model is used to obtain smooth approximation in the input image's target region and in the next stage thresholding is performed using the approximation obtained in the first stage to retrieve object of interest. Artificial bee colony optimizer is modified by using a set of optimal foraging strategies for image segmentation in order to balance the tradeoff between exploration and exploitation was proposed by author in [6]. In [7] author presents infrared segmentation method which is based on clone threshold an growing immune field. In [8] a method for extracting thresholding was proposed by the author which is based on VMD(variational mode decomposition) and the improved version of this will decompose the histograms into various sub modules in order to minimize the objective function of otsu's and two methods are used to extract the thresholds they are cross point and minimum point search methods. A reviewed Two Dimensional fuzzy fisher is presented by the author in [9].

In [10] A combined distribution function is fitted into the images regularized histogram which will be representing a class of pixels by the author. Author in [11] presents a segmentation technique which is completely based on grey-wolfkoptimizer. Author presents a segmentation technique for segmenting tongue images using thresholding and also uses RGB color models in [12]. In [13] an image segmentation threshold value determining method, comprising: defining a plurality of image regions of a first sensing image; determining a first, a second part image segmentation threshold values according to a first, second image regions of the image regions; performing a first, a second image segmentation operation to the first sensing image according to the first, the second part image segmentation threshold values to acquire a first, a second segmented images; and selecting one of the first part image segmentation threshold value and the second part image segmentation threshold value as the first image segmentation threshold value according to the first segmented image and the second segmented image. 3D Otsu based thresholding algorithm is proposed and for medical image segmentation the author also present an multi-scale image representation in [14].

A modified firefly algorithm was proposed for color image segmentation by author in [15] which is used to find the optimal multilevel threshold. And the performance of modified firefly algorithm is compared with firefly algorithm, levy search based firefly algorithm, Brownian search based firefly algorithm. To segment images accurately the proposed level set approach in [16] which uses histogram analysis and the proposed method is compared with LBM (Lattice Boltzmann Method) by the author in the same work. Author in [17] For image segmentation, to find the optimal multilevel thresholding author compares the ability of moth-flame optimization and whale optimization algorithm. In this article [18] To solve image segmentation problem a threshold selection technique is proposed by the author which is fast and context-sensitive, Image energy curve is used in this technique. This technique will work in two stages, in the first stage from the energy curve select the thresholds which are middle of two peaks and then in the second stage use GA (genetic algorithm) to detect the optimal thresholds from their defined bounds. Dynamic inertia weight is used with particle swarm optimization to select optimal threshold to improve the accuracy of medical image segmentation is proposed in [19].

Thresholding algorithm proposed by Wellner's is used along with PSO algorithm to segment ultrasound image of liver cyst in [20]. Multi-level and bi-level thresholding techniques are used for high resolution image segmentation which is proposed by author in [21]. In This article [22] Author presents a satellite image segmentation mechanism in which, (Maximum Renyi entropy) MRE based multi-level thresholding is used to improvise object and background separation in the hyper-spectral satellite images. A segmentation algorithm in which MPSO (modified particle swarm optimization) is combined with 2D K-L(Kullback-Leibler) divergence in order to improve the accuracy of multilevel thresholding in image segmentation [23]. In [24] to better visualize rock fractures author presents a TILT method (Technique of Iterative Local Thresholding) which is used to analyze 3D xCT images In this paper [25] author improves CT liver image segmentation by further improving the level set method usage in the preprocessing phase in liver edge detection. In paper [26] author presents a segmentation method for satellite images called MABC (modified artificial bee colony) algorithm and to find optimal multilevel thresholds author uses various objective function over MABC, in this paper [27] Author proposes an quantum-behaved PSO algorithm which is dynamic in nature and context vector will be updated when a particle completes a cooperation operation with rest of the particles.

In this article [28], author presents a multilevel thresholding technique for color satellite image segmentation . In the article [29] author says that to do segmentation of images thresholding of histogram is one of the most important technique. To obtain optimal multi-level threshold author presents a BDE algorithm (beta differential evolution) based on Otsu criterion over a given image, In this article [30] a MPSO algorithm is proposed by the author, adaptive population and adaptive inertia are introduced into MPSO to improve the performance of PSO. To master the downside of thresholding mechanisms in the situation of corrupted images, author propose a multi-region thresholding methodology which gives better performance in segmentation of corrupted images was proposed by author in [31]. By making use of wavelet domain gray stretch in this article [32] author presents a binarization technique.

A new image segmentation algorithm was proposed by author which mixes 2D Otsu with enhanced Firefly algorithm to solve the downside of 2D image threshold segmentation is proposed by the author in [33]. Author in [34] propose 2D MRI image segmentation. In this article [35] author propose an energy curve based multilevel thresholding by merging thresholding criteria with evolutionary computational algorithms. Histogram dependent, Mean, EDGE maximization, visual technique, P-tile are the various thresholding techniques used by researchers, In [36] author uses the before said techniques on the satellite images, to select the segmented Image. In this article [37] a threshold based segmentation method was proposed by the author which uses PSO and 2D Otsu algorithm.

