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Segmentation Features for CT Scans: A Taxonomy

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Abstract--- *Image segmentation is a crucial task in medical imaging applications, segmentation can aid in several medical acts such as planning therapy radiation, automatic labeling of anatomical structures, lesion detection, surgical intervention, virtual surgery simulation, intra-surgery navigation, etc. Despite works done in imaging segmentation it stays challenging because of problems linked to image acquisition conditions and artifacts such as low contrast images, similar intensities with adjacent objects of interests, noise, etc. In the last decade a big variety of algorithms was proposed for this aim. A widely recent used method consists of using artificial intelligent to achieve the segmentation task based on present labeled images. In this paper we review the relevant proposed approaches in medical imaging segmentation, with a focus on the methods based on AI and specially the deep learning methods, we summarize the accurate algorithms in a taxonomy followed by a comparison discussion. Finally, we present the new researches directions that aim at overcoming current limitations in segmentation task.*

Keywords--- *Segmentation, Medical Image, CT Scans, Image Features, Image Representation, Deep Learning.*

I. INTRODUCTION

Artificial intelligent and machine learning have played an important role in image processing and specially in medical field imaging. The techniques proposed improve the quality of computer-aided diagnosis by facilitating image interpretation, image fusion, image registration and image segmentation. Image-guided therapy, image retrieval and analysis are results of success in automatic image processing. The main aim of machine learning techniques is to extract information from the images and represents it effectively and efficiently.

In imaging analysis, feature extraction and representation is a crucial step for processing. How to extract ideal features that can reflect the intrinsic content of the images as complete as possible is still a challenging problem in computer vision. In this paper, we focus our review on the latest development in image feature extraction and representation we provide a survey on image features representation techniques. In particular, we analyze the effectiveness of the deep learning algorithms in automatic image segmentation, including some classic models and their illustrations in the literature.

First we describe the medical image modality used for our study, next we detail challenges encountered in CT images segmentation, then we introduce a taxonomy of relevant methods used for segmentation that consider specifies of medical images, finally, we present the results of applying multiple deep architectures to the CT images segmentation problem, and comparing their classification performances and computational power requirements based on the most nested features.

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II. IMAGE REPRESENTATION

The image representation choice is an important step for a successful analytics, modeling an image with a minimal data and without spatial information loss is one of the active research field, many images representation was presented in literature [1], in this document we will be interested in the intensities images, an image is processed as pixel matrix representation. An image then will be represented by a function f(x, y) where x and y are the coordinates of a point of the image and f(x, y) represents the observed information. A big advantage of this representation includes lower computational complexity and less memory usage. Medical images in CT-Scanner can be presented in 2D as well as in 3D. An element is called pixel in the 2-D domain while in 3D domain it is called voxel. A 3D images can be represented as a sequential series of 2D slices.

III. COMPUTED TOMOGRAPHY IMAGING

Computed tomography scanner produces quality and more detailed images of body organs than standard X-rays scanners. Using X-ray and equipped with a computer for the treatment of acquired images, this scanner can show more details for solid organs such as bones or soft organs such as liver and muscles. In standard X-rays, we aim a beam of energy to the studied part of the body. A plate behind the part of the body captures energy beam variations after it passes through the skin, bones, muscles and other tissues. Although it does not provide a enough details about internal organs and other structures. In a CT scan, an x-ray beam moves in a circle around the body, this allows to have many different views of the same organ or structure. These views are subsequently sent to a computer that interprets the x-ray data and forms a two-dimensional (2D) or three-dimensional (3D) displays on a monitor. Scanners can be performed with or without 'contrast'. Contrast refers to a substance injected or taken orally that reveals more clearly the organ or tissue being studied. [2] As instance, and in case of bones images, CT scans give detailed information about the bone tissue and structure. It gives healthcare providers more information related to injuries and/or diseases of the bone and can be used to assess bones, soft tissues, such as cartilage, muscles, and tendons; and joints for damage, lesions, fractures, or other problems. Generally, a CT scan may be done when another type of exam, such as an X-ray, MRI, or physical exam, does not give enough information.

CT imaging advantages include {Citation}

- Availability and relatively cheap
- Spatial resolution is high
- Scan performed in short time
- A view of a large portion of the body
- