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Soft computing approaches for image segmentation: a survey

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Abstract Image segmentation is the method of partitioning an image into a group of pixels that are homogenous in some manner. The homogeneity dependents on some attributes like intensity, color etc. Segmentation being a pre-processing step in image processing have been used in the number of applications like identification of objects to medical images, satellite images and much more. The taxonomy of an image segmentation methods collectively can be divided among two categories Traditional methods and Soft Computing (SC) methods. Unlike Traditional methods, SC methods have the ability to simulate human thinking and are flexible to work with their ownership function, have been predominantly applied to the task of image segmentation. SC techniques are tolerant of partial truth, imprecision, uncertainty, and approximations. Soft Computing approaches also having advantages of providing cost-effective, high performance and steadfast solutions. In this survey paper, our emphasis is on core SC approaches like Fuzzy logic, Artificial Neural Network, and Genetic Algorithm used for image segmentation. The contribution lies in the fact to present this paper to the researchers that explore state-of-the-art elaboration of almost all dimensions associated with the image segmentation. The idea is to encapsulate various aspects like emerging topics, methods, evaluation parameters, the problem associated with different type of images, databases, segmentation applications, and other resources so that, it could be advantageous for researchers to make effort in developing new methods for segmentation. The paper accomplishes with findings and concluding remarks.

Keywords Deep learning · Fuzzy logic · Fuzzy c means · Genetic algorithm · Image segmentation · Neural network · Soft computing

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1 Introduction

Image segmentation is the process of partitioning an image into group of pixels grounded on some homogeneous features like color or intensity to extract some meaningful information [23, 55]. Image segmentation as a preprocessing phase is a part of almost all computer vision system in the real world complex applications, ranging from object extraction to medical images, satellite images, video and traffic surveillance system etc. [4, 36, 62, 177, 184, 236]. The extent to which an image has to be segmented is entirely dependent on the application. The identification and localizing of objects is the crucial task for image processing community [81, 157, 196].

There are number of methods that are used to perform image segmentation. The classification of methods has been grouped into two categories known as traditional methods and soft computing methods. The traditional methods are the conventional methods that are simple and easy to implement. They accomplish and results in exact solutions to the problem of segmentation. Most commonly the traditional methods are divided among four different classes based on their nature of working as (a) Region based segmentation, (b) Clustering, (c) Edge based segmentation, and (d) Thresholding [105]. The inefficiency of these approaches lies in the fact that they cannot deal with real life complex problems that are tolerant of partial truth, imprecision, uncertainty, and approximations. Therefore to deal with such problems Soft Computing techniques are used [157].

The motivation behind Soft Computing is to achieve artificial intelligence by simulating thinking capability of a human brain to solve the ambiguities or real world complex problems. Soft computing is a combination of computing techniques and biological structures that provide new methods for more dynamic, competent and reliable solutions. The theory of soft computing was introduced by Lotfi A Zadeh in 1990s. According to him, SC is a group of methods that primarily compromises of Fuzzy logic (FL), Artificial Neural network (ANN) and Genetic algorithm (GA) [90, 181]. Unlike hard computing, SC techniques are tolerant of imprecision, uncertainty, partial truth and approximations [21]. The flexibility of working with their ownership function makes them more powerful. Soft computing approaches because of their adaptive nature and accuracy are predominantly used and favored by researchers. SC approaches also having advantages of providing cost-effective, high performance and steadfast solutions to complex problems. SC methodologies have been applied in areas like scientific research, medical, engineering, management etc [91, 186, 196, 198].

So, the objective of this survey paper is to present the applications of image segmentation using core Soft Computing methods. The conceptual theory related to the task of segmentation applications using SC methodologies identified and presented in this work. The contribution of the article lies in the fact to present this paper to the researchers that explores state-of-the-art elaboration of almost all dimensions associated with the image segmentation using soft computing methods. The idea is to encapsulate various aspects like new techniques, emerging topics for segmentation, evaluations parameters, problems associated with specific images, databases, applications, future works, and other resources so that, it could be advantageous for researchers to make efforts in developing new methods for different applications of image segmentation.

Organization of the article is as follows, In Section 2, the scope and contribution of the article have been given. Section 3 compromises of some basic definitions related to the concept of image processing and description of some soft computing methodologies used for segmentation. The segmentation task performed on MRI images, while surveying using Soft Computing methods has been given in Section 4, likewise Section 5 presents segmentation task carried out for Computed tomography (CT) images, Section 6 for other medical images, Section 7 shows Synthetic-aperture radar (SAR) image segmentation, Section 8 for complex real world images and Section 9 for further applications of image segmentation. In section 10 the various finding from the survey have been listed out and discussed. Finally Section 11 concludes this article followed by references.

2 Scope and contribution

The concept of object retrieval from an image using Soft Computing has been evaluated by number of researchers from numerous perceptions. However, it is outside the scope of this article to address all problems in detail. So in an exertion to deliver a more severe review of current papers in this area, paper primarily emphases on image segmentation using core soft computing approaches like as FL, NN and GA. Since these techniques give the approximate results, are used in number of critical applications like extracting WM, GM, CSF and background from the MRI brain image, finding out objects from complex real world scenes etc. The highlights of the article are given as follows:

1) The contribution of the article lies in the fact to present this paper to the researchers that explores state-of-the-art elaboration of almost all dimensions associated with the image segmentation using soft computing methods.
2) The problem associated with different images are presented separately that affects segmentation results.
3) Comparative analysis of various approaches is distinctly presented in the table.
4) Various terminology used like object segmentation, object detection, image segmentation, scene parsing, semantic image segmentation, instance segmentation and object recognition are defined separately.
5) Some new concepts like neuro-fuzzy, deformable models, metaheuristic approaches were also introduced.
6) Databases that are used most frequently have been introduced.
7) Most widely used parameters used for evaluating performance are also included in this work.
8) Other repeatedly used factors like noises for validating algorithm, tools for implementation purpose are also part of this work.
9) Segmentation application were presented so that one can explore some infrequent topic as a part of research work.

3 Some definitions and methods

In this section we have presented the basic terminologies that are used throughout this article along with the description of some of approaches that were introduce for the purpose of image segmentation.

1) *Image segmentation*: the method of dividing an image into some homogeneous or non-homogeneous regions to identify some object or extract some information from it. This process is dependent on the attributes of Region of Interest (ROI) or objects such as color, the intensity of pixels, shape, size etc. [22, 50, 125, 212]. Steps for segmentation [10] shown in Fig. 1.

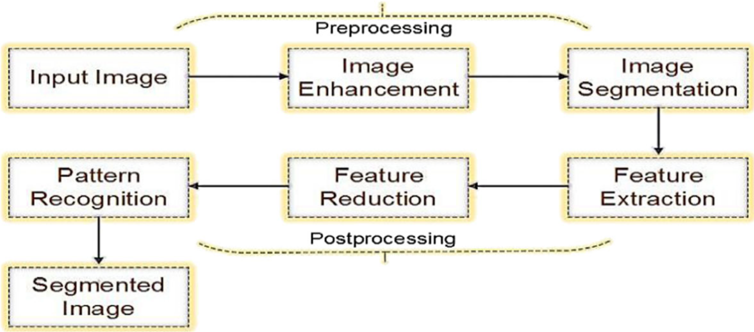

Fig. 1 Segmentation steps

2) *Image thresholding:* is one of the most common and simple segmentation method. Given as, let the pixel located at position (a, b) with gray scale value $g_{a,\ b}$ for a given threshold value Δ_t the pixel belongs to category A if $g_{i,\ j} \leq \Delta_t$ otherwise belongs to category B [25, 165].
3) *Clustering:* an unsupervised procedure of grouping a set of entities into classes of alike features [217]. It has been extensively applied in a number of fields, like geology, engineering systems, machine learning, statistics, medicine, etc. [63]. It is alike segmentation of an image. Among various clustering algorithms, fuzzy algorithms, FCM, Gustafson-Kessel (GK) and non-fuzzy algorithms like k-means (KM), are most popular [26].
4) *Region based segmentation:* the regions which are having similar value and are neighbors are grouped and regions which are dissimilar values are grouped into other. This process starts with the center of objects and grows until it reaches the boundary.
5) *Edge based segmentation:* by applying filters the edges or non-edges are identified depending on that filter output. Here pixels which are not separated by the edges belong to the same classification.
6) *Image Enhancement:* improvement in an image to make it convenient or easier to analyses so that further analysis can be done. This can be done by changing values like brightness, contrast, sharpening or removing noise etc.
7) *Feature:* the attribute of an object like its color, shape, size etc.
8) *Feature extraction:* the process of reducing the dimensionality of an image by representing the region of interest as feature vectors [71, 178, 223].
9) *Soft Computing:* a consortium of techniques which are used to simulate the human thinking capabilities in order to solve problems of real world [95, 109]. The taxonomy of SC is given in Fig. 2.
10) *Fuzzy sets (FSs):* Let $X = \{x_1, x_2,.., x_n\}$ be any non-empty set. A fuzzy set F of X (Zadeh 1965) can be defined as:

$$F = \left\{\{x, \mu_F(x)\} \llcorner x \in X\right\} \tag{1}$$

where, $\mu_F(x)$: →[0,1] is the degree of belongingness of x in X and the degree of non-belongingness of x in X can be obtained by using the eq. $1 - \mu_F(x)$.

11) *Fuzzy Logic (FL):* In 1965 an extension to the classical set theory named as Fuzzy Logic (FL) was proposed by Lotfi A. Zadeh and Dieter Klaua. FL provides computational

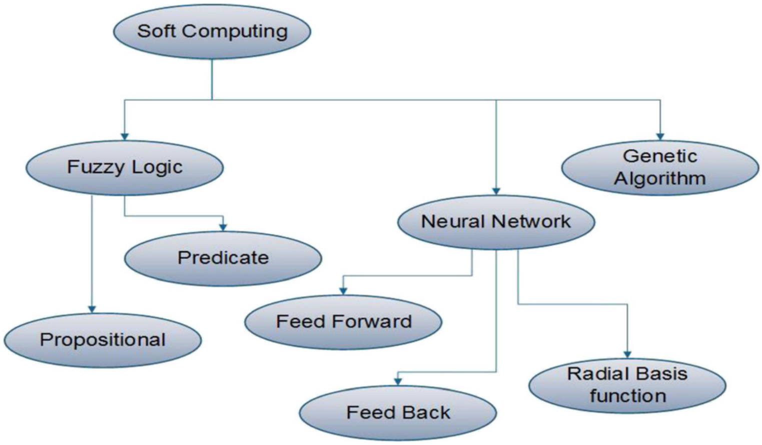

Fig. 2 Soft computing approaches

power to SC. Over the interval [0, 1], it is a set by means of graded membership [30]. FL is an exact multivalued logic theory that uses fuzzy set theory (FS). Dissimilar to probability theory, FL is used to handle impreciseness of input and domain information [170, 243]. FL is used to provide rapid, modest and adequate approximations for the real world complex problems [112, 122]. FL is most often used for control engineering [52]. Mathematically denoted by Refer to (2) [8, 30, 245].

$$A = \int_A \frac{\mu_A(x)}{x} \tag{2}$$

where A = fuzzy set, X = universe of discourse, $\mu_A(x)$ is a continuous membership function describing the degree of membership of points in X in the fuzzy subset A.

12) *Fuzzy c-means algorithm (FCM):* is a nonlinear iterative optimization approach that is built on an objective function [32, 57]. The motivation behind Fuzzy c means is to find cluster centers (centroids) so that, dissimilarity function can be minimized. Proposed by Dunn in 1973 and improved by Bezdek in 1981, FCM is based on Fuzzy sets (FS). It accomplishes unsupervised clustering [131] that allows segmenting images automatically under circumstances of vagueness and fuzziness [164, 183]. In FCM a part of data can belong to two or many clusters. It has proven to be an effective tool for partial volume effect, but it does suffer from the problems like drifting off the center of clusters and sensitiveness among classes due to intensity overlap [187]. FCM does not involve spatial information for an image given, so it does suffer from noise [19, 107, 136, 190, 232, 246, 250]. Limiting to these problems, FCM has proven to be an efficient algorithm for pattern recognition, image segmentation, machine learning etc [78]. The objective function (weighted distance), is well-defined as for separating $\{x_k\}_k = 1:N$ into c cluster is Refer to (3).

$$J_{FCM} = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} = \|x_k - v_i\|^2 \tag{3}$$

where c = no. of clusters (predefined), N = no of pixels from given image, x_k = gray value of the k-th pixel, v_i = center of the i-th cluster, u_{ik} = membership of the k-th pixel in the i-th cluster, having every pixel constriction = $\sum_{i=1}^{c} u_{ik} = 1$; p = is the amount of fuzziness generally higher then 1; ‖ ‖ = the standard Euclidean distance [43].

13) *Fuzzy c-means algorithm with spatial information (FCMS):* FCM algorithm suffer from the drawback of not having spatial information within its objective function, which lead the FCM sensitive against the image artifacts. Thus involving spatial information within the objective function a new method was proposed named as Fuzzy c-means with spatial information. In proposed FCMS the pixels get affected by the labels of the neighbor pixels. This led to the non-segmentation of boundary regions of an image and also blur image segmentation.
14) *Soft fuzzy rough c-means (SFRCM):* with the introduction of rough sets for the purpose of handling uncertainty and ambiguity present in the medical images the segmentation performance has been improved for the proposed algorithms. Soft sets are basically mapping of parameters to the universe and vice versa. Soft sets are mathematical approach that has been used to find the rough region of an image. The soft sets differs from the conventional rough sets that require parameters like threshold value, weight parameters etc. The soft sets finds the similarity among the most similar clusters from the present and previous step. One of the success of this method is that it does not have any criteria for negative pixels, so all the pixels takes part in clustering process. The centroid are formed by using the histograms of the centroids.
15) *Improved anisotropic multivariate student t-distribution based hierarchical fuzzy c-means method (IAMTHFCM):* to deal with the problem of centre point acting as an independent noised point, an anisotropic neighbor patch information is associated by defining a new inner-relationship among neighbors. This improves the FCM by introducing the necessary spatial information with it. Student t-distribution is used to model the probability density function of the images into finite mixture clusters with an additional parameter known as degree of freedom r. Thus the new method is known as improved anisotropic multivariate student t-distribution based hierarchical fuzzy c-means method.
16) *Rough Possibilistic Fuzzy Type-2C-Means (RPT2FCM) with Random Forest (RF):* this method includes both possibilistic and probabilistic methods for clustering purpose. The Random Forest (RF) that is trained with the help of crisp sets has been imposed for the purpose of classification of data. The uncertainty of the data is handled by using type 2 fuzzy theory. Keep in mind the lower and upper approximation Rough fuzzy sets are used that can handle uncertainty and vagueness in an appropriate manner.
17) *Fuzzy-based artificial bee colony optimization (FABC):* the algorithm combines the theory of artificial bee colony optimization with fuzzy membership function. The method is unsupervised in nature that is used for the purpose of clustering. The cluster centers have been optimized adopting the working criteria of artificial bee colony optimization method. Fuzzy c means is used to find the cluster centres also known as centroids by minimizing the dissimilarity function.
18) *Local Membership Relative Entropy based FCM (LMREFCM) and Local Data and Membership Relative Entropy based FCM (LDMREFCM):* in conventional hard c means algorithms a single Kullback–Leibler (KL) membership distance also known as membership relative entropy (MRE) function has been employed for fuzzification and regularization. But in the proposed LMREFCM an additional MRE function is

introduced that increases the performance of the algorithm by improving fuzziness and regularization. And in the proposed LDMREFCM local data information is associated that makes the proposed algorithm robust against noise.

19) *Bias Corrected Possibilistic Fuzzy C-Means (BCPFCM), Bias Corrected Possibilistic Neighborhood Fuzzy C-Means (BCPNFCM), and BiasCorrected Separately weighted Possibilistic Neighborhood Fuzzy C-Means (BCSPNFCM):* to overcome the problem of bias field and noise concepts of possibilistic and fuzzy membership have been combined. Image has been modelled by using weighted typicality measure and weighted fuzzy membership. The moulded algorithm is therefore known as Bias Corrected Possibilistic Fuzzy C-Means (BCPFCM). Then by utilizing neighbourhood information resulted in two other methods knows as Bias Corrected Possibilistic Neighborhood Fuzzy C-Means (BCPNFCM) and BiasCorrected Separately weighted Possibilistic Neighborhood Fuzzy C-Means (BCSPNFCM).
20) *Interval-valued intuitionistic fuzzy sets (IVIFSs):* with the introduction of a new parameter known as hesitation degree a new approach known as intuitionistic fuzzy sets (IFSs) as a generalization of FSs was introduced by Atanassov in 1986. Interval-valued fuzzy set (IVFS) and interval-valued intuitionistic fuzzy set (IVIFS) are the newly developed concepts that can handle the problem of vagueness quite efficiently.
21) *Artificial Neural Networks (ANN):* is a highly parallel connectionist model based on the connection of artificial neurons [2]. The motivation behind ANN is to form a structure like human brain using biological neurons that are highly robust, reluctant to noise, etc. ANN simulates the brain in two respects: 1) By learning, knowledge is collected by the network 2) Synaptic weights (interneuron connection strengths), used to store the acquired knowledge [96, 148, 216]. Error Back Propagation (EBP) method is used for finding and adjusting the appropriate weights that produce desired output. Another feature of ANN is that it learns from the past and does not use any rule sets [27, 74]. The learning can either be supervised or unsupervised. ANN is adaptive to the system and changes its structure accordingly [122, 162, 194]. There are basically three layers in an ANN i.e. 1. Input 2. Hidden 3. Output. Mathematically ANN can be Refer to (4).

$$U = \sum_{j=1}^{m} w_j x_i \tag{4}$$

where x_i is the set of inputs and w_j are the weights.

22) *Backpropagation network (BPN):* designed by Rumelhart, Hinton, Williams (1985), Werbos (1974) and Parker (1985) used by the feedforward neural networks. The BPN calculates the error of the network with the help of some method like gradient descent. BPN has been used in number of applications like voice speech recognition, medical diagnosis, pattern recognition etc. The network has the drawback of slow rate of convergence and local minima problem.
23) *Multi-Layer Perceptron (MLP):* an MLP is a feed-forward neural network with a set of one or more hidden layers which learns a feature representation, facilitates a linear classification that is jointly learned in the final layer. Each layer is composed of a set of artificial neuron units, each of which applies a nonlinear activation function to an inner product of its input vector and a vector of weights. A unit's input is a vector of the outputs of all units in the preceding layer (in the first layer, it is the input vector fed to the model) [218].

24) *Pulse Coupled NN (PCNN):* PCNN is a single-layer, 2-D, and laterally connected network of integrate-and-fire neurons. The PCNN is categorized in the unsupervised neural network group, so it does not need any training stage. The PCNN theory is based on the early work of Eckhorn in the 1990s. The PCNN model is inspired by biological studies on the mechanism underlying the visual cortex of the small mammals. This specific region of the brain, which is a part of the completed mammalian visual system, receives information from the eyes and converts it into a stream of pulses. The receptors are interconnected; when one receives the information, it alters the behavior of other surrounding receptors. PCNNs have been proved to be very useful for different fields of image processing and image recognition with promising results in applications regarding object extractions, edge detection, texture analysis, multichannel image analysis, image fusion, and target recognition. This model has the capability to extract (in an automatic way) essential information from an image, such as edges and textures [42, 88, 111].
25) *Self-organizing map (SOM):* Kohonen's Map is also another example of one of the most popular NN that use a nonparametric unsupervised competitive learning algorithm. Self-organizing feature map (SOM) given by Kohonen in 1982 network is a simplified model of the feature-to-localized-region mapping of a brain. SOM automatically organizes itself according to the input data using a similarity factor like Euclidean distance. Topological relationships of the SOM are conserved in the input and adjacent inputs are mapped to adjacent neurons studies that use SOM needs to cluster the output of the network because it has more output neurons than the tissue types to be segmented [39]. Clustering the similar output neurons is usually performed by using an additional NN that uses weight vectors as input. It can convert complex, nonlinear statistical relationships between high-dimensional data items into simple geometric relationships on a low-dimensional array. The characteristic that distinguishes the SOM net from the other classification algorithms is that in SOM similar inputs are associated not only to the same cell, but also neighborhood cells contain similar information. In this sense, the SOM is both a similarity graph and a clustering diagram. The SOM neural network usually consists of a 2-D grid of nodes. Each node in the 2-D lattice topology is associated with a reference vector corresponding to an input [88].
26) *Deep learning:* one of the novel theory for computational intelligence, having an exceptional capability of learning high-level features from the low-level feature. Generally used in the applications of target recognition and classification, Deep learning has a unique capability of initialization through unsupervised learning and then fine tuning through supervised fashion [33, 37, 108, 110, 126, 137, 146, 150, 249].
27) *Convolutional neural networks (CNNs):* is unique deep learning methods, were first introduced in the 1990s but not much appreciated. But in the year 2006 Hinton and Salakhutdinov initiated it again [44]. CNN is a hierarchically organized structure (generally three layers). Input layer, Convolution layer, Pooling layer, Fully Connected layer are the basic layers of CNN [221]. CNNs are a special kind of NN for processing data that has a recognized, grid-like topology. By stacking numerous convolution layers and pooling layer, CNN is constructed to form a deeper architecture. CNN is hard to train but there are two important facts lies in the composition of CNN i.e., local connections and shared weights. By using a set of weights each neuron is associated with the previous layer through local patches [64, 82, 108, 138, 139, 160, 163, 171, 205,

225]. It is important to set proper weight (connections) of CNN since the power of CNN comes from that. CNN has been deployed to many pattern recognition tasks, image classification, object detection, feature extraction etc.

28) *Self-generating neural networks (SGNN):* is a special type of neural network designed in 1992, influenced from the working of SOM implemented within a self-generating neural tree (SGNT) structure. SGNN is used for classification and clustering. This network has high performance because of its simple architecture, self-organizing capability and higher speed of learning.

29) *Spiking neural network (SNN):* also known as third generation neural networks generally used to solve problems associated with medical fields. The power and strength of this neural network is generated from the modelling of synaptic interactions between neurons. The SNN does have the capability of fast learning and memorization. The SNN overcomes the neural network that models the average firing of neurons by modelling the precise time of the spikes fired by a neuron. Thus achieving higher computational power than sigmoidal activation functions.

30) *Genetic Algorithm (GA):* John Holland is known as the father of GA who invented it in the 1960s. GAs are effective, parallel, adaptive, dynamic, search and optimization method. GA is inspired by the genetic adaptation of natural evolution. A unique feature of GA is being a global optimization method [1, 55, 57, 113, 192]. GA acts as a blind optimization method that does not makes use of derivatives to discover search space, rather it uses a function named as fitness function to guide the search. This important feature of GA makes it different (robust in nature) from other methods like greedy techniques or gradient descent that uses local search for optimization [6, 77, 151, 122, 155, 180, 185, 216, 242]. By using a large number of population and generations, an optimal solution can be achieved [119, 239]. The convergence for GA is given by the eq. 5 by considering an exclusive selection approach, where r and s = probabilities, $s = 1\text{-}r$, A = max no. of generations, P_i = no. of generations earlier to buffer refreshment in the i_{th} evolution, $i \geq 1$ than expected convergence = C Refer to (5):

$$C = \frac{r(1-s)^{(A-1)}}{1-(1-r)^{(A-1)}} \tag{5}$$

31) *Genetic Sequential Image Segmentation (GeneSIS):* is a commonly used classification algorithm used for the purpose of image segmentation. The algorithm uses object extraction algorithm (OEA) based genetic algorithm that segments the object one after another or sequentially. Because of this the algorithm becomes simpler and thus decreasing the problem of search space complexity. GeneSIS algorithm gives higher accuracy and provides a better description qualities [152, 153].

32) *Particle swarm optimization:* PSO was developed by Russell Eberhart and James Kennedy in 1995, it is population based stochastic optimization method motivated by social behavior of bird flocking or fish schooling. PSO is quite similar to Genetic algorithm or evolutionary computation. A group of individuals known as particles move in phases all over a region. At every phase objective function is being evaluated for each particle. On the basis of this evaluation the new velocity of particle has been decided by the algorithm. And this procedure continues until finding an optimal solution. PSO is simple, easy to implement and has been used in number of applications.

4 Soft computing approaches for segmentation of magnetic resonance imaging (MRI) images

MRI helps in number of disease treatment process. MRI plays an important role to identify tumor by creating detailed and cross-sectional images of the brain. It distinguishes among tissues to be normal and tissues that get affected by cancerous cells. MRI defines whether the tumor is cancerous or not, the size of the tumor, location of the tumor, helps in treatment such as radiation or surgery and monitoring the treatment [89, 93, 106, 169, 174, 191]. MRI images are classified on the basis of 3 tissue types i.e. 1. White matter (WM) 2. Gray matter (GM) and 3. Cerebrospinal fluid (CSF) [5, 45, 129, 251] as shown in Fig. 3. The manual interpretation of these images becomes a critical and complex task for clinicians to extract meaningful and important information. So the number of methods has been proposed to perform this task using computerized methods.

Various studies and approaches have been developed to identify tissue and tumor from the brain MRI images. Our aim is to present some of the novel work and thus further we had categorizes those works among three approaches given as follows.

A new hybridized method named as Rough Possibilistic Type-2 FCM clustering (RPT2FCM) with Random Forest (RF) was introduced by Jnanendra Prasad Sarkar et al. in [187]. This method segments MRI images by reducing the effect of uncertainty and ambiguity by using rough sets. The method also gains superior clustering results by adopting rough sets. The rough sets has also been incorporated in [156] by Anupama Namburu et al. by proposing method named as Soft fuzzy rough c-means (SFRCM). Another novel work is presented by Yunjie Chen et al. in [43] where they introduced an improved anisotropic multivariate student t-distribution based hierarchical FCM (IAMTHFCM) method for segmentation of MRI into WM, GM and CSF regions. This method uses histogram based initialization that helps in defining the uncertainty in finding the previous cluster and the present clusters obtained are alike. The lower and upper approximations for choosing the appropriate centroids is done with the help of cluster prototype.

The segmentation of 3D MRI is the latest among the segmentation methodology. In [70] Chaolu Feng et al. proposed a method named as bias correction embedded FCM (BCEFCM) for carrying out 3D MRI segmentation. The nonlocal spatiotemporal regularization function is used to maintain the segmentation consistency. Jeetashree Aparajeeta in [12] proposed three variants of FCM 1. Bias Corrected Possibilistic FCM (BCPFCM) 2. BCP Neighborhood FCM (BCPNFCM) 3. BC Separately weighted PNFCM (BCSPNFCM) for MRI images. The images consist of noise has been considered along with estimating the bias field by using Possibilistic theory and fuzzy membership. Fuzzy c

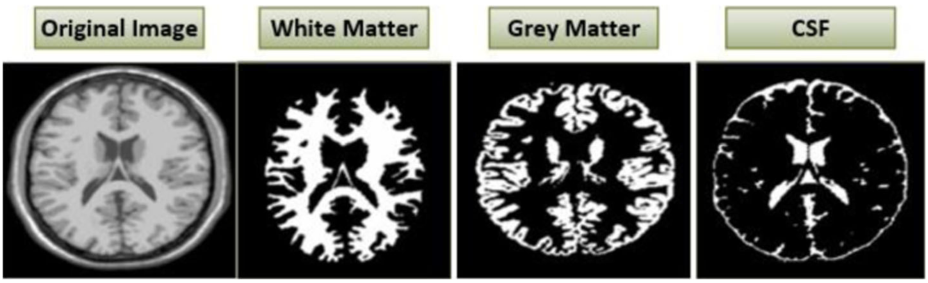

Fig. 3 MRI tissue segmentation

means by including local spatial information with it is heavily used for subdivision of images. Hanuman Verma et al. in [219] used an enhanced intuitionistic FCM (IIFCM) algorithm by introducing local spatial information for brain image segmentation. The hybridization of methods also presents efficient results as shown in [220] by G. Vishnuvarthanan et al. by proposing SOM-FKM procedure that supports the radio surgeon with an automatic tissue and tumor segmentation.

The use of deep learning has made it easy to perform critical and complex task in the field of medical image segmentation. Mohammad Havaei et al. in [87] uses Deep Neural Networks (DNNs) for identification of glioblastomas (tumor). The capability of deep learning shows effective results even for such a multifaceted task. Sergio Pereira et al. in [168] also proposed a CNN that segments MRI images. They have also included intensity normalization as a preprocessing phase. The concept of CNN is advanced towards 3D CNN in [172] that was used to identify CMBs. Qi Dou et al. set up a well-trained model that implements candidates to discriminate CMBs from hard mimics. This method is quite efficient in terms of cost and accuracy as well. Other variants from neural network family also achieves good accuracy in segmenting MRI. Self-organizing maps were used by Ayse Demirhan et al. in [60] for segmenting MRI into its consequent parts. The SOM is further enhanced and fine-tuned by using Learning vector quantization. The hybridization of neural network is also seen in the work presented by Aboul Ella Hassanien et al. in [85] were they uses fuzzy sets, ant-based clustering and MLPNN classifier, in combination with statistical-based feature extraction technique to identify Benign or Malignant from breast cancer MRI imaging. Weighted Probabilistic NN (WPNN) is another example for hybrid methods that combines SOM algorithm for general normal brain tissue segmentation from MRI images proposed by Tao Song et al. in [201]. The method also uses probabilistic density function (PDF).

Payel Ghosh et al. in [77] presents a GA which attains a derivative-free optimization technique of a level set function for image subdivision. In this proposed work, segmenting contours are used for candidate representation and evaluated with a fitness function that simplifies the optimization technique and eliminates the requirement of energy function for image subdivision. This work further aims at the automated 3D subdivision of an image by considering every shape, regional properties and relative position as one dimension. This paper incorporates 2 algorithms First one is GA based on fuzzy inter-cluster hostility index and second Automatic clustering differential evolution (ACDE) algorithm. Che-Lun Hung and Yuan-Huai Wu in [94] proposes a novel parallel FCM method that integrates two algorithms, a GPU-based FCM and Genetic Algorithm (GA) on multiple NVIDIA embedded GPU systems for brain MRI segmentation. The proposed algorithm consists of two parallel programming models-the MPI and CUDA. This work presents an algorithm that is supervised in nature for class levels based method and introduces Chabrier's algorithm for the classification of pixels that are not labelled into some comparable pixels done automatically by Sourav De et al. in [59]. Combining the GA and VEM algorithms as a hybrid GA-VEM algorithm, for GMM-based brain MR image segmentation was proposed by GuangJian Tian et al. in [213]. GMM is investigated using VEM, and initialization of the hyperparameters of the conjugate prior distributions of GMM parameters, involved in the VEM algorithm was done with the help of the GA. The method present in this article is named as Hierarchical Genetic Algorithm with fuzzy learning vector quantization network (HGALVQ) for MRI segmentation by Jinn-Yi Yeh et al. in [237].

4.1 Discussion

In this work, we have tried to present some of the best methods which has been employed from the literature along with various comparative details given in Table 1. Magnetic resonance imaging (MRI) is predominantly employed for the pre-diagnosis and post-diagnosis treatment of brain tumors. MRI helps the doctor to analyze and plan the treatment policy. MRI has been a very crucial technology for medical sciences. Commonly the region of interest among the different classification of MRI images is to classify the given brain MRI image into 4 tissues or regions 1. GM 2. WM 3. CSF and 4. Background. Segmentation was also carried out for identifying the tumor, as well as the extracted region to be Benign or Malignant. This has been the case with breast MRI images to identify breast cancer. The other MRI segmentation applications include extracting cerebral micro bleeds (CMBs), and ventricles [86]. The methods presented are automatic in nature but some of them do require some manual interpretation. Soft computing approaches mainly fuzzy family has been applied for segmenting MRI images. As it is seen from the Table 1 Fuzzy C means and its variants have been most widely used for MRI images. Generally Brain Web, IBSR and BRATS publically available database is used for considering MRI images. The important parameter for FCM are fuzziness (m), neighborhood window (nw) and cluster (c). The values of m, nw and c was taken to be 2, 3 × 3, and 2 in most of the cases. Deep learning model have been also deployed for segmentation purpose. Momentum (mm) and Learning rate (lr) are very important parameter for any DNN family, generally lr varies but mm was observed to be 0.9 fixed for most of the work. Different approaches shows their work efficiency and some of them are listed in the table. The MRI images can be segmented either in 2D or 3D as it was seen in the literature. Jaccard Similarity (JS), Accuracy, Dice Similarity coefficient (DSC), Specificity (SP), Sensitivity (SE) are some of the evaluation parameters which are used to check the accuracy of identifying the region of interest from an image and evaluating any method performance. Segmentation accuracy for brain web MRI database is given in Fig. 4.

4.2 Problem associated with MRI images

1) To handle the intensity of brain tissue is one of the vital features of MRI segmentation.
2) MRI contains complex and critical information with superior quality makes it a difficult task to perform.
3) MRI artifacts like noises, partial volume effect and bias filed effect impair the performance of algorithms.
4) A number of preprocessing phases are required for segmenting the MRI image

5 Soft computing approaches for segmentation of computed tomography (CT) images

Computed Tomography (CT) images is a specialized version of X-ray that gives the more detailed picture of the inside of the body. CT generates those soft tissues that were not recognized by X-ray. Like MRI, CT scans can be done for any part of the body [193]. CT scans are used for the purpose of diagnosis and treatment of cancer, surgeries, injury, cardiac disease, stroke etc [18, 83, 204]. During this survey, we have noticed CT scans segmentation

Table 1 Comparative table for MRI segmentation using SC approaches

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[187]	Rough Possibilistic Type-2 Fuzzy C-Means (RPT2FCM) for MRI	Brain Web/181	DB = 0.38358, ARI = 0.72755, Minkowski Score MS = 0.64725, Percentage of Correct Pair %, CP = 85.82549 / 26.67 s
[43]	Anisotropic multivariate student t-distribution based hierarchical FCM (IAMTHFCM) for MRI	Brain Web, IBSR	JS = 73.29 ± 8.12
[77]	Genetic algorithm for 2D and 3D CT and MRI	Oregon Health & Sci. Univ. (OHSU)	DSC for 2D = 0.45 & for 3D = 0.69
[156]	Soft fuzzy rough c-means (SFRCM) for MRI into WM, GM, CSF	Brain Web/20, IBSR/20,BRATS/10	SA = 0.8930, JS = 0.8930 / 17.06 s
[61]	RCLFCM for Tissues from brain MRI	Brain Web	SA = 0.9816, V_{pc} = 0.9835 and V_{pe} = 0.0093 / 49.23 s
[70]	Bias correction embedded fuzzy c-means (BCEFCM) for Brain tissues from MRI	Brain Web/30, IBSR	SE = 0.07, SP = 0.06, JS = 0.9345 / 12 s
[12]	Bias Corrected Possibilistic Neighborhood FCM (BCPNFCM) & Bias Corrected Separately weighted (BCSPNFCM) for MR image	Brain Web/ IBSR	ME for BCPNFCM & BCSPNFCM = 4.2302 & 4.6967, JS for BCPNFCM & BCSPNFCM = 0.4166 ± 0.06 & 0.3866 ± 0.11 / 5 s & 10s
[219]	Improved intuitionistic FCM (IIFCM) for Brain image	IBSR	DSC = 0.7433, SE = 0.1788, SP = 0.3076 / 14.51 s
[220]	Self-organizing map and Fuzzy K means SOM+FKM for Tumor and tissue present brain	Harvard Brain Repository/38	MSE = 2.151, PSNR = 41.85, JS = 31.54%, DSC = 34.85% / 2.8 s
[103]	Fuzzy local Gaussian mixture model (FLGMM) for Tissue from brain MRI	Brain Web/20, IBSR/20	JS = 0.8738 / 23.50 ± 2.84 s, 765.41 ± 35.04 s
[87]	Deep neural network (DNN) for Brain Tumor	BRATS 13/6000	DSC = 0.85 ± 0.5, SP = 0.90 ± 0.5, SE = 0.86 ± 0.5 / 25 s to 3 m
[168]	Convolutional neural networks for Brain Tumor (gliomas) from MRI	BRATS13 & BRATS15	DSC for 13 = 0.88, 0.83, 0.77 & for 15 = 0.78, 0.65 & 0.75 / 8 m
[172]	3D CNNs for Cerebral micro bleeds (CMBs)	320 volumetric MRI	SE = 93.16% / 1 m
[60]	Self-organizing map + learning vector quantization (SOM + LVQ) for Tissue segmentation of MRI	IBSR, BRATS12	For IBSR JS = 0.93, SE = 0.99, SP = 0.99, and for BRATS DSC =0.44 for training & for challenge = 0.24 / 20s
[85]	FS, ant-based clustering with Multilayer perceptron (MLPNN) for Benign or Malignant in MRI breast	25 images	SA = 95.1%, MAE, RMSE, RAE are 0.0339 0.1433 7.535%
[161]	Self-organizing maps (SOM) for MR image segmentation	IBSR & IBSR 2.0	SE = 75%, SP = 88%, JC = 0.60 ± 0.085
[201]		5 MRI images	Relative overlap ratio

Table 1 (continued)

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
	Modified probabilistic Neural Network (WPNN) for Brain tissue segmentation		46.8% for CSF 77.4% for GM 69.1% for WM
[94]	GPU-based FCM + GA for Brain MR	BrainWeb	Not define (N) / 1.186 s
[59]	Genetic algorithm (GA) for MR image into tissues	Not define (N)	Correlation coefficient (ρ) = 0.9896, Empirical measure(Q) = 0.0014
[213]	GA-VEM for MRI	IBSR	SA = 0.7702 ± 0.1435, and 0.8570 ± 0.0458
[237]	Fuzzy learning vector quantization network for Multi-spectral human-brain MRI	From hospital in Taiwan	SP = 0.9739, SE = 0.9220, JS = 0.4266 / 92.415 s
[69]	Parallel genetic algorithm for Lateral ventricles	Brain Web	N

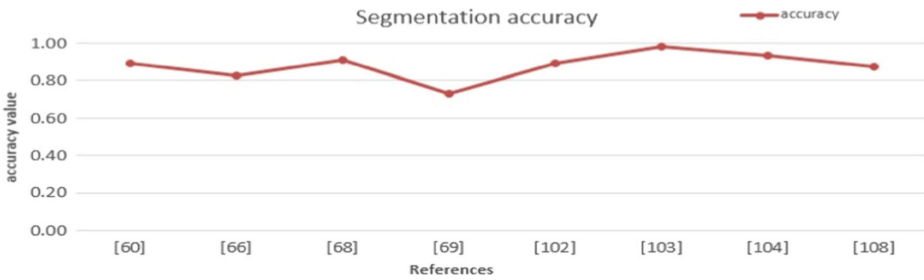

Fig. 4 SA for brain web database

has been used most commonly for liver or lungs images [116]. A CT scan image is shown in Fig. 5.

In [16] A. Baazaoui et al. proposes a method named as entropy-based fuzzy region growing (EFRG) for identification of tumor and multiple tumor regions. The proposed method is semiautomatic in nature that uses region based entropy and a membership degree based on a fixed threshold value. Eugene Vorontso et al. in [126] presents a novel framework for segmentation of liver tumor using Voxel classifier based on a MLP deformable model. T. Manikandan & N. Bharathi in [141] by implementing fuzzy clustering and Ezhil E. Nithila and S.S. Kumar in [158] by implementing region-based active contour model and FCM performs the segmentation of the suspected nodules from the CT images.

In [11] Marios Anthimopoulos et al. performs the ordering of ILD patterns from CT images. They uses a convolutional NN (CNN) for this purpose. Another novel work was proposed by Ching-Wen Huang et al. in [92] by using neighborhood membership in order to maximize benefits and reduce noise influences with a GA cast-off concurrently to select the optimal parameters using FCM clustering technique and preserving the benefits of the same. The method proposed by them is known as Novel Intuitionistic fuzzy c-means clustering algorithm (NIFCMGA). In [179] Holger R. Roth et al. shows that the Pancreas segmentation from CT images is another area of interest. A semiautomatic method for bine segmentation is another application of CT images. [98] K. Janca uses a semiautomatic

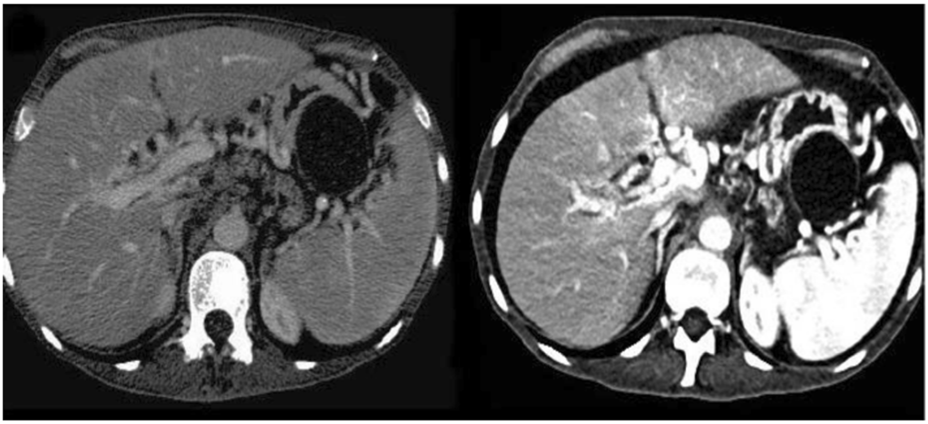

Fig. 5 CT scan image

approach to perform this task. Author has also worked on segmentation of thyroid and volume estimation by using Progressive learning vector quantization NN (PLVQNN) that was proposed by Chuan-Yu Chang et al. in [38]. For the segmentation of pancreas from the CT scan image Holger R. Roth et al. in [179] presents a probabilistic bottom-up method. In [98] K. Janca tries to make a system that will segment bone from CT images in a semi-automatic fashion and using the same for further study it with the 3D objects recreation. Progressive learning vector quantization NN (PLVQNN) was proposed by Chuan-Yu Chang et al. in [38] for automatically segmenting thyroid and volume estimation.

5.1 Discussion

Computed tomography (CT) images are another important part of medical sciences that helps in number of treatment or diagnosis processes. The segmentation of Liver CT images was generally carried out by the researchers to detect tumors and along with this authors have also developed some methods to segment Bone CT images. Table 2 gives further details of the segmentation carried out for CT images. LIDC-IDRI is the database available for CT images. Evaluation parameters like Accuracy, DSC are the most common to judge the effectiveness of the segmentation.

Table 2 Comparative table for CT segmentation using SC approaches

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[16]	Entropy-based fuzzy region growing (EFRG) for Multiple tumor region	4 images	AOE 19.905%, RAD = 15.451%, DSC =0.881
[222]	Multilayer perceptron (MLP) for liver tumor	40 abdomen with 95 colorectal images	DSC = 0.80 ± 0.11, SA = 0.88 ± 0.11, SE = 0.84 ± 0.13, SP = 0.92 ± 0.16
[141]	Fuzzy Auto-seed Cluster Means Morphological (FACMM) for Suspect nodules	907 images	SE = 100%, SP = 93%, SA = 94%
[158]	Active contour model (ACM) & FCM for lung nodules	LIDC-IDRI	SA = 98.95 / 1 m
[195]	K-means, FCM and Gustafson–Kessel algorithms for Liver image	Liver disorder with 341 & Wine with 178 samples	SA for K-means = 76%, FCM = 71% & Gustafson–Kessel =83%
[11]	Deep CNN for Classification of ILD patterns	14,696 image patches, from 120 CT scans	SA = 85.5% / 20s
[92]	Neighbourhood intuitionistic FCM clustering algorithm GA (NIFCMGA) for Diagnosis of abnormalities from MRI & CT	2 MRI and 2 CT	Mean misclassification error = 70.29 / 17.123 s
[179]	Deep ConvNets (Convolutional networks) for Pancreas subdivision in abdominal CT	CT images of 82 patients	DSC 71.8 ± 10.7% / 1 to 3 m
[98]	Genetic algorithm (GA) for Bone segmentation	J. Morita Mfg. Corporation/80	SA = 0.761 / 3 h
[38]	Progressive learning vector quantization (PLVQNN) for T hyroid segmentation	241 CT images assimilated from 3 patients	SE = 78.7%, SP = 94.7%, SA =91.5% / 5.07 s

5.2 Problem with CT images

1) The problem of noise and other subsequent information presents makes it a difficult for segmentation.
2) Detection of boundaries for a specific region that has to be segmented is also a complex task with CT images for example while segmenting lung differences in pulmonary inflation with an elastic chest wall will create huge inconsistency in volumes and margins.