- Edge detection based image segmentation

Edge Detection is considered as the most important and basic step in image segmentation according to author in [38]. Change in intensity is used by this technique to split object of the image and background of the image. Gray histogram is the foremost important technique for edge detection and gradient is the next technique for edge detection which is used mostly as said by the author in [39]. Based on region growing and edge detection author propose a new image segmentation technique in [40] .There are two types of Edge Detection techniques

- Parallel techniques
- Sequential techniques

Based on similarity

- Region based image segmentation

A novel programmed segmentation technique based on pattern matching and enhanced region growing is presented by the author in [41] technique will be consisting of 3 steps in the first step from the CT image bone is removed and in the second step pattern/template matching technique is used to identify lung tumors and in the last step seeds are retrieved and used to make the segmentation process fully automatic. In this paper [42] author provides technique for segmenting tissue in a CT image to converge region of interest into one of the tissue classes. In this paper [43] Author presents an CRF model which is hybrid in nature for segmentation of radar images basing on the generation of super pixels the proposed model splits SAR images into segments namely homogeneous regions and heterogeneous regions and edges. In this article author agrees and presents [44] For segmenting imagery topic models are used widely. To address the downside in the visual world representation, author in article [45] propose a structure-aware tagging technique by means of happening and cooccurrencepprobability ofccolor values for each early label in a united outline.

In this article [46] Image segmentation, the piercing of an image into groups of same pixels built on the region of interest(ROI), is a general stage for most of the radical image processing and it can also be used in object recognition. Image segmentation basically has an impact on the altogether enactment of all automated image examination scheme due to highest rank of its eminence. Image segmentation can be executed by repetitively splitting the entire image or by combining together a big number of small regions till a listed condition is achieved. Thresholding is a traditional, easy and of great importance technique in gray scale image segmentation. In this paper [47], author propose an ultra-sonographic image segmentation using thresholding based on minimization of function of bi-entropy to detect cholecystitis and gallstones in the gallbladder, author in article [48] propose a novel technique to segment ultrasound images to diagnose the gallstones in gallbladder. In this paper author [49] presents a novel technique which is based on Spectral Cluster and Region Growing for synthetic aperture radar image segmentation is introduced. In this paper [50] author present a novel technique for image segmentation which contains single objects and multiple objects and this method is very effective and robust. To enhance the image 2D gabor filter is used which will make it easy to extract the regions. Morphological operations are applied over the transition regions to retrieve contours and regions of objects, and last but not least object extraction is done from the object region.

In this article [51] author proposed an Image segmentation technique which is hybrid in nature and is also robust which segments single-objects by manipulating noticeable transition region. In this paper [52] supervised semantic label prediction and unsupervised region creation are the two important observation made by the author to propose a semantic image segmentation which is a region based technique. Author in This study [53] Concerned about the usage of color alone property for the reduction of the system difficulty. As an answer for ranking problem similarity measure existing between neighboring regions can be used which is based on the mathematical morphology technique. In this paper [54] author presents a new technique for image segmentation which is based on the idea of multi-scale stochastic regional texture and the appearance template [55]. An unsupervised technique for segmenting image based on texture data and level-set techniques was proposed by author in [56]. By making use of mean-shift based clustering algorithm, a new region-based image segmentation technique was proposed by author in [57]. Firstly, this technique extracts color, texture and location features of each pixel of an image and then it creates clusters using mean-shift clustering approach.

In this article [58] author proposed a method which improves the normalized cut image segmentation technique, in this method, a un-directed graph is considered where the nodes in the graph will be specifying the regions and weights will be specified with the intensity. This technique successfully solved the problem of normalized cut image segmentation technique. a hybrid color based image segmentation was proposed by the authors in [59]-[60] initially edge detection technique is used to instrument line process in order to detect edges vectoraangle and is used as a measure the distances between the pixels. A new image segmentation technique was proposed by author in [61] which combines region growing technique with morphological operator. this technique will be consisting of various stages in the first step image is enhanced using morphological closed operation and in the second step dilation residue edge detector is used to perform edge detection and in the next step they perform image segmentation using growing seeds and region growing process and in the last step edge detection and region merging is performed on the images Snake boundary condition method. In this article [62] author proposed a new technique which is used to enhance edge detection results. In this article [63] author proposed a novel edge based image segmentation method which is destined for ultrasound images. This technique involves various stages in the first stage edge detection is performed on the ultrasound images using phase symmetry and in the second stage noise is reduced using median filter and in the last stage final edge base segmentation image is produced using edge extraction and edge linking.

- PDE based image segmentation

In this paper [64] author Present a fast technique for segmenting images namely active contour approach which uses local prefitting energy. Author in this article [65] propose a new region dependent active contour approach through local cover resemblance measure for image segmentation. Author in this article [66] presents a new active contour approach for segmenting image and this approach get a feel for local kernel drawing to improve the discriminative

skill to delineate nonlinear choice boundaries among classes. A novel vigorous active contour approach is used to eradicate confines of active contour approach for both multi-object medical image segmentation and 2D single object image segmentation and this approach was proposed by the author in [67]. In this article [68] author proposes a new region based approach for the image segmentation by bringing together a local similarity aspect, which depends on the local spatial distance inside a local window and local intensity dissimilarity to enhance the segmentation outcome.in this article [69] authors propose a novel approach for underwater image segmentation which is achieved by integrating co-saliency discovery and local statistical active contour approach together.

In this article [70] author propose a technique for image segmentation which is achieved by combining active contour model with machine learning. In this paper [71] author present a novel technique which is based on active contours employed using level-set approach for medical image segmentation. It makes use a level-set progression which is on the basis of minimization function of an objective energy. a new active contours approach which integrates with the students t-mixture approach through anticipation maximization technique is presented by the author for 2 phase image segmentation which are complicated in [72]. In this article author presents an [73] Active contour approach was used for image segmentation. In this paper [74] Level-set approach was presented by the author segmenting images. In this article [75] Because of smooth and very accurate segmentation outcome, author propose a LSM for image segmentation. In this paper [76], author present a novel alternative of level-set approach and also presents a ternary variational level-set approach which involves L_0 function regularizer and L_0 gradient regularizer in separate back ground. Author in this article [77] propose a level-set method which is based on region-based, called KL-MLBF, and also based on the multi-scale local binary fitting (MLBF) and the Kullback-Leibler (KL) divergence. In this article [78] author propose an active contour approach which will integraterregion-scalableffitting energy and optimizedlLaplacian ofgGaussian (LoG) energy is presented for image segmentation. For object detection in underwater images Sidescan sonar image segmentation is used. For sonar image segmentation in this paper [79], author present a strong and fast approach, where noise and inhomogeneity in the intensity are dealt very effectively The proposed technique combines the alien means-based speckle filtering (NLMSF), bristly segmentation by making use of k-means clustering, and reasonable segmentation using an enhanced region-scalable fitting (RSF) approach.

In this article [80] author tries to solve the difficulties in automated image segmentation. Though one-dimension contour and two-dimension contour surface signs have been extensively used in existing work, three dimensional depth info of an image, an essential signal rendering to human visual insight, is but ignored in automated image segmentation. In this paper, author studies how to completely use one-dimension contour, two-dimension surface, and three-dimension depth sign for segmenting images. Initially,3 basic segmentation units are established for these cues respectively. The presented three-dimensional depth cue is having the ability to segment distinct textured area even with homogenous color, and unite homogenous textured zones, which can't be attained using up-to-date techniques. Initial Contour (IC) is the important step in level-set is the image segmentation technique which is owed to initiate the effective course. In this paper [81] author propose a novel approach which author named as Morphological Region Based Initial Contour (MRBIC), is presented to downside this problem.

In this article [82] author presents a new energy based level- set technique is presented in which the energy capability is well-defined by dissimilarity between the assessed and real likelihood thicknesses of the controls and partial differential equation is defined for identifying the base of the vigorous work. In this paper [83] author present a new automatic tongue segmentation approach through integrating a polar edge finder and active contour model (ACM) approach. In this paper [84] author propose a segmentation algorithm of stochastic images, and is established to distinct cardiac hollows from the CMR images background. To reason for noise and hesitations in pixel standards, a generalized polynomial chaos increase is rated with a level-set function to grow boundaries dynamically of cardiac hollows. In this paper [85] For segmenting medical images author proposes a new region-based active contour approach, author present a unique fitting energy model which is based on Gaussian Probability distribution to retrieve the MAP (maximum a posteriori probability) estimation. In this paper [86] author present a novel BUS image segmentation approach which is based on level-set approach and neutrosophic similarity score (NSS). An Edge-based active contour approaches are effeciant in image segmentation with inhomogeneity in intensities however they fail when its applied to medical images consisting poor boundaries. To resolve this downside, author of this paper [87] propose a methodology to develop a collection of ESFs for edge-based active contour approaches to segment images with poor boundaries. Motivated from the cross entropy, author of this article [88], present a novel active contour approach for segmenting images. The variant level-set approaches are extensively used in segmentation of images. To fetch the objects from the images with inhomogeneity, an enhanced local and global binary fitting active contours approach is presented in this paper [89] by the author. In this paper [90] author presents a level-set approach for segmenting image. To deal with noise, author implant a Markov Random Fieldeenergyffunction to the traditionalllevel-set energy function.

In this paper [91] , a convex texture based image segmentation approach is presented by the author. initially, from the original image features of texture are extracted, and the 2 types of texture properties are merged altogether to accurately built a discriminative property space by appending each other. In this paper [92], author present a new level-set approach for segmentation of images which combines the intensity and texture terms for 2-phase natural image segmentation which are complicated. In this paper [93] author propose a new level-set approach for difficult segmentation of image, in which local statistical studies and universal similarity measures are both mixed up into the building of energy functional. In this article [94] author presents a novel active contour technique. Author in this article [95] propose a new region-based active contour approach for segmenting image by making use of the variant formulation of level-set. In this approach, author builds the image fitting based on local likelihood energy functional by labelling the nearest intensities with Gaussian distributions locally present. In this paper [96] author present an effective multi-scale local region based level-set approach is presented for image segmentation with inhomogeneity in intensity.

In this paper [97], for two-phase image segmentation author present a severely convex energy functional in a level-set formulation. In this paper [98] author present an Active contour model (ACM) which is the most popular framework for image segmentation. In this article [99] author propose an important feature level-set method based ACM for segmenting images.in this article [100] author present an ACM which comprise of an effective segmentation of energy-based image. They normally address the segmentation problem as an optimization problem, which will be expressed in terms of a suitable functional, In this paper, author present a new ACM technique which integrates in a global and unsupervised way our proposed approach is named as SOM-based Chan–Vese (SOMCV) active contour model. In [101] author propose an Active contours which are having a wide variety of applicability in segmenting medical image. to resolve the customary snake approaches Gradient vector flow (GVF) field have been proposed by the author.