6 Soft computing approaches for segmentation of other medical image applications

Other than MRI and CT the most common ones used for the segmentation, we have gone through some interesting medical image diagnosis. The development of computerized methods helps analysis of diseases, injuries, surgeries etc. for pre and post treatment planning and diagnosing.

There are number of medical images segmentation applications. Based on the literature in this section we try to present some of the interesting works for the application of image segmentation in the medical field. Buket D. Barkana et al. in [24] by using fuzzy logic, SVM, ANN, and classifier fusion performed the segmentation of retinal images into blood vessels for the diagnosis of diabetic retinopathy. Khosro Rezaee et al. in [24] also performed retinal image segmentation by using skeletonization and a threshold based on Fuzzy Entropy. They also adopted Wiener's filter and adaptive filter for removal of blur noise and extraction of blood vessels. And at last, by employing fuzzy entropy, an optimal threshold for discriminating main vessels of the retina from other parts of the tissue is achieved.

Zahra Rezaei et al. in [175] presents a novel work for identification of Thin-cap Fibroatheroma (TCFA) or "vulnerable plaque" from Virtual Histology Intravascular Ultrasound (VH-IVUS) images by using a hybrid method named as HFCM-kNN. V.P. Ananthi and P. Balasubramaniam in [7] presents a new automatic subdivision technique grounded on interval-valued intuitionistic fuzzy similarity measure called as IVIFSs to fragment leukocytes in blood smear images. Detection of the lesion from skin image is a complex task, Filipe R. Cordeiro et al. in [56] does it by adopting fuzzy based GrowCut technique. Their approach works in 2 phases 1. By applying differential evolution optimization algorithm for automatic selection of internal points 2. In a way to deal with complexity to define lesion borders with the use of Gaussian fuzzy membership functions modification of cellular automata, evolution rules have been done. In [128], a new fuzzy clustering technique intended for lip image segmentation is offered by Shu-Hung Leung. With the help of an elliptic shape function, the clustering method takes together the color statistics and the spatial distance into consideration. Because of the function, the new method is capable to discriminate the pixels having identical color information but positioned in diverse regions.

The concept of deep learning has been examined by Yan Xu et al. in [233] to segment glands (instances) in colon histology images. They uses deep multichannel NN for this purpose. In [217] Mark J. J. P. van Grinsven et al. adopted selective sampling strategy SeS-CNN for the identification of hemorrhages on color fundus images. They shows that their method substantially speed up the time-consuming training process of CNN with a SeS. Yading Yuan et al. in [241] proposed a 19 layer DCNN for skin lesion identification. The effectiveness of the proposed work is that, it does not require any past knowledge or information. A patient-specific ECG heartbeat classifier was proposed by Serkan Kiranyaz et al. in [121] by implementing 1D CNN. Francisco Veredas et al. in [72] uses NN and Bayesian Classifiers for spontaneous tissue extraction in wound images with the help of a mean shift technique and a region-growing approach for improved region extraction.

6.1 Discussion

Table 3 present the details about the methods and their performance along with other factors. Other than MRI and CT images computer aided diagnosis has also been carried out for other medicinal images. Leukocytes from blood smear images, Retinal vessel segmentation, Identification of TCFA in VH-IVUS image, Mammographic images for Lesion segmentation, Patient-specific ECG heartbeat classifier, and Wound tissues segmentation are some of them. Frequently it was seen that fuzzy family and genetic algorithm have been used for segmentation due to complex nature of medical images in different situations. The evaluation of work and choice of database is dependent on the type of application. But Accuracy, DSC, JS, SP and SE are some of the common evaluation parameters.

6.2 Problem with medical images

1) The distinguishing region of interest with the structures present in the medical images.
2) Medical images do suffer from partial volume effect.
3) Noise is the major problem with medical images.
4) RF inhomogeneity is another factor.

7 Soft computing approaches for segmentation of synthetic aperture radar (SAR) images

The SAR images are high-resolution multispectral images that are segmented to for better understanding and analysis [79]. The segmentation is performed based upon applications like the classification of different boundaries, identification of objects, region classifications based upon attributes like color, size etc. in this part we are presenting the soft computing approaches used for separating SAR images into different parts. Example for SAR segmentation is given in Fig. 6.

A novel method named as Voronoi Tessellation (VT) and Hidden Markov Random Field (HMRF) based FCM (VTHMRF-FCM) is proposed by Quan-Hua Zhao et al. in [248] for texture segmentation. The objective of FCM is defined by using a regularization term of Kullback–Leibler (KL) divergence. Another method using FCM is presented by Ronghua Shang et al. in [190] named as CKS_FCM for segmentation of SAR images. FCM achieves initial clusters with the help of clone to avoid getting into local minima and then by applying some nonlocal filters by adjusting parameters the noise is reduced. Another variant of FCM is adopted by Jian Ji and Ke-Lu Wang in [102] named as fuzzy clustering algorithm with enhanced nonlocal spatial information (FCM_INLS) that has adaptive distance measure and self-tuning filtering degree parameter, integrating with the nonlocal spatial information attained by the nonlocal mean technique into the FCM for SAR image segmentation.

In [99] Umer Javed et al. presented a method termed as to be a fuzzy weighted active contour model. This method is basically adopted for classification of water and land region

Table 3 Comparative table for other medical images segmentation using SC approaches

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[217]	CNN for Color fundus image segmentation for hemorrhages	The Diabetic Retinopathy Detection challenge Kaggle1 and Messidor	AUC curve Az = 0.894 and 0.972 / 960 m
[24]	FL, ANN, SVM, and classifier fusion for Retinal vessel segmentation	DRIVE and STARE	SA = 93.82%, 92.4%, SE = 72.28%, 75% SP = 97.04%, 94.3%
[175]	Skeletonization & threshold based on Fuzzy Entropy for Analysis of retina blood vessels	DRIVE and STARE	SA = 94.63%, 95.21%, SE = 0.8, 0.7189 SP = 0.06, 0.9793
[176]	FCM and kNN (HFCM-kNN) for Identification of TCFA in VH-IVUS image	599 Gray-scale IVUS images	SA =98.02%
[7]	Interval-valued intuitionistic fuzzy sets (IVIFS) for Leukocytes from blood smear images	100 through 1 WBC, 270 through 2 WBC	SA =0.9766, DSC =0.9412, SSIM = .9584, JS = 0.7735 / D1 = 1.6 s & for D2 = 0.25 s
[56]	Fuzzy semi-supervised version of the GrowCut for Lesion segmentation	57 images from MiniMIAS mammography	SE = 0.83 ± 0.21, SP = 0.88 ± 0.17, AOM = 0.62 ± 0.20, BAC = 0.86 ± 0.11
[128]	Fuzzy clustering for lip images	5000 lip images	SA =97.28% / 5.34 s
[233]	Deep multichannel NN to segment glands	MICCAI 2015 Gland Segmentation	DSC = 0.870
[124]	Convolutional neural networks for medical images	ImageCLEF 2016	Classification accuracy of 82.48, 96.59, SA = 82.48 / 14,722 s & 39,394S
[241]	Deep Convolutional neural networks for Skin lesion segmentation	ISBI 2016 Skin Lesion Analysis, and the PH2	SA =0.955, DSC = 0.912, JI = 0.843, SE = 0.918, SP = 0.966 /27 s
[121]	1D CNN Convolutional neural networks for Patient-specific ECG heartbeat classifier	MIT/BIH arrhythmia database	SA =98.83, SE = 94.93, SP = 98.8, Ppr = 92.1 for VEB, SA = 96.8, SE = 64.56, SP = 99.1, Ppr = 98.26 for SVEB / 2 m
[167]	Multiple thresholding, wavelet transform, & GA for Breast cancer from Mammogram images	Digital Database for Screening Mammography (DDSM)	SE = 95% / 11.05 s
[231]	Self-generating NN (SGNN) + GA for Dermoscopy images	Caucasian race and Xanthous race	Caucasian race Mean (SD) XOR, Hausdorff distance, JS = 15.0(9.6), 43.0(41.2), 85.5(9.2), for Xanthous race Mean(SD) XOR, Hausdorff distance, JS = 20.7(14.1), 56.1(42.9), 80.3(12.4) / 9.3 s & 12.1 s
[72]	Bayesian classifier + NN for Wound tissues segmentation	113 images	SE = 77.53, 78.23, SP = 94.38, 94.55, SA =91.01, 91.29 / 11.7 s
[51]	Bell fuzzy multilayer perceptron (BF-MLP) + GA for Medical image	44 images from National Biomedical images archive	SA = 95.5%

from the SAR image. The proposed work is based on local variance and entropy fuzzy inference engine (FIE), which cast off to allocate weights to pixels of the level set function. Another novel work was proposed by Imane Sebari and Dong-Chen He in [188] named as

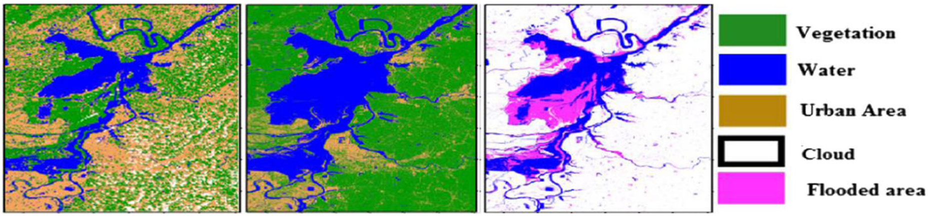

Fig. 6 SAR image pre and post-earthquake segmentation [197]

object oriented image analysis (OBIA) for segmentation of natural classes such as tree, lawn, soil, water and segmenting man-made classes such as building, road, parking area.

SegNet a DCNN network having the three key components an encoder, a decoder and a pixel wise cataloging level is proposed by Vijay Badrinarayanan et al. in [17]. The proposed method is used for the pixel wise semantic segmentation of indoor and road side scenes. SeNet another variant of deep learning network is proposed by Dongcai Cheng et al. in [48] using DeconvNet as fundamental. SeNet is implemented for the classification of sea-land area. Lei Wang et al. in [226] proposed a CNN for the segmentation and estimation of ice concentration from SAR extracts. Gong Cheng et al. in [47] proposed a method named as rotation-invariant CNN (RICNN) model that is used for identification of objects from the satellite images. Lei Wang et al. Yu Zhou et al. in [240] proposed a polarimetric SAR (POLSAR) images terrain classification framework using DCNN. The result of the San Francisco case shows that slant built-up areas, which are conventionally mixed with the vegetated area in polarimetric feature space, can be successfully distinguished after taking spatial features in consideration.

Alireza Taravat et al. in [211] presents a new approach for automated dark spot recognition from SAR with the amalgamation of Weibull multiplicative model based filter which is applied to each sub-image and then PCNN technique is used for segmenting that filtered sub-image. In [199] Suman Singha et al. have used two ANN. The first ANN is used to segment the SAR image for identifying pixels belonging to candidate oil spill features. And second ANN classifies objects into oil spills and look-alikes with the help of extracted statistical feature parameters.

Genetic algorithm is used by M. Izadi et al. in [97] segmentation of damaged roads for both pre-event and post-event high-resolution SAR images. Akansha Singh and Krishna Kant Singh also uses GA for identification of flooded areas in SAR image. The proposed method is semiautomatic in nature that uses radial basis function. A hybrid dynamic genetic algorithm (HDGA) was proposed by M. Awad et al. in [15], in this method the genetic algorithm is extended using a hill climbing, randomizing and improved mutation operators. Another application of genetic algorithm was adopted in [101] by Byoung-Ki Jeon et al. for roads detection in spaceborne SAR images. In [154] Stelios K. Mylonas et al. uses Genetic Sequential Image Segmentation (GeneSIS) algorithm for segmenting the satellite images by extracting a single object at each iteration. A new genetic based clustering algorithm, multicentre based automatic clustering technique (MCVGAPS) have been developed by Sriparna Saha and Sanghamitra Bandyopadhyay in [182] for remote sensing satellite images segmentation.

7.1 Discussion

Synthetic-aperture radar (SAR) segmentation is one of the complex segmentation among all the types of images segmentation. The satellite images have been segmented to classify among natural and man-made objects generally. The applications of SAR partitioning lies in classification of natural objects like water region, land region, sea region, ice concentration from sea, dark oil spot from sea etc. and from man-made classes roads, buildings, tree etc. the databases like RADARSAT I & II, University of Pavia, ISODATA, IKONOS, Indian Pine are most widely used by the authors, other than that databases are application dependent. Deep neural network due to its learning capability has been most extensively used for this kind of image segmentation. Learning rate, batch size, dropout rate and momentum are the important features of any DNN method. The values of learning rate is generally varied from 0.01 to 0.03, 0.001 to 0003, batch size varies from 64 to 128, dropout is 0.3 and momentum is 0.9 for most of the algorithms. The Genetic family has also been deployed for SAR image segmentation more often. The important parameters for GA are population (P), the number of generations (N), mutation (P_m) ranges from 0.01 to 0.05 and crossover (P_c) varies from 0.5 to 0.9 but most commonly 0.8 is used. Segmentation accuracy is the most commonly used evaluation parameter to check the performance of the proposed method. Table 4 illustrates several details of the work conducted for segmentation purposes. Segmentation accuracy for SAR images is given in Fig. 7.

7.2 Problem with SAR images

The satellite images contains lot of information thus it is dependent on the type of application where it has been utilized but most commonly the problems can be

1) The SAR images contain the number of textured regions or different backgrounds make it difficult to handle.
2) The SAR images also dependent on ground truth properties and enlightenment changes.
3) The quality of an image that has to be used for segmentation purpose.
4) SAR images are high-resolution multispectral images, becomes difficult to handle.

8 Soft computing approaches for segmentation of complex real world images

The most typical task is to identify the object from the real world complex images. As we know that the object can be anything that exists in the real world. To identify and classify the boundaries for a region of interest is itself a difficult job to be performed. The complex nature and a large amount of information present in a real-world image make it difficult for evaluating its ground truth. A number of approaches have been presented but till date, no such approach came out with superior performance to segment such type of images. An example for a real-world scene is given in Fig. 8.