Important techniques of PDE are Level-set, Snakes, and Mumford shah method [102]. A new segmentation technique was proposed by author of this article [103], fuzzy C-means classification based PDE geometrical Contour model which is used for image segmentation. Geometrical complexity, ROC and orientation of image are handled carefully by feature extraction scheme PDE models are also used to extend the watershed method by the author [104] and

they start comparing watershed method with their proposed scheme and based on results author confirms that PDE methods outperform watershed segmentation algorithm.

- Clustering

In this paper [105] author proposes a technique for segmenting remote sensing images, new optimum-path forest clustering algorithm, in this paper [106] author proposes a technique including a network clustering prototype for bulk segmentation in mammograms, using watershed transform in first step to split an image into regions and compute the features of the image. Then a graph is created from the attained regions and features. The networking clustering classical is applied over to understand clustering of nodes in the graph. In this article [107] an enhanced native excitatory overall suppression swaying network algorithm is proposed by the author which is utilized for preprocessing of image and tracking the target. Splitting and combining of maximum and minimum next to pixel values can be done with correction army. The way of grating scanning repetitive merging and segmentation enhances the time taken by preprocessing of target tracking.

In this article [108] author presents a new image segmentation procedure built on neutrosophiccC-meansclustering andiindeterminacyffilteringmmethod. In this paper [109] author analyzes the best well-known and novel clustering procedure and delivers an study on their viability for equivalent application in this proposal [110] author shares his opinions on Image segmentation. Density based clustering techniques can be used to segment color images DBSCAN, which is utilized to detect the arbitrary formed clusters. Self-Organizing Map (SOM) is addimensionalityddecreasing technique which can be used to decrease the dimensions of image processing jobs. This article presents a fusion technique of SOM and DBSCAN (SOM-DBSCAN) for image segmentation. To exactly segment images with these prejudices, a local inhomogeneous intensity clustering (LINC) technique is presented by the author in this article [111].

Customary FCM clustering procedure has meagre noise resistance and there are some clustering consequences in image segmentation. To resolve this problem, a new imagecclustering algorithm built on SLICssuperpixel and handover learning is presented in this paper [112] by the author. To minimize the dependence on the user-specific parameter, authors in this article [113] analyze how and why the dominant sets clustering outcomes will get effected by the similarity measures. As an outcome author uses histogram equalization to transform similarity matrix before clustering. While this change is exposed to eliminate the sensitiveness to similarity measures efficiently, it also fallouts in over-segmentation. in this proposal [114] author present a segmentation mechanism for THz image using weighted feature space and also use simple random sampling in K-means Clustering. Recent developments in depth imaging, deliver stress- free access to the coordinated depth with color namely RGB-D image.

In this paper [115] Unsupervised technique was proposed by the author for segmenting and understanding RGB-D indoor image. based on the geometry and the color of the scenery author consider a statistical image creation technique. In this paper [116] author present his opinions on Breast cancer, its a highly varied illness and very natural among women universal. Inter-observer and intra-observer errors happen often in examining the lesion slice of medical images, provides high unpredictability in outcomes understandings. Computer Aided Diagnosis system (CAD) plays a key role to handle this unpredictability. Segmentation is the second important stage in CAD system to retrieve the required part precisely for differentiating benign tumor from malignant tumor. Here Regularization parameter and Ant Colony Optimization are combined with customary K-Means process to segment the lesion slice with extreme boundary conservation. In this article [117] author proposes a new phantom clustering technique with superpixels used for segmenting images (SCS) is proposed. In specific, a new kernel fuzzy similarity measure is proposed, and it makes use of association dissemination in partition matrix got by kernel fuzzy C-means clustering (KFCM) along with this, the superpixel is presented into image segmentation to lighten the computational overhead of affinity matrix.

In this article [118] K -means clustering process is an unsupervised process and it is used to segment the important area from the contextual. But aftore using K-means technique, first part widening enhancement is applied over the image to enhance the superiority of the image. Subtractive clustering technique is data clustering technique where it creates the centroid basing on the possible value of the data points. In this article [119] author presents a novel image segmentation technique which combines two techniques called k-means clustering technique and dynamic PSO. The methods of calculation of its inertia weight and calculations methods of learning factors are enhanced to guarantee DPSOK algorithm possess a symmetry on optimization competence.

In this paper [120] author presents an effective image segmentation method using K-means clustering method combined with Fuzzy C-means procedure thresholding followed to this and level set segmentation phases to deliver an precise brain tumor detection. Based on split and merge technique a fusion algorithm was proposed by the author in this article [121] For segmenting an image to detect fruit defect. Original image is split into regions by making use of k-means approach and then a merge process is then initiated based on graph representation using minimum spanning tree in which similar regions are merged into new similar ones. SLIC technique presents excellent performance in superpixel creation for optima imagery. SLIC will work unwell in the images where too much noise is present. To solve this problem in this article [122] authorkhavekupgradedkthekclusterkcenterkstarting-kstepkandkthekpostkprocessing-kstep,kandkthenkapplykthekSLICksuperpixelksegmentationkprocessktokthekpolarimetricksynthetickaperturekra-dark(PolSAR)kimagekprocessingkfield.

In this paper [123] To segment noisy images a level set technique was proposed by author which is achieved by combining local and global fitting energies. In the proposed technique the input images LRS information is the base for energy of the local fitting, that is going to reduce accurately the noise effects, correntropy based K-means technique is used by global fitting energy to analyze the samples that are at the cluster center.the advantages of local robust statistics features and global information are combined in the proposed model with which it can handle the in homogeneity in intensity and images with noise. In this article [124] author presents a fruitful data clustering process which is enhanced that makes use of prim's sequential illustration of MST, for segmenting images.