The segmentation of real-world complex images based upon soft computing approaches is further divided among three parts as follows:

Generalized Gaussian Density (GGD) is implemented by Siu Kai Choy et al. in [54] for object segmentation. The presented work is unsupervised whose learning is based on fuzzy model-based learning algorithm. The strategy of the Iteratively Fuzzy Region Competition (IFRC) model is used to perform a two-phase Fuzzy Region Competition model iteratively for multiphase $N-1$ times and to compute one fuzzy membership function per round for image segmentation was proposed by V. R. Borges et al. in [31]. Using a bi-level segmentation operator, which combines fuzzy 2-partition entropy maximization with binary GC optimization Shibai Yin et al. in [238] presents a fuzzy based algorithm that, uses the super pixels as

Table 4 Comparative table for SAR segmentation using SC approaches

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[111]	Pulse-coupled neural networks (PCNN) for Sea ice extraction	RADARSAT I ScanSAR over Baltic sea ice	N
[44]	Convolutional neural networks for Hyperspectral image (HSI) classification for 1D, 2D, 3D	Indian Pine, Univ. of Pavia, Kennedy space centre (KSC)	SA for 1D = 85.09 + −1.20, 2D = 89.09 + −1.18, 3D = 98.00 + −1.10 / 27.92 s, 46.15 s, 7.93 s
[153]	Genetic Sequential Image Segmentation (GeneSIS) + SVM for Satellite images	University of Pavia, Indiana, Karonia lake images	For Univ. of Pavia OA = 95.46, AA = 97.21, k = 93.95, For Indiana OA = 95.33, AA = 97.41, k = 94.65, For Karonia lake agriculture area OA = 81.47, AA = 86.31, k = 74.24, For Karonia lake wet land area OA = 94.85, AA = 92.45, k = 91.85
[152]	Genetic Sequential Image Segmentation (GeneSIS) for Object-based classifica-tion scheme for handling remotely sensed data	University of Pavia, Indiana, Karonia lake	University of Pavia Overall Accuracy =88.96, Avg. Accuracy = 93.86, Kappa = 85.67, Indiana OA = 94.51, AA = 97.02, Kappa = 93.72, For Karonia OA = 83.26, AA = 85.42, Kappa = 72.94
[248]	Voronoi Tessellation & Hidden Markov Random Field (VTHMRF-FCM) for Texture image sub division	RADARSAT II	SA = 99%, kappa = 0.99
[99]	Active Contours and Fuzzy Logic for Water and Land	Ajkwa river	Mean RSF = 18.55 / 11.65 s
[188]	Object-Based Image Analysis (OBIA) for Urban information from VHSR multispectral	Ikonos image of Sherbrooke	An overall segmentation rate of 80% was observed. SA accuracy manmade classes are of 81%, 75% and 60%
[17]	SEGNET for Road & indoor scene like building, tree, sky, car, symbol	CamVid road scenes dataset SUN RGB-D	SA =71.20 / 455.60 ms
[48]	Structured Edge Network (SENET) for Sea–land segmentation	Natural-coloured images from Google Earth	Land precision (LP), land recall (LR), overall precision (OP), and overall recall (OR) = 99.69, 98.15, 98.12 and 98.11, Avg. F1-MEASURE (%) = 92.78 / 650 ms
[47]	Rotation-invariant CNN (RICNN) for Object detection	VHR object detection	SA =90% / 8.77 s
[226]	Deep Convolutional neural networks (CNN) for Ice concentration in SAR images	RADARSAT-2	Mean error Esgn = 0.01 on average, Overall bias of the estimated ice concentration = 0.08, largest mean error (Esgn) = −0.11, mean absolute error (EL1) = 0.13 / 10 m

Table 4 (continued)

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[240]	Deep convolutional neural networks (DCNN) for POLSAR images terrain classification	AIRSAR records of San Francisco CA & Flevoland Netherland	San Francisco accuracy = 99.43% and 90.23% and Flevoland = 99.20% and 97.66%
[211]	Weibull multiplicative model and Pulse-Coupled NN (WMM + PCNN) for Dark-spot detection	60 Envisat and ERS2 images	SA = 93.66% / 7 s
[97]	Adaptive Neuro-Fuzzy Inference System (ANFIS+GA) for Roads damage detection after earthquake	Quick Bird pan-sharpened images from the Bam earthquake	SA = 94%, kappa = 0.91
[197]	Genetic Algorithm (GA) and Radial Basis Function NN (RBFNN) for Flooded areas from satellite images	LandSat 8 OLI images of Dongting Lake in south China	Pre flooding image SA = 94.92% Overall Kappa = 0.9237 and post flooding image SA = 96.09%, Kappa = 0.9338
[154]	Genetic Sequential Image Segmentation (GeneSIS) for Segmentation of remotely sensed images	Taxiarchis, Kerkini and Center of Pavia	For Taxiarchis OA = 93.38, AA = 94.11, k = 0.907, For Kerkini OA = 85.18, AA = 87.19, k = 0.820, For Center of Pavia OA = 98.18, AA = 97.64, k = 0.976 / 9.6 s
[182]	Multicenter-based automatic clustering (MCVGAPS) for Land into multiple regions	SPOT-3D of part of city of Kolkata India, Landsat-V	Avg. ARI MCVGAPS = 0.75 ± 0.01, for the SPOT image 0.72 ± 0.01, Landsat image = 0.71 ± 0.01
[15]	Hybrid dynamic genetic algorithm (HDGA) for Satellite Image	Landsat ETM+,IKONOS II	SA = 97% and 90%
[14]	Self-organizing-maps-Hybrid GA (SOM–HGA) for Airport/urban, crop, shrubs segmentation	ISODATA, IKONOS	SA = 92.66%
[101]	Genetic Algorithm (GA) for Detection of roads in SAR	ERS-1 and SIR-C/X-SAR	SA = 92.2% / 4 m
[75]	Self-Improving Convolution Neural Network (SICNN) for Classification of hyper-spectral data	Indian Pines and Pavia University	For Indian Pines Overall Accuracy = 81.66, SA = 89.64, kappa = 0.7933, For Pavia Univ. Overall acc. = 82.67, SA = 82.18, kappa = 0.7716
[189]	Convolutional neural networks (CNN) for Objects from high resolution images	UCMerged	SA = 98.6% / 30s

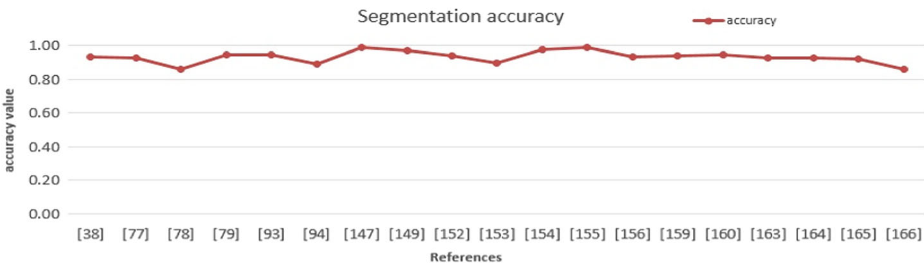

Fig. 7 Segmentation accuracy (SA) for SAR images

segmentation primitives and partitions all the super pixels iteratively. Ajoy Mondal et al. in [149], proposes a robust fuzzy energy based active contour by using both global and local information to segment (noisy and blurred) images with high-intensity inhomogeneity or non-homogeneity. The local information in the proposed method is generated based on both the spatial distance and the pixel intensity. Feng Zhaoa et al. in [247] proposed a method named as multiobjective spatial fuzzy clustering algorithm (MSFCA) that overcomes the sensitivity of can present better segmentation results. This method also uses an optimization tool named as Non-dominated Sorting Genetic Algorithm-II (NSGA-II). A novel FC-SSCSVM is proposed in [40] which makes use of SSC and linear SVM to learn fuzzy rule for object recognition from multifaceted scenes by Guo-Cyuan Chen and Chia-Feng Juang.

In [104] Xiao-Liang Jiang et al. proposes two variants of FCM known as FCM with spatial constraints (LCFCM_S) and its robust version LCFCM_S1 for image segmentation. The proposed methods uses correntropy criterion that makes them robust against noise and outliers. Ebrahim Aghajari et al. in [3] presented a hybrid approach by using the features of SOM and Extended FCM to form a new concept named as SEEFC for the segmentation of images taken from BSD database. Local Membership Relative Entropy based FCM (LMREFCM) & Local Data & Membership Relative Entropy based FCM (LDMREFCM) was proposed by R. R. Gharieb et al. in [76]. The proposed methods incorporates membership relative entropy (MRE) and modified local spatial data information. In [130] by Yan-ling Li and Yi Shen proposed an automatic fuzzy clustering algorithm (AMFCM). This method achieves automatic clustering by collecting similar pixels without knowing the number of clusters. Region Splitting and Merging FCM Hybrid Algorithm (RFHA) that consist of two main modules: Region Splitting and Merging (RSM) and FCM as an adaptive unsupervised clustering method for color image subdivision was proposed by Khang Siang Tan et al. in [208].

Fig. 8 Example for real world scene [142]

Feedforward neural network using FCM (FFNN) was proposed by S. Arumugadevi et al. in [13] for color image segmentation. The NN is trained with the help of Levenberg-Marquardt back-propagation algorithm and the labels obtained from FCM have been utilised as a target or FFNN. A deep Convolutional was proposed by Fayao Liue et al. in [135] for estimation of depths from single monocular images. The proposed works aims to explore the capacity of dep CNN and continuous CRF. Another novel work was presented by Sourav De et al. in [58] named as a parallel self-organizing NN (PSONN) model and a parallel version of the optimized MUSIG (ParaOptiMUSIG) for segmentation of color images. In [144] B. Meftah et al. proposed a Spiking neuron networks (SNNs) for edge detection and segmentation of images. The use of SNN quite effectively handles the parameter setting issues addressed by the other networks. Siddhartha Bhattacharyya et al. adopted a self-supervised multilayer self-organizing NN (MLSONN), a supervised pyramidal neural network (PyraNet) and a bi-directional self-organizing NN (BDSONN) model that are suitable for multilevel image segmentation.

By using two entropies named as Tsallis and Renyi S. Abdel-Khalek et al. [1] presented a 2D image segmentation method based on genetic algorithm in [1]. The segmentation of ccolor images is the recent trend among the researchers therefore Ahmad Khan and Muhammad Arfan Jaffar in [114] proposed a fixed length GA incorporated with two networks named as ANN and SOM. Hui Wei and Xue-song Tang [228] have presented a new method for shape representation by using the concept of FCSs based on GA. In summary, this representation shows the essential structural logic of a contour, has been designed for learning the shape representation for object recognition. This proposed method aims at the study of geometrical shapes for conceptual description, shape recognition and retrieval. In [115] Ahmad Khan et al. also proposes a method for color image segmentation named as Spatial fuzzy genetic algorithm (SFGA). The method is unsupervised in nature whose performance depends upon the two factors 1. Number of clusters should be known prior to segmentation and 2. The cluster centers is to be initialized. Therefore to overcome these issues a progressive technique based on SOM is presented. A GA is proposed by Kamal Hammouche et al. in [84] for segmentation of various images that is different from the conventional algorithm which uses a novel representation of chromosomes. The threshold value does not require encoded or decoded operations because it uses binary encoding. Authors have also used a wavelet transform for reducing the length of the original histogram which is then used for determining a multilevel thresholding values which in turns produces the efficient results. The results were also improved by utilizing a leaning method and to deal with problem specific properties an innovative mutation operator is used. For the range image segmentation a method was proposed by Paulo Fabiano Urnau Gotardo et al. in [80] that is based on an improved robust estimator to iteratively identify and excerpt distinct planar and quadric surfaces. Further to quicken the optimization process for extraction of surfaces while preventing premature convergence a genetic algorithm was used. Hang Joon Kim et al. in [117] presents a hierarchical distributed genetic algorithm (HDGA) which is unsupervised and parallel for segmenting noisy and blurred images. Adopting a distributed genetic algorithm gray level image subdivision has been performed by Philippe Andrey and Philippe Tarroux in [9].

8.1 Discussion

Various details of the segmentation methods have been given in Table 5. Another complex area of image segmentation is to identify objects from the real world images. The objects can be

Table 5 Comparative table for real world images segmentation using SC approaches

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[54]	Fuzzy Generalized Gaussian Density (GGD) for Images with various textures	GGD & Weizmann	SE = 4.35%, JS = 0.9022 / 8 s
[3]	Self-Organizing-Map (SOM) & Extended FCM (SEEFC) for Segmentation of various images	BSD500	SE = 84.56%, SA = 88.1%, Q index = 0.0798 ± 0.41
[31]	Iterative fuzzy region competition algorithm IFRC for Multiphase segmentation for different images	MIAS, BSD	Accuracy = 84.45%
[104]	Local correntropy-based FCM clustering algorithm with spatial constraints (LCFCM_S) and simplified (LCFCM_S1) for Various images with spatial constraints	BSD500	DSC for LCFCM_S = 0.9361, DSC for LCFCM_S1 = 0.9281 / LCFCM_S = 44.89, for LCFCM_S1 = 21.58 s
[32]	Fuzzy-based artificial bee colony optimization (FABC) to segment various images	Brodatz album	Davies–Bouldin, Xie–Beni, β-index, Dunn index for MR1 = 1.1111, 0.6230, 2.0444, 2.6975, MR2 = 1.9808, 3.1453, 3.1226, 0.4640 / MR1 = 5.3125 & MR2 = 15.1250
[1]	GA for Various images	8 images	PSNR values for Tsallis entropies =5.08 and Renyi entropies = 6.09
[238]	Fuzzy c- partition entropy for Bird, camera, flower & boats	BSD	F-measure with super pixels = 4.5595 without super pixels = 5.8777, PRI = 0.7769, VoI = 2.3067, GCE = 0.2215, BDE 10.66 / 10.8 s
[76]	Local Membership Relative Entropy based FCM (LMREFCM) & Local Data & Membership Relative Entropy based FCM (LDMREFCM) for Natural image segmentation	Lena image & 2 images from BSD	Vpc for LMREFCM = 0.9511 ± 0.0004 & for LDMREFCM = 0.9589 ± 0.0002, Vpe for LMREFCM = 0.0768 ± 0.0008 and for LDMREFCM = 0.0633 ± 0.0003 / 1.5 s
[132]	Fuzzy-based GWO & aggregation algorithm and fuzzy-based modified discrete GWO & aggregation algorithm for Multilevel image threshold problem for different images	BSD500	PSNR = 21.281, MEAN = 18.0808 and STD = 0.0955 values for six different images
[149]	Active contour & Fuzzy to detect objects based on curve evolution	Various images / 22 images	Jaccard Error = 0.17, Avg. F measure = 0.992, Mean Region entropy = 5.083 / 30.310 s
[247]	Multi-objective spatial fuzzy clustering algorithm (MSFCA) for Synthetic and real images segmentation	BSD	Clustering accuracy (CA) = 0.8555, ARI = 0.4973
[140]	Rough-fuzzy-possibilistic c-means (RFPCM) and M-band wavelet packet analysis for Text-graphics segmentation	Document (real life) images / 50 document images	Considering M-band wavelet packets and feature selection JS = 0.88, DSC = 0.94, SP = 0.94, SE = 0.92, for text-graphics JS = 0.89, DSC = 0.94, SP = 0.92, SE = 0.95
[130]	Automatic modified fuzzy c-means (AMFCM) for Various images	Cameraman, brain & Lena image	V_{pc} and V_{pe} = 0.9219 and 0.1744
[40]			Detection rate = 94.63, Avg. Precision = 78.38 / 1.75 s