- Watershed transformation technique

In this article by the author [125] proposed a new marker-based watershed method for image segmentation using Gabor filter for smoothing the image and watershed segmentation method is used to segment image to detect lung cancer at the early stages a new method was proposed by the author in this article [126].

- Mean shift method

In this paper [127] Author propose a mean-shift based algorithm which is adaptive in nature and removes noise and using its mode seeking skill it strengthen the clustering parameters. To guess the class labels of tissues, pixels which are noise free and bias field author formulated this approach. In this study [128] on a single GPU and a task scheduling method author performed a parallelization of the mean-shift algorithm. A new model is proposed in article [129] by the author From a saliency map image spatial information which is content based is extracted and included into the conventional Gaussian mixture model. A mixture of Gaussian distribution by means of a trimmed likelihood estimator and generalized gamma is done by the author to propose a novel finite mixture approach in this article [130]. In this paper [131] For segmenting images a level set model which is robust is proposed by the author .

In this article [132] a novel image segmentation approach is presented by the author which exposes the benefits of decision trees and CRFs and author of this paper [133] Propose a novel estimation technique based on Bayesian applicability to k-class image segmentation which is fast and unsupervised. In this paper [134],

author propose a concurrent segmentation approach of images with the help of bias correction and inhomogeneity in intensity. For controlling the quality and for the purpose of review a novel vision based technique is proposed by the author of this article [135]. Interactive image segmentation is used in the proposed method by the author where the main idea is to use Gaussian mixture model, once the segmented frame is obtained measures are taken in order to reduce noise. Author in this work [136] Structure prediction method is proposed which is obtained by combining the deep learning with G-CRFs. For segmenting seeded images a new sub-MRW technique was proposed with label prior by the author of this work [137]. In this work [138], adaptive constraint propagation is used to segment interactive images and this technique is called ACP cut and this technique is proposed by the author.

In this work [139] Author presents a novel segmentation algorithm for brain MRI images which is based on LVGM model. In this work [140] a new MRF segmentation approach is proposed which is based on superpixel to perform automated cervical cell analysis in the MRI images. A novel method was proposed for segmenting MRI images in which union of different channels is performed [141], in this article [142] authors presents a technique for MRI brain images

In this article authors [143] Segmentation of SAR images is proposed by the author through a ranked visual semantic and a latent model which is based on adaptive neighborhood. This method will segment SAR into regions which are homogeneous.

Authors in this article [144] Author performed and extension to Shannon entropy which is applied over continuous random variables. And this article verifies the modification done for this extension and propose a new entropy called average entropy. Author of this article [145] propose a novel technique for image segmentation using variation in intensity homogeneity and concurrently estimate the bias field. In this paper [146] Author propose a novel MRI segmentation in which MRF classification is merged with bias field to minimize the energy and the basic estimation is completely based on k-means algorithm. In this article [147] Based on disjunctive normal shape model author proposed a new image segmentation mechanism. In this article [148] author propose a novel loosecut procedure that can address the scenarios where the alone bounding box loosely shields the object here author proposed a novel MRF model for segmentation, an additional energy word is included to inspire consistent tagging of alike look pixels and a overall similarity constraint to better differentiate the forefront and background.

- Soft computing approaches

Fuzzy set theory:

In this article [149] author propose a combined method to unsupervised depiction of learning, clustering for pathology image segmentation. There are two steps in this proposal first step is to study feature depiction of training patches using the spherical k-means from the targeted image and in the second step author put on traditional k-means to the depictions which are extracted by the centroids and then assign labels to the clusters. Author in this article [150] Proposed a MRI brain image clustering method for segmentation and in this article [151] author propose a novel hybrid mechanism which will unite intuitionistic fuzzy c-means and firefly algorithm for segmenting image, based on fuzzy cellular automata framework In this article [152] author presents an effective automated image segmentation mechanism and its proposed for treatment of the uncertain ascription of pixels status thru segmentation process. Based on pareto In this article [153] author presents akintervalktype-2kfuzzykc-meanskmechanism for segmenting color image.

In the article [154] two clustering algorithm comparison is done they are fuzzy c-means and k-means based on centroid. In this article [155] author presents a self-adaptive agreement search built fuzzy clustering mechanism for image segmentation is proposed. In this article [156] author propose a automated image segmentation mechanism which exploits an unsupervised fuzzy c-means clustering mechanism for multispectral T1 and T2-weighted. A gaussian model is presented In this article [157] by the author and it shows the connections exists betweenkdifferent color planes to reinforce the connections equally on a color plane and amongst color planes in a neighborhood. Author in this article [158] puts his focus on brain image segmentation to identify the brain tumor by making use of spatial fuzzy clustering mechanism. Author in this article [159] proposes a new fuzzy mechanism which is based on unsupervised learning technique with boundary correction for segmenting images. In this article [160] author based FCM for segmenting texture image. In this article [161] author presents one enhanced FCM technique which will solve various problems, a hybrid procedure for segmentation built on soft sets that is rough FCMis presented to intellectual the gray and white matter and the cerebro spinal fluid from MRI image was proposed by author of this article [162].

In this article [163] author share his view on researchkaims at enhancing the segmentation quality on the FCM technique which categorize the patterns with the lbackground. Author in this article [164] presents an rough form of the K-means procedure which can be used for the segmentation of image, with the objective to minimize thekarea required topsynthesize it on a hardwarektarget. Author in this paper [165] presents an enhanced rough FCM clustering technique in which a parameter selection mechanism is intended to adaptively alter the weighted parameter dependent on the distributive character of to each cluster in its place of physically choosing a persistent parameter. FCM clustering technique has been extensively used in segmentation of image that plays an significant role in a diversity of applications in image processing, the overall efficiency of FCM mostly depends on the first cluster centers which are difficult to identify. To overcome this problem, author of this paper [166] proposes a novel technique for image segmentation, A New technique which is built on kExtended kFuzzy kC-Means (EFCM) and kSelfkOrganizing-kMap (SOM) named kself-organizing-map based kextended kfuzzy c-means (SEEFC) has been planned and applied for image segmentation by the author in this article [167].

Author of this paper [168] proposes an enhanced fuzzy clustering procedure, which acquaint with pixel significance into the fuzzy issue and could approximation the damping degree accurately. In this paper [169], author presents a C-means procedure is fuzzified and make conform by joining both local data and membership data. Author proposes a resolution in this article [170], which allows the actual segmentation of SAR images by assuring noise-free and edge part protection concurrently. In this article author [171] provides, a relative study has been ended using clustering procedures based on intuitionistic fuzzy set and neutrosophic set to segment the medical images, in this article [172] author present an outline to image segmentation in the imagekmodel in which intensities of the detected image are observed as a artefact of the truekimage and the biaskfield.

Author in this article [173] proposed an image segmentation algorithm FABC. Author in this article [174] presented a novel approach, named an enhanced intuitionistickfuzzykc-means, which reflects the local spatial data in an intuitionistic fuzzy way. Author in this article [175] proposeskclonekkernelkspatialkFCM which advances segmentation routine in several ways. in this article [176] author presents a novelssemi-supervisedsfuzzy clustering procedure named as sSSFC-FS dentalxX-ray imagessegmentation . In this article [177] Author proposed a localccorrentropy-baseddfuzzy c-meansccclustering algorithm withsspatial constraints (LCFCM_S) anddits simplifiedmmodel. Author in this article [178] propose a new technique for color image segmentation. In this article [179] author propose an enhanced technique for edge identification and image segmentation by making use of fuzzy cellular automata. In this article [180] author present a robust fuzzy clustering arrangement for limited mixture prototypical fitting, which activities the advantages of the combination of the non-symmetric Student's t-distribution and mean template to decrease the compassion of the segmentation fallouts with deference to noise.

In this article [181] author propose a hybrid procedure, called Rough Possibilistic Type-2. In this article [182] author propose a

fuzzy c-means algorithm based on MapReduce which is fast to paralyze the segmentation of the images. Author in This article [183] describes a multioobjectivesspatialffuzzycclustering algorithmfforiimage segmentation. In this article [184] author present the idea of FuzzyiImagesSegmentation, provided that an procedure to shape fuzzy borders based on the present relations amongst the fuzzy boundary set delinquent and thehhierarchicaliimages-segmentation problem. author in this article [185] presents a new unsupervised FuzzycC-Means for segmenting image. A new technique for segmenting images based on PSO and outlier refusal joint with level set is anticipated in this article by the author [186]. A new bi-convexFfuzzyVvariationalIimageSsegmentation technique is proposed in this paper [187] by the author.

In this article [188] author presents a new fuzzy clustering procedure for image segmentation, in which the Mahalanobis distance is applied to describe the dissimilarity degree. Author in this paper [189] implement brFCM procedure, which is a variant of the FCM technique. for a robust and stable image segmentation in this article author [190] presents a newrregion-basedffuzzyaactiveccontour model with kernel metric.To remove noise from the image fuzzification function can be used in this paper [191] by the author which convert gray-scale image to fuzzy image and to have better outcome dissimilar morphological actions can be joint with fuzzy methods. Based on fuzzy rule a new segmentation technique was proposed by author in [192]. Based on fuzzy connectedness a new image segmentation technique was proposed by author of this article [193]. Based on fuzzy dissimilarity and feature divergence in this article [194] author proposed a fuzzy color image segmentation.

4.2. Artificial neural networks-based image segmentation

Author in this article [195] speaks about segmentation of semantic image and Deep Learning is used as one of the tool which makes three main offerings they are, in the first step, they bring lime light on upsampled filters based convolution, and in the second stage, they present "atrous spatial pyramid pooling (ASPP)" for object segmentation at multiple measures. And in the final stage, they enhance the object boundaries localization by integrating techniques from probabilistic graphical models and Deep Convolutional Neural Network(DCNN)'S's. In this article [196] author Present Convolutional Oriented Boundaries (COB), which yields contours which are multiscale and region chain of command starting from Convolutional Neural Networks (CNNs) based generic image classification. In this article [197] author present an far and wide amenable Deep Convolutional Neural Network(DCNN)'S for segmentation of semantic images with integral consciousness of semantically relevant boundaries. In this article [198] author propose a general training technique that includes functional past information into CNNs via a novel regularisation approach, and is trained far and wide. Author in this article [199] propose a segmentation lung CT image by making use of U-net architecture, one of the most widely utilized architecture in deep learning for image segmentation.