Table 5 (continued)

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
	Fuzzy classifier Self-splitting clustering and Support vector machine (FC-SSCSVM) for Exact object recognition from multifaceted scenes	beverage can, red cup, notebook, cosmetic bag & toy fish	
[207]	Fuzzy C-Means (FCM) based Hierarchical Approach (HA) for Color image segmentation	7 images / 140 images	MSE = 2.1309, F (I) = 2.7968 F′ (I) = 2.8508, Q (I) = 0.6546 MSE, F(I), F′(I), Q(I) for 140 images are 0.6890, 0.5710, 1.2400, 0.5690
[208]	Region Splitting and Merging-FCM Hybrid Algorithm (RFHA) for Color image segmentation	7 images / 140 images	For 7 images MSE =2.0932, F(I) = 0.5346, F′(I) = 0.5421, Q(I) =1.8521, for 140 images = 3.0900, 7.5600, 7.6600, 0.4900
[53]	Fuzzy Region Competition with Spatial/Frequency Info. For Multiphase image segmentation model	Weizmann database	Error = 1.01%, SA, the errors of Region Competition RC method results in (a) 4.02%, 1.13% and (b) (11.7%, 0.55%)
[203]	Adaptive Fuzzy-K-means for various images	Various images	F(I) = 6.8880, F′(I) = 0.2933, Q(I) = 1.3515 / 4.57 s
[230]	Two-dimensional FCM clustering method (PSO + FCM) for Noisy image segmentation	Synthetic image	SA = 99%
[13]	Feedforward NN+ FCM for Color image	BSD	SA =98% / 9.5 s
[58]	Parallel optimized multilevel sigmoidal activation function (ParaOptiMUSIG) for Segmentation based on color intensity	Lena and baboon	Lena image Mean ± SD = 0.8907 ± 0.0491, Baboon image Mean ± SD = 0.9252 ± 0.0293, SA for Lena =0.8789, SA for Baboon = 0.9301
[144]	Spiking neuron networks (SNN) for Image segmentation and edge detection	50 images taken from the BSD	PSNR = 65.409, MSE = 93.845, MAE = 7.841, NCD = 0.083
[29]	Self-Supervised Multilayer self-organizing NN (MLSONN) &Supervised pyramidal NN (PyraNet) for Multilevel image segmentation	Lena image, a brain slice (biomedical image)	For MLSONN Lena F = 0.6627, F′ = 0.6071, Q = 0.9739, entropy E = 0.7923, for Brain image F = 0.5514, F′ = 0.6407, Q = 0.9030, E = 0.6812, for PyraNet Lena F = 0.8946, F′ = 0.7833, Q = 0.5533, E = 0.9871, for brain F = 0.5811, F′ = 0.7952, Q = 04801, E = 0.9110
[114]	Fixed length GA (GA + SOM) for Various images	BSD / 300 images	Avg. PRI 0.8332 and VoI 1.9239
[228]	GA for Shape extraction and object classification	CE-Shape-1, INRIA horses, ETHZshape classes, MPEG-7	Accuracy = 84.68%, Recognition accuracy = 99.23%, Precision = 92.42 / 3.7 s
[115]	Spatial fuzzy (SFGA) for color images	BSD/ 300	PRI = 0.7852 & VoI = 1.9182 / 2.3 m
[200]	Genetic programming for Texture Image	Brodatz textures	SA = 99.83% & 97.48% / 0.59 s
[84]	GA+ Wavelet transform for Various images	8 images	Uniformity U = 1.1007 /32 ms
[117]	HDGA for Noisy & blurred images	50 images	Evaluation function F = 40.86

anything that exists in the world the most widely used the real world images are taken from Berkley Segmentation database (BSD). GA has been used frequently for this purpose. The evaluation parameters like DSC, JS, SE, precision, and accuracy are used to authenticate the performance of the work presented by the authors. The table also gives the computational efficiency of the proposed algorithms. Segmentation accuracy for BSD database is given in Fig. 9.

8.2 Problem with real-world images

1) Identification and classification of boundaries for an object is a critical task in case of real-world images.
2) Multiple object and their contours separation make difficult for object separation.
3) Presence of noise within an image is another major factor influencing this type of segmentation.
4) The quality of an image also effects such type of segmentation process.

9 Soft computing approaches for segmentation of other applications of image

The focus of our work is to present various applications of image segmentation using soft computing approaches. Though we have categorizes the applications among certain groups, we have included a number of interesting image segmentation fields. In this part, we have presented such applications keeping in mind that a lot of work for separation of the region of interest from images can be done other than the most common segmentation areas like MRI, SAR, BSD, etc. An example for such type of an image is shown in Fig. 10.

This work is also classified among three core soft computing approaches given as follows:

In this part a number of unique segmentation work has been presented. In [20] Xiangzhi Bai et al. proposed a sea surveillance system by identifying some appropriate activities from sea images. Authors have work with Fuzzy inference system (FIS) for segmentation of sea images. Another novel work named as an adaptive FCM (AFCM) has been presented by Hongbao Cao et al. in [34] for segmentation of M-FISH images. The authors have also included a cataloging technique that improves the performance of the proposed wok named the new method as IAFCM. A method based on fuzzy approach was proposed by P. Javier Herrera et al. in [100] was presented to obtain disparity maps by segmenting hemispherical images. The objective of

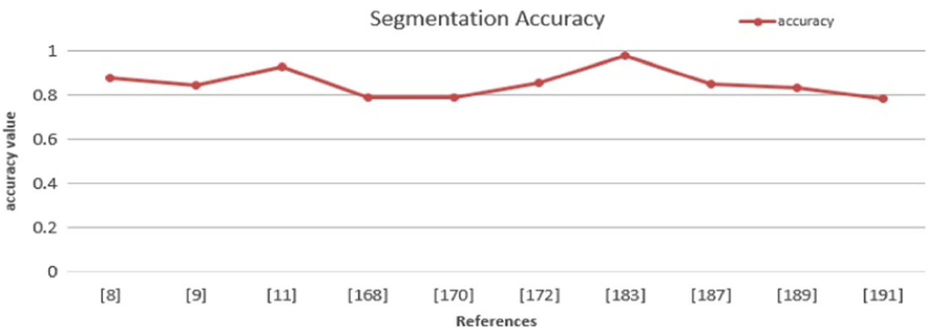

Fig. 9 Segmentation accuracy (SA) for BSD database

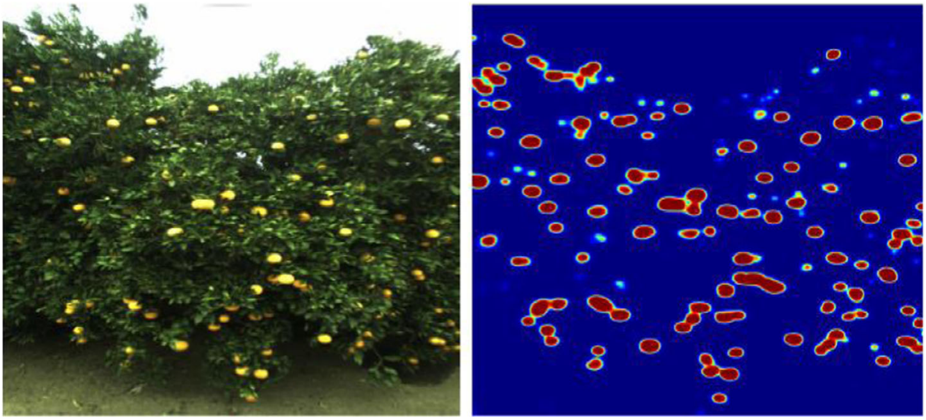

Fig. 10 Counting of fruit (oranges) taken from [46]

segmentation is to segment trunks of the trees because they contains higher amount of wood. The method works in two phases 1. The identification of texture is done and classified among textures of interest to be either matched or discarded and figures out six attributes of each pixel as features by using both Otsu and FKM methods 2. epipolar, similarity, and uniqueness are the 3. a stereovision matching process is designed. The elimination of leaves with the help of OM method brings the novelty to automate FKM based method.

Now a days we have been some of the automated process for document scanning and classification. Based on this Laura Caponetti et al. proposed a novel method based on neuro-fuzzy for document page segmentation. The method showed effective results in correctly distinguishing between background, text and graphics of the document. Another unique work has been seen in the work proposed by Z. Chi and H. Yan in [49] by introducing a fuzzy based technique for map image segmentation. The method also incorporates a thresholding method which is easy to implement and fast in processing. Maria Celeste Ramirez Trujillo et al. in [215] presents segmentation of carbon nanotube images which is important in nanotechnology by using neural network.

Byung Kwan Kim et al. in [120] uses GoogLeNet a deep learning network along with micro-Doppler signature (MDS) for the purpose of drone classification. The 3D objects segmentation is also the new application for image segmentation task. Therefore in [67] Alexey Dosovitskiy et al. proposed a neural network for caarying out this task. Ahmed Fakhry et al. in [68] proposes a simple yet powerful model named as a residual deconvolutional network (RDN) having capability of naturally balancing the tradeoff between increasing contextual window that is required for multi-scale reasoning and the ability to preserve pixel level resolution for segmentation. Scene text identification and classification is done with the help of CNN in [209] by Youbao Tang and Xiangqian Wu. This method is novel in the sense that it would be quite handful in number of applications compromising of medical, defense, etc.

Fruits such as apple and oranges can also be counted from deep neural network a novel and interesting area for segmentation was proposed by Steven W Chen et al.in [46] that counts fruits from the given image. Di Wu et al. in [229] proposed a DDNN with HMM. DDNN is used to learn high-level spatiotemporal representations and automatically extract the relevant information from the data. The input to this network is multimodal whereas HMM is used to solve the temporal dependencies which segments and classifies the multimodal data stream. It has two feature learning methods (i) for processing of skeleton features: Deep Belief Networks. (ii) For RGB-D data: 3D Convolutional Neural Networks. A DCNN for human parsing cataloguing grounded on Doppler radar was proposed by Youngwook Kim et al. in [118]. The network does not use any explicit domain knowledge for extracting features, and the spectrogram itself served as input data to the DCNN. A novel Co-CNN architecture for the human parsing task was also proposed in [133] proposed by Xiaodan Liang et al. this work integrates the cross-layer context, global image label context, semantic edge context and local super-pixel contexts into a unified network. A CNN for fingerprint liveness detection, was proposed by Rodrigo Frassetto Nogueira et al. in [159]. Fan Zhang et al. in [244] proposed a CNN for aircraft recognition which combines a candidate region proposal network (CRPnet) and a localization network (LOCnet) to extract the proposals and simultaneously locate the aircraft, which is more efficient and accurate, even in large scale VHR images. Pichao Wang et al. in [227] proposed a weighted hierarchical depth motion maps (WHDMM) with three-channel deep CNN (3ConvNets), for human action recognition from depth maps.

In [210] Jiexiong Tang et al. emphasizes on the applications of maritime security and traffic control for ship detection on spaceborne images. The JPEG2000 compressed domain is used for fast ship candidate extraction, DNN is utilized for high-level feature representation and classification, and ELM is employed for efficient feature pooling and decision making. The difficulties of the higher resolution results in larger data volume and results which get affected by weather conditions like clouds and ocean waves. The idea is to capture the driver gestures like postures of normal driving, functioning the shift gear, smoking or eating, and busy with a cell phone have been substantiated using CNN by Chao Yan et al. in [235]. Working with sparse Laplacian filter for unlabeled data and softmax classifier as output phase for labeled data Zhen Dong et al. in [66] proposed a semi-supervised CNN for the vehicle category identification. In [224] Fuliang Wang et al. used ANN for rapid void detection from the X-ray image. The image is divided into small blocks using an image processing method for multi-threshold image cutting and feature extraction. Then finding and locating the block that contains void. A hybrid DNN (HDNN), by dividing the maps of the last Convolutional layer and the max-pooling layer of DNN into several blocks of variable receptive field sizes or max-pooling field sizes, to permit the HDNN to extract variable-scale features was proposed by Xueyun Chen et al. in [41]. Steve Lawrence et al. in [202] have presented a fast, automatic system for face recognition system that combines local image sampling, a SOM neural network, and a CNN. Present results using the Karhunen–Loeve (KL) transform in place of the SOM, and a MLP in place of the convolutional network.

9.1 Discussion

There are many other applications of image segmentation. Table 6 listed a number of segmentation applications like identification of human activities, document page segmentation, underwater image segmentation, fingerprints segmentation, face recognition etc. the databases used are based on the applications. The algorithm used does vary for the segmentation area depending upon the images. But it was seen that neural network plays an important role in identifying the required area of interest. The most commonly used evaluation parameter is Accuracy and some authors have also used JS to validate their results of segmentation. The table also gives the computational efficiency of the various soft computing approaches. SA for different is given in Fig. 11.