Author in this [200] article propose a fully automatic procedure for segmenting of the myocardium and right and left ventricular cavities on short axis cardiac MRI using two-dimensional and three-dimensional CNNs. In this article [201] propose a segmentation of semantic images which is completely based on deep neural networks. Author in this article [202] propose an image segmentation approach that integrates Fuzzy Cellular Neural Networks(FCNN) with residual networks. A new interactive image segmentation based on deep learning procedure is proposed, by combining CNN into a bounding box and segmentation pipeline which is based on scribbles and also proposed image precise well tuning to make a CNN approach which is adaptive to a particular test image which can be any of supervised or unsupervised one is proposed by the author in this article [203].

Author in this article [204] propose a novel two layer network association of Pulse Coupled Neural Network(PCNN)Iin whichEexcitatory and inhibitory connecting inputs happens. Author in this article [205] propose a extremely glued convolutional network which has three parts: combined feature unsampling, feature downsampling and multiple predictions for segmentation of semantic image. Author in this article [206] presented radial plain function Neural Networks image approach is created by the backing of many imageSself-extractionFfeature mechanism, which integrates IDELA and RBFPSO techniques to grow the global RBFNs image describer. A new three-dimensional multi-modal FNN design for segmentation of brain MRI is proposed in this article [207] by the author .Author in this article [208] proposed a new technique for brain MRI segmentation using deep learning approach to retrieve initial labelling and graphical approaches to yield the final outcome. in this work [209], author shows that a multi-class three-dimensional FCN taught on CT images which are manually labeled of numerous anatomical constructions can attain modest segmentation outcomes while escaping the necessity for handcrafting features approaches. To detect the biomedical images Allow-poweraarchitecture for edgeddetection are presented by the author [210] in this article. The outcome of edge detection are given to the system, and it will detect the illnesses by making use of image classification designed based on CNN. A novel varied and basic pulse coupled neural network approach was presented by the author in this article [211].

In this article [212] author propose a new aircraft kind recognition procedure which is depending on Deep Convolutional Neural Network(DCNN)'S. Initially an network for segmenting aircraft is designed to retrieve sophisticated segmentation outcomes then a important detection network is presented to obtain aircrafts ways and bounding boxes and they are utilized to align the outcome of segmentations. Author in this article [213] propose a influential approach for electron microscopy based image segmentation that is trained far and wide and does not depend on previous information of the data.

Author in this article [214] propose a automated technique that segments three-dimensional brain MR Images into dissimilar tissues using Fuzzy Cellular Neural Networks(FCNN) and handover learning. In this article [215] author presents a weakly supervised CNN that only needs imagellevel explanation. They also present a segmentation approach which is based on graph and it utilizes thecclassaactivation mapsttrained on foodddatasets as a top downssaliencymmodel. Author in this article [216] propose a control Fuzzy Cellular Neural Networks(FCNN) to segment automatically the skin lesions. In this article author [217] presents an automated pattern recognition scheme by making use of FCN and was presented to concurrently refer to the classification and segmentation of HEp-2 sample images. The presented technique converts the residual network (ResNet) to fully convolutional ResNet (FCRN) making the network to do the task of segmenting semantic images. In this article [218] author propose a DAN ie; new deep adversarial network approach for segmenting biomedical images, targeting to attain constantly better segmentation outcomes on both unannotated images and annotated images. Author in this article [219] present a new Convolutional Neural Network architecture, Densely Connected Convolutional Networks (DenseNets), which presented excellent outcomes on the task of image classification.

Author in this article [220] propose to analyze the background modeling and segmentation of object from highly messy natural images in the Deep Convolutional Neural Network (DCNN)'S feature domain in spite of conventional pixel domain. Author in this article [221] present an active deep learning procedure which will combine active learning and FCN to minimizeaannotation exertion by makingjjudicious submissions on the most effective annotation parts. Author in this article [222] propose a novel deepf framework, calledRRegional InteractiveSSegmentationNNetwork (RIS-Net), which is used to extend the view of the provided inputs to get theLlocalRregionalIinformation surrounding them forLlocalRrefinement. In this article [223] propose a fully automated approach for left ventricle, right ventricle and myocardium segmentation from cardiac MRI by making use of Deep Convolution-

al Neural Network(DCNN)'S. Author in this article [224] present a new approach to diagnose and segment brain tumors in MRI images using a NN which is based on the Dynamic recurrent neural network(DRN) [225] addressSthe problemOofCcombining shapePpriors within theFFCN frameworkFfor segmentation.

In this article [226] authors propose a CT image segmentation by making use of specific FCN, which is well-organized and actual in real-world applications, along with the data augmentation technique which was involved in the training period. In this article [227] author presents a novel algorithm for segmentation which is based on Pulse Coupled Neural Network(PCNN) to the ultrasonic image. targeting the problematic which is difficult to diagnose thepparametersffor the Pulse Coupled Neural Network(PCNN)nin the previously used segmentation algorithm, so the new image segmentation method was presented that lined automatic optimization skill of particle swarm optimization and utilized to improve maximum entropy function as the main fitness function. Based on Tversky index Author in this article [228] presented akgeneralizedklossffunction to resolve the problem of dataiimbalance and to attain much better differences betweenpprecisions and recall in training three-dimensional Fuzzy Cellular Neural Networks(FCNN).

Author in this article [229] Propose an technique to three dimensional image segmentation which is based on a volumetric, Fuzzy Cellular Neural Networks(FCNN). Our Fuzzy Cellular Neural Networks (FCNN) is trained on end-to-end MRI volumes portraying prostate and starts to predict segmentation for the entire volume at once. Author in this paper [230] proposes a DCN for quality assessment of object segmentation. Here, initially end-to-end for object quality evaluation two large data-sets are presented. The segmentation outcomes of the presented datasets are produced from easy and difficult segmentation datasets respectively. After that three different types of DCN are proposed by the authors to learn object segmentation quality.to utilize both the background and foreground information author propose awweightedmmasklayer, author in this paper [231] present a technique for volumetric segmentation that studies from lightly annotated volumetric images. In this article [232] author propose to practice FCNs for the segmentation of iso-intense phase brain MRIs. In this article [233] authors examine whether a single CNN can be qualified to do dissimilar segmentation errands. In this article [234] author Presents a technique for the programmed segmentation of MRI brain images into a numeral of tissue classes using a CNN.

In this article [235] author presents a technique to segment lesions in CT abdomen images automatically using CFCNs and dense Three dimensional CRFs. In This paper [236] author focusses on the use ofeEchosState Networks, an effeciant form ofrreservoirr computing, to advance in segmentation of microscopic cellular images. In this article [237] author Express the vessel segmentation to a boundary detection delinquent, and use the Fuzzy Cellular Neural Networks(FCNN)s to make a vessel probability map. Author in this article [238] Propose to make simpler approximate parameters of Pulse Coupled Neural Network(PCNN), and put on it into image segmentation. Author in this article [239] propose a deep learning method for segmenting sub-cortical assemblies of the brain MRI data. A new method namely Pulse Coupled Neural Network(PCNN)-based level set algorithm, is presented in this paper [240] by the author to mammographic image segmentation. Author in this article [241] propose a new approach for instinctive segmentation of anatomical structures on Three Dimensional Computer Tomography images by elective from a FCN. In this article [242] author present two iris segmentation models, they are MFCNs and HCNNs for segmenting noisy iris images.

Author in this article [243] present a label propagation technique based on segmentation to a publicly accessible dataset on interstitial lung images. By making use of data augmentation author in this article [244] present a network and training strategy . here author focuses on semantic image segmentation In this paper [245] author tries to combine rich information into Markov Random Field, and author solve MRF by using Deep Parsing Network (DPN) which is a Convolutional Neural Network (CNN). To segment isointense brain MRI author in this article [246] propose to use CNNs. Author in this article [247] propose to use a pre-trained large convolutional neural network to create deep topographies for CRF learning. Author in this article [248] propose an effective technique using Deep Convolutional Neural Network (DCNN)'s to attain obviouscclassificationaandssegmentation. For the segmentation of SAR images author in this article [249] propose a wavelet CNN based Markov Random Field. In this article [250] author present a new DNN architecture intended for semantic image. In ANN, each pixel of an image is characterized with a neuron collection of neurons which will arranged into an image and images are charted to the neural network and next is to train the neural network using training models and new image segmentation will be performed on the basis of trained images proposed in this article [251].

"For image segmentation, most widely used artificial neural networks are Hopfield, Back Propagation Neural Networks (BPNN), Feature Finding Neural Network (FFNN), Multi Layered Feed Forward Neural Network (MLFF), Self-Organizing Maps (SOM And Pulse Coupled Neural Network(PCNN)". Image segmentation can be performed in two steps in neural networks they are classification of pixel and detection of edge was proposed by the author in this article [252]. A Novel FLANN was presented by the author to deal with color image segmentation [253] and it involves several stages in the step one removal of noise is performed by utilizing averaging filter and in the next step RGBSV space is constructed using HSV conversion pixels and in the next stage clustered outcome of an image is obtained using FLANN clustering and in the last homogeneous color pixels are placed individual as segments and numbering is done to each segment. A fact c-means basedttraining for FHNN [254] was proposed by author in this article [255].

4.3. Genetic algorithm-based image segmentation

In this article[256] , using energy curve author propose a image segmentation technique, in this there are three steps in the First, the preliminary thresholds are carefully chosen in the central of two successive peaks on the energy curve Then depending on the cluster soundness measure, the optimal quantity of possible thresholds and the boundaries where the best value of each possible threshold may be are determined. In the last step genetic algorithm is used to sense the optimal value of individual possible threshold from their corresponding defined bounds. Author in this paper [257] presents a genetic algorithm for coalescing illustrations of learned information such as regional properties, knownsshapes, and relativepposition ofoobjects into a single structure to do automatic 3D segmentation. For segmenting medical images author in this article [258] defines a hybrid levelsset method and this novel geometric deformable prototype syndicates information of region and edges with the preceding shape information make known to by means of deformable registration. Proposed system works in two steps in the first step the genetic algorithms are used to train the level set parameter and the next step is the proper segmentation, even in the presence of noise in line for the essential of right diseases study, segmentation of MRI rests till now a stimulating problem Author in this paper [259] Basing on the method of shuffled Frog Leaping algorithm author proposes a novel meta-heuristic procedure for segmenting MRI. In this novel model, there is no requirement to filter the original image. Novel fitness function presented here is used to assess fast the particle frogs and organize them in descending order.

5. Conclusion

Various techniques of image segmentations are discussed in this review and an overall information regarding all the techniques in regards with image segmentation are shown here in this review and research in the fields of image segmentation which is going on in the recent times are exposed in this paper. After a lengthy anal-

ysis of various image segmentation techniques, it's learned that hybrid solution for the image segmentation is being the best approach to solve the image segmentation problem because hybrid solution is a combination of two or more techniques which is the more efficient way to solve the image segmentation problems.

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