Table 6 Comparative table for other segmentation applications using SC approaches

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[131]	MapReduce-based fast FCM (MRFFCM) for Underwater image	Fish4Knowledge Project	N
[20]	Fuzzy inference system (FIS) for Infrared Ship image subdivision	80 infrared ship images	ME = 0.0183, RAE = 0.3734 / 5.8187 s
[34]	Improved Adaptive FCM using a gain field (IAFCM) to segment M-FISH	M-FISH database of 20 cells with 120 images	Correct detection rate (CR) = 89.5 ± 10.5% and false detection rate (FR) = 3.6 ± 2.8% / 14 s
[100]	Otsu & Fuzzy K Means (FKM) for Stereovision matching in hemispherical images (Forest environment)	A set of 2700 samples	Avg. % of error and SD (σ) For 2 Class based on SA (correlation) 30.1 and 2.9, sb (color) 16.2 and 1.3, sc (texture) 18.1 and 1.7, sd = 14.3 and 1.1, se = 35.2 and 3.6, sf (Laplacian) 32.1 and 3.1, % of error and σ, for MVC 8.9 and 0.8
[35]	Neuro-Fuzzy methodology for Document page segmentation	Document Image Database	SA = 97.51%, with noises ranging from [0,1] SA = 85.68% / 35 s
[166]	Fuzzy connectedness using dynamic weights (DyW) for MR, CT, and infrared images	Phantom database	SA = 99.15%
[49]	Thresholding and Fuzzy rules for Gray scale geographic map images	22 grayscale map images	N / 20.2 s
[215]	ANN for Carbon nanotube images	41 carbon nanotube, SEM, & TEM images	SA =84.19% / 23 s
[120]	Convolutional neural networks + Micro-Doppler signature (CNN + MDS) for Drone classification	Anechoic chamber & outdoor measure -ment, 53,410 & 13,560 images	SA =89.3% to 94.7%, Two types of drone at 50 & 100 m height are classified with 100% accuracy / 500 ms
[67]	Convolutional neural networks for 3D models of chairs, tables, cars	ShapeNet dataset	SA = 96.23%
[68]	Residual Deconvolutional network for Electron Microscopy (EM) image segmentation	2D neurite segmentation challenge & ISBI 2012 challenge validation dataset	ISBI 2012 challenge validation dataset Rand error, Warping error, Pixel error = 0.0282, 0.0026, 0.0937
[127]	Convolutional neural networks for Characterizing plaque composition in carotid ultrasound	56 test images	SA = 0.75 ± 0.16, SE = 0.70, SP = 0.80, Pearson's correlation coefficients = 0.92, 0.87, and 0.93, for the lipid core, fibrous, and calcified tissues / 52 ms ± 13 ms
[209]	Cascaded convolution neural networks (CNN) for Scene text detection and segmentation		

Table 6 (continued)

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
		ImageNet dataset, ICDAR2011, ICDAR2013, the Street View Text dataset(SVT)	ICDAR2013/ICDAR2015 for Precision, Recall, F-measure = 0.919, 0.871, 0.895, for text detection = 0.9470, 0.8560, 0.8992 / 1.36 s
[46]	Deep learning for Counting apples and oranges	Oranges and green apple image taken in day and night	For oranges, SE = 0.957, SP = 0.051, for best ROC threshold = 0.03 with best mean = 0.813 threshold = 0.38, For apples, SP = 0:961, SE = 0.033, for best ROC threshold = 0.02 with best mean = 0.838 for threshold value = 0.37, Intersection over Union (IU) = 0.813
[229]	Deep Dynamic NN & Hidden Markov Model (DDNN+ HMM) for Gesture separation and classification	ChaLearn LAP dataset	JS = 0.81 / 300 s
[118]	Deep convolutional neural networks (DCNN) for Human detection and activity classification	12 human subjects performing 7 activities	SA = 97.6% for human detection, accuracy = 90.9% for human activity classification / 127 s
[133]	Contextualized Convolutional Neural Network (Co-CNN) for Human parsing task	ATR dataset and the Fashionista dataset	F-1 score = 81.72% for large dataset, by newly collected large dataset for training, Co-CNN can achieve 85.36% in F-1 score
[159]	CNNVGG CNNAlexnet for fingerprint liveness detection	50,000 real and fake finger prints	SA = 97.1% / 650 ms & 230 ms
[244]	Coupled CNN for aircraft detection from VHR	Sydney Int. Airport, the Tokyo Haneda Airport, & the Berlin Tegel Airport database	SA = 89.1%
[227]	Weighted hierarchical depth motion maps (WHDMM) for human action recognition from depth maps	MSRAction3D,MSRAction3DExt, UTKinect-Action, & MSRDaily-Activity3D	SA = 85%
[210]	Deep neural network and extreme learning machine (DNN + ELM) for Ship detection on space borne images	Spaceborne artificial images	SA =97.58, missing ratio = 2.42, false ratio = 1.44, error ratio = 3.86 / 2.68 s
[235]	Convolutional neural network (CNN) to automatically learn and predict pre-defined driving postures	SEU driving dataset	Accuracy for SEU dataset = 99.3% on the Driving-Posture-at Night dataset, Driving-Posture-in Real dataset = 95.77% conventional approaches with hand-coded features SA = 99.47%
[66]	Convolutional neural network (CNN) for Vehicle type classification	BIT-Vehicle dataset/9850 images & BIT-Vehicle dataset 3618 daylight, 1306 nightlight	For 9850 images SA = 88.11%, for 3618 images SA = 96.1%, for 1306 images SA = 89.4%

Table 6 (continued)

Ref. No.	Method and specification	Dataset / No. of images	Result / Runtime
[224]	ANN for Rapid void detection from X-ray	25 binary images	TSVs from a single 2-D X-ray image very effectively / 10s
[41]	Hybrid Deep convolutional neural networks (HDNN) for Extracting multiscale features from vehicle database	Vehicle dataset of the city of San Francisco/ 63 images	SA based on false alarm rate (FAR), precision rate (PR), and recall rate (RR) = 99.7% / 7.5 s
[202]	SOM+ Convolutional n/w + Multilayer perceptron (SOM + CN) for Face recognition	ORL database	Overall error rate = 1.87% / 0.5 s

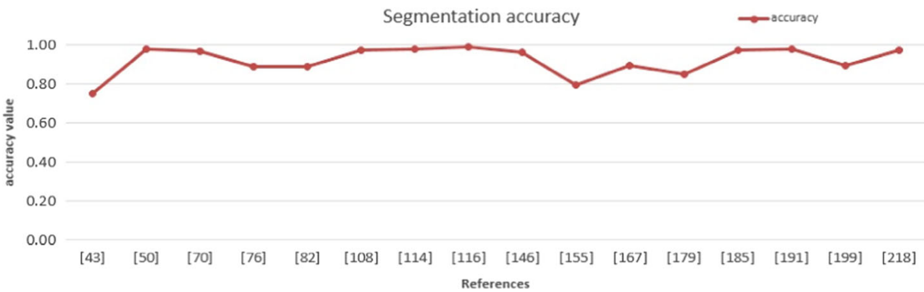

Fig. 11 Segmentation accuracy (SA) for different applications

9.2 Problem with images

1) Presence of noise is a major factor that influences the performance of the methods.
2) The quality and resolution of an image also have an impact on the performance of the algorithms.
3) This type of images does suffer from the problem of co-localization.
4) The background of an image as well as the presence of saliency object within a real-world image also effects the separation of objects from such type of images.

10 Outcomes

Survey on image segmentation using soft computing approaches are an extensive category of the research area in artificial intelligence along with image processing. The role of segmentation is to divide an image into its coherent parts that is easier to understand and analyse for extracting some meaningful information from it. The summary extracted from the survey has been given in tables by categorizing them among methods used, the domain used, databases used, different parameters involved for segmenting an image and finally results specified with computational efficiency of the proposed methods. Authors were highly interested in the domain of medical system using fuzzy logic for identification of diseases, prediction, and diagnosis them. Based on the survey we can say that applications of neural network have been deployed for complex scene detection such as human activity identification, classification of hyperspectral data, and classification of objects from real world scenes. NN approaches like SOM, PCNN, MLP etc. working synergistically with other methods also improves the performance of the methods. Genetic algorithms have also shown promising results in the field of medical, SAR and other images. Though these SC techniques are sufficient enough to solve complex real world problems from the survey, it has been observed that hybridization of SC techniques shown results more accurately and efficiently. Figure 12 shows the occurrences of core soft computing approaches separately.

In this survey work, utmost of the articles collectively for journals, conferences etc. of different categories are retrieved from online databases like IEEE Xplore, Elsevier, and Springer. Figure 13 depicts the yearly distribution of papers included in this paper. According to the collected papers from various online databases, it is seen that from the year 2010 onwards, researchers mainly focused on the SC techniques rather than conventional techniques for image segmentation. But from the year 2014, a lot of usages of SC techniques have been noticed especially in the year 2016 a tremendous work on image segmentation applications

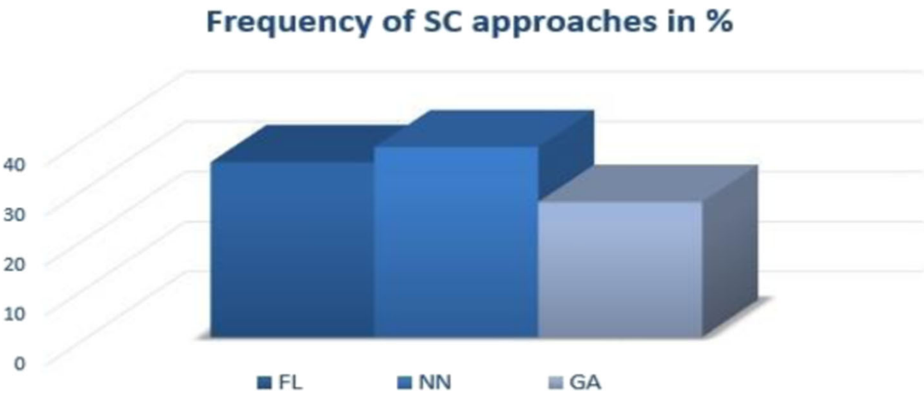

Fig. 12 Core SC approaches frequencies

using SC methods has been observed. From the year 2009, a new direction in the FL was noticed working with the applications of SC technique and other advanced learning algorithms.

The findings from the literature generally compromises of the various aspects like the emerging subjects for segmentation, more importantly the new methods and concept for accomplishing the task of segmentation, and the inimitable applications in the area of segmentation. So in order to incorporate these concerns we have categorized the various outcomes from the survey into 8 different classes discussed as under separately.

10.1 Emerging subjects for image segmentation

Form the literature it has comprehended that authors have used number of terms like object segmentation, object detection, image segmentation, scene parsing, semantic image segmentation, instance segmentation and object recognition for performing the number image segmentation in different applications. Based on this the emerging areas for segmentation includes scene parsing, instance segmentation, semantic segmentation and segmentation of compound images. Though the functionality of the mentioned terms and their results for classification could vary but the objective of these terms remains the same that is to partition or segment an image. Here we will try to introduce these different terms that could be beneficial for the researches to use them suitably.

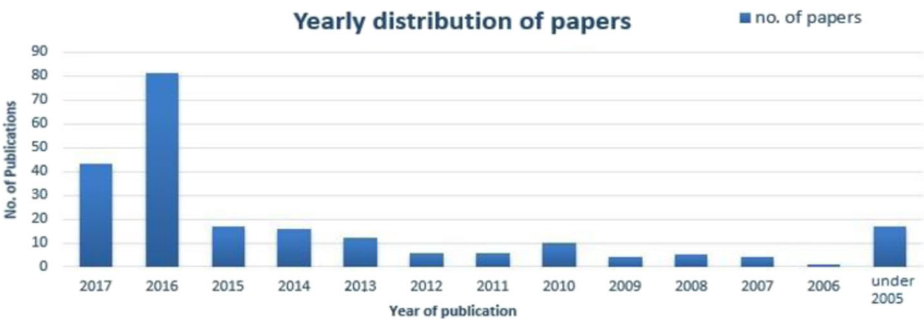

Fig. 13 Graph for yearly paper publication

1) *Object recognition:* is the methodology of identifying the desired object in the given image and localizing it by using bounding box while labeling them. In object recognition the objects present in an image are predefined to some classes already existing into the dataset that is used.
2) *Object detection:* is same alike the object recognition but in this the objects are belongs to only two classes for classification *A*. Object with bounding box and *B*. Object without bounding box [65].
3) *Object segmentation:* in this the objects are identified alike the object recognition but by classifying the pixels of the given image.
4) *Image segmentation:* it is the method of extracting super pixels from an image by segmenting regions of the given image. The objects are not labelled in this but the region that is dependable with each other should be belonging to the same segment.
5) *Semantic segmentation:* it is a process of classifying each pixel into its predefined class. Semantic segmentation or Scene labeling also termed as pixel wise or pixel label classification that attempts to classify every pixel into its class or non-class. In this every object has been assign a label to be in a class or non-class [28, 65, 134, 206, 214].
6) *Instance segmentation:* it is the process of classifying all the objects, individually present in the given image weather they are of same type or belong to the same class. However it is the most difficult task among all to perform by labelling each object separately (example for compound objects).
7) *Scene parsing:* it is the process of dividing an image into parts and assigning a class label to each parts without explicitly dividing them. Scene parsing is also known as strict segmentation [143].

10.2 Emerging approaches

Various soft computing methodologies have made it easier to solve typical problems of segmenting an image in faster and effective way and therefore are in focus as author's research areas. Category wise classification of SC based object extraction methodologies helps in solving and understanding specific problems in the number of applications. Form the survey, we have noticed that the number of work presented are having common theory and methodologies that were used for segmentation of different image application areas. However, some of the authors employed hybrid methodologies like collaborating FL-NN, NN-GA, GA-FL and other techniques including deep learning, designates that, the inclination of expansion on approaches is also dissimilar due to author's research interests and abilities in the methodology and domain. Some of the recent approaches are

1) *Metaheuristic approaches:* that provides a sufficiently good solution to an optimal problem is the new among all used for the purpose of segmentation. The main aim of this method is to use the state-space search to find the optimal solution from a given set of sub-solutions/sections. These approaches works on both local as well as global variables. Metaheuristic are not problem specific, rather are approximate and non-deterministic. Metaheuristic are experimental in nature, describe empirical results based on the experiments on certain algorithms [145].
2) *Neuro-Fuzzy:* also known to be Fuzzy Neural Network (FNN) a combination of ANN and FL is the most extensively used model for segmentation. Working on the linguistic rules and it also involves the membership functions. This hybrid intelligent system provides interpretability and accuracy with hybridization results.

3) *Deformable models:* used widely in computer vision is a combination of algorithms and techniques. It models the variability of a certain class of an object. Deformable model provides an abstract model of the object class by modelling the constraints separately. The deformation model should satisfy some problem specific constraints [145].
4) *Deep learning:* one of the novel theory for computational intelligence, having an exceptional capability of learning high-level features from the low-level feature. Generally used in the applications of target recognition and classification, Deep learning has a unique capability of initialization through unsupervised learning and then fine tuning through supervised fashion [171].

This recent trend shows that the development of Soft Computing methodologies and domains like deep learning is fascinated towards expertise orientation as the world is heading towards artificial intelligence.

10.3 Future works and inimitable applications

A lot of emphases has been to be made by the researchers for selecting their area of interest conducting their research work. Our aim is to present some of the future work, as excerpt while doing literature survey. As we have gone through the number of papers for surveying, we have tried to discuss the interesting areas of image segmentation application. Interesting domains like segmentation of geographic map images in order to identify geographic regions, underwater images segmentation for underwater species classification [173], floods and other type of natural disasters evaluation, segmentation of fruits from the tree using real world images, Stereovision matching in hemispherical from Forest environment images, classification of objects from drone images of natural scenes, recognition of sign boards or other road scenes objects etc. are some topics of interest that, one can explore for further research.

10.4 Tools

There are number of tools available that is compatible with images for performing segmentation. From the survey we have noticed that researchers were interested in using software, libraries and tools like MATLAB, PYTHON, and JAVA.

10.5 Noises

The noises were included with the images in order to check the effectiveness and resistance of the proposed method. As it is seen from the survey mostly the authors have work with two type of noises named as Salt and Pepper noise and Gaussian noise. These noises are included with the original images and then the system is tested under different values of noises. Other than these two noises some author has also used another noise named as Poisson noise, but the other two are the most frequently used.

10.6 Databases

There have been lot of concern among the researchers for selecting the database for their work. In this part we try to present some of the database that have been utilized for various image segmentation applications. The most widely used databases are BSD database, Brain Web, IBSR etc. below are the description given for some of them.

1) *Berkeley Segmentation Dataset (BSD):* is a publically available widely used database containing images of various subjects with gray and color images for segmentations [123]. Initially, this database was available with 300 images of which 200 are for training and 100 are for test purpose and known as BSD300. Now an enhanced version of this database is available as BSD500 with 200 fresh test images. It contains dataset as well as result of segmentation. Dataset is available by an image and by human subject and benchmark result by the algorithm and by the image. The dataset of images about 22 MB and the human segmentation about 27 MB is free to download for educational purposes or for non-commercial research.
2) *The Internet Brain Segmentation Repository (IBSR):* is a freely available database for non-commercial research use for MRI brain image segmentation. Supported by the NIH under Grant number 1 R01 NS34189–01 from the National Institute of Neurological Disorders and Stroke (NINDS), IBSR consists of images for different subjects, like an Adult Male and 5 year old Child: T1-weighted MRI data with complete expert segmentations, 20 Normal Subjects: T1-weighted MRI data with gray/white/other expert segmentations (3.1 mm slice thickness), 2 Tumor patients: various scans over time, 18 Scans: T1-weighted MRI data with expert segmentations of 43 individual structures (1.5 mm slice thickness), Registered multi-echo scans.
3) *Brain Web: Simulated Brain Database (SBD*): available free for educational purposes. The database contains realistic MRI data volumes that are produced by MRI simulator and available into 2 categories (i) Normal Brain (ii) MS Lesion Brain Database. The SBD was generated using different parameters like 1. Pulse sequence as in the ICBM {T1, T2, PD} template of custom simulations 2. Noise as the reference tissue for the noise computation: White Matter (WM) for T1 and Cerebrospinal fluid (CSF) for T2 and PD images. 3. Intensity non-uniformity (INU) as the field A was used for T1 images, field B for T2 images, and field C for PD images.
4) *Indian Pines:* The database consists of scenes of 145 times 145 pixels and 224 spectral reflectance bands in the wavelength range $0.4–2.5 \times 10^{-6}$ m collected over the Indian Pines (a test site) located in North-western Indiana by AVIRIS sensor. The database contains 2:3 agriculture images, and 1:3 forest images or other natural vegetation images. It also compromises of 2 major dual lane highways images, a rail line, some men made structures like house with low intensity, and smaller roads. The database is available in MATLAB data files as size of 6.0 MB for Indian Pines, 5.7 MB for corrected Indian Pines, and 1.1 KB for Indian Pines ground-truth.
5) *Pavia Centre and University:* Prof. Paolo Gamba provided this database who was associated with laboratory of Telecommunications and Remote Sensing, located at Pavia University in Italy. The database consists of two scenes acquired by the ROSIS sensor during a flight campaign over Pavia, northern Italy. The database is available in MATLAB data files with size of about 123.6 MB for Pavia Centre, 34.1 KB for Pavia Centre ground-truth images that contains about 7456 samples classified in 9 classes, scenes of Pavia University with size of about 33.2 MB and 10.7 KB for Pavia University ground-truth images that contains about 42,776 samples classified in 9 classes respectively.
6) *Digital Retinal Images for Vessel Extraction (DRIVE):* used for partitioning of blood vessels from retinal images [73]. The database consists of images taken from a diabetic

retinopathy screening program occurred in The Netherlands. This program consists, screening of population for about 400 diabetic patients aged between 25 and 90 years. DRIVE also contains 40 randomly clicked photographs separated among 20 for test and 20 for training, out of which 33 images do not show any sign of diabetic retinopathy, and only 7 shows some signs early diabetic retinopathy.

7) *Structured Analysis of the Retina Project (STARE):* the database contains about 400 raw images. STARE program was funded by U.S. National Institutes of Health, under the guidance of Michael Goldbaum, M.D., at the University of California, San Diego in 1975. The Images and clinical data were collected by the Shiley Eye Centre at the University of California, San Diego, and by the Veterans Administration Medical Centre in San Diego.
8) *RADARSAT-1 & 2 ScanSAR Wide:* available only after project approval. This database consists SAR images and most widely used database for SAR image segmentation. RADARSAT 1 was launched in the year 1995 and was the first Canadian project under Canadian Space agency (CSA) related to satellite images. The database can be used for commercial and non-commercial purposes. The database contains several applications images like agriculture, hydrology, geology, forestry, coastal zones etc. RADARSAT 1 was launched in the year 2007 it is an extension to RADARSAT 1 project incorporation of CSA and MacDonald Dettwiler Associates Ltd. of Richmond, BC (MDA). The main objectives for this project is to continue the efforts of the RADARSAT 1 project while focusing on the governance of environment changes, surveillance of coastal regions and management of natural resources.
9) *Fish4Knowledge:* Fish4Knowledge is funded by the European Union Seventh Framework Programme. Ground-Truth datasets well known as the dataset for underwater image segmentation consists of 3 ground truth datasets that are Underwater benchmark dataset for target detection against complex backgrounds, Fish species recognition, Trajectory-based fish behavior analysis from the Fish4Knowledge project.
10) *PlanktonSet 1.0:* dataset is collected in the subtropical Straits of Florida from 2014 to 05-28 to 2014–06-14. Imagery data were collected using the in Situ Ichthyoplankton Imaging System (ISIIS-2) as part of a NSF-funded project to assess the biophysical drivers affecting fine-scale interactions between larval fish, their prey, and predators.

10.7 Evaluation parameters

A large number of algorithms has been used for image processing and image segmentation. The performance of these algorithms can be evaluated on the basis of various evaluation parameters. The main purpose of evaluating an algorithm is to understand the behaviour of the algorithm when it deals with different categories of images and also helps in estimating the best parameters used for evaluating an algorithm for different applications. The algorithms are being chosen on the basis of their application domain as this might also involve comparison with similar type of algorithms to rank their performance. To assess the performance of an algorithm is a tedious job as it depends on various factors which can be understood by Fig. 14.

The inertness to which an algorithm can be evaluated is directly proportional to the no. of parameters it requires. The performance is also even punched by the nature of the image. Evaluating a set of smooth images may produce a higher accuracy than the use of more rough images containing complex regions. There are no guidelines specified as to how the process of

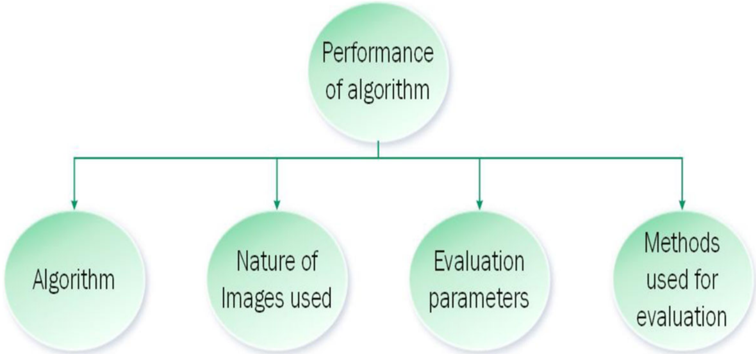

Fig. 14 Factors affecting the performance of algorithm

evaluation must take place but there is a need for some facets to be premeditated such as testing protocol, testing regime, performance indicators, performance metrics and image databases.

1) *Testing Protocol*: it relates to the succeeding advent used to perform testing. There are three basic maxims- visual assessment, statistical evaluation, and ground truth evaluation. The first stage of performance evaluation involves how well an algorithm has performed by obtaining a qualitative impression. For example, when we start working on a new algorithm, a few sample images may be used in a coarse assay of the suitability of existing algorithms by means of visual assessment. Visual assessment usually means the comparison of processed image with the original one. The algorithms judged as useful in the first stage are investigated in the next stage using quantitative performance metrics and ground truth data to check their accuracy. The final stage might go through a no. of cycles and looks at aspects of performance such as robustness, adaptability, and reliability.
2) *Testing Regime:* it relates to the strategy used for evaluating the images. It consists of four basic categories: evaluative, boundary value, random and worst case testing. The exhaustive testing deals where an algorithm is presented with each and every image in the database to be tested. Such an approach is eye-opening and should be limited only to the verification component of the design process. The boundary value testing evaluates a subset of images being identified as representative. Random testing refers to where the images are selected indiscriminately. It is a more statistically based process of evaluating an algorithm as it provides us with more realistic conditions. The last regime is the worst-case testing. It usually processes the images having rare or unusual features.
3) *Performance Indicators:* performance indicators are the basic need of the performance evaluation as they convey the quality of an algorithm. Basic performance indicators are given by Fig. 15 along with description.

a) *accuracy:* performance of the algorithm with respect to some reference.
b) *robustness:* the capacity of an algorithm for tolerating various conditions.
c) *sensitivity:* the responsiveness of an algorithm to small changes in features.
d) *adaptability:* dealing with variability in images.
e) *reliability*: the degree to which an algorithm, when repeated using the same stable data, yields the same result.
f) *efficiency:* the practical viability of an algorithm (time and space).

Fig. 15 Performance indicators

4) *Performance metrics and image databases*: this implies that which images should be used to test a particular algorithm. It also deals with the multifariousness and intricacy of the selected images. It also relies on how many databases are used in the selection process and the significance of the images to the segmentation task.

Evaluation parameters are the basis to authenticate the accuracy of the method. There are the number of evaluation parameters used to verify the segmentation results. Most commonly the performance of any method can be evaluated by using two ways i.e. 1. Qualitative evaluation and 2. Quantitative evaluation. Supervised in nature qualitative comparison is the most widely used metrics, based on the intervention of human to analyze the segmented accuracy. On the other side the quantitative evaluation is based on the statistical performance of the ground truth image and segmented image. A brief overview of several statistical performance evaluation parameters applied in the segmentation of images are given below. Amongst the following parameters Dice Similarity Coefficient (DSC), Jaccard Similarity (JS), Specificity (SP), Sensitivity (SE), Segmentation Accuracy (SA) and Computational efficiency remains most commonly used.

1) The performance of any work is patterned by computational efficiency this, in fact, is another effort, to present important aspect for validating the segmentation performance of the proposed methods and it is one of the major criteria for evaluating them.
2) *Dice index or Dice Similarity Coefficient (DSC):* provides the measure of degree of overlap between two segmentation, if DSC = 1 perfect match, DSC = 0 no match.
3) *Jaccard Similarity (JS) or Jaccard coefficient (JC) or Tanimoto's index:* used to compare similarity and diversity of image given by an intersection to the union, JS generally between 0 and 1, a higher JS better segmentation [234].
4) *Kappa coefficient (κ):* it is defined as the difference between the Overall accuracy (OA) between estimated accuracy (EA) over the difference between 1 and EA, lies between 0 and 1. Higher Kappa (κ) value better segmentation results.
5) *Segmentation accuracy (SA):* lies between 0 and 1, segmentation accuracy defines the accuracy of the segmented image. The best result is achieved when SA = 1 [147].

6) *Specificity (σ) or True negative ratio (TNR):* defines the capability of an algorithm to segment the normal regions exist in the input image, also termed as False Alarm Rate (FAR), lies between 0 and 1, the segmented value near to 1 shows better segmentation.
7) *Sensitivity or True positive ratio (TPR):* Sensitivity values defines the proper classification or segmentation of the input image. Sensitivity is also known to be Recall or Overlap Function (OF) or Object Recognition Rate (ORR), lies between 0 and 1, the segmented value near to 1 shows better segmentation [147, 155].
8) *Regional area error (RAE):* used to compute accuracy of the desired area measurement, RAE supposed to be equal to 0 for the best state of segmentation.
9) *Peak signal to noise ratio (PSNR) and Root mean square error (RMSE):* is used to compare the similarity of the segmented image against original image depending on the MSE for each pixel. Higher PSNR better segmentation.
10) *Validation evaluation partition coefficient (V_{pc}) and Validation evaluation partition entropy (V_{pe}):* when V_{pc} is high and V_{pe} is low, it implies the membership values are less fuzzy in segmentation results and the tissues are classified correctly or when $V_{pc} = 1$ and $V_{pe} = 0$.
11) *F(I), F'(I) and Q(I) function:* although the three formulae differ, these functions are used to penalize the segmentation that forms too many regions and has non-homogeneous regions by giving them larger values. The smaller value of three functions indicates the better segmentation result.

10.8 Contribution

The review explores state-of-the-art elaboration almost all dimensions associated with image segmentation. Primarily focusing upon the soft computing approaches the review work also incorporated various aspects like emerging topics for segmenting an image, new methods, and inimitable applications for segmentation. The paper also includes introduction to different databases, evaluation parameters, tools and noise that can assist the researchers and academicians for carrying out their work in this domain.

11 Conclusion

This survey paper presents applications of image segmentation using soft computing approaches. The power behind soft computing methods is to achieve artificial intelligence by simulating thinking capability of a human, to solve the complex real world problems. Soft computing methodologies involving computing techniques and biological structures together provide new methods for more dynamic, competent and reliable image segmentation solutions. The conceptual theory related to the task of image segmentation applications using soft computing approaches identified and presented separately in this work. Primarily emphasis is on core SC approaches like Fuzzy logic, Artificial Neural Network, and Genetic Algorithm. The contribution of the article lies in the fact to present this paper to the researchers that explores state-of-the-art elaboration of almost all dimensions associated with the image segmentation using soft computing methods so that, it could be advantageous for researchers to make effort in developing new methods to perform segmentation.

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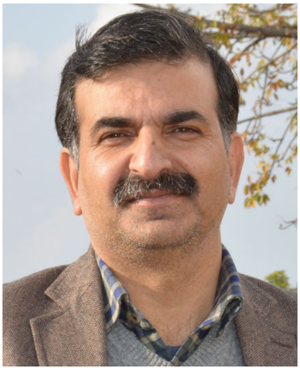

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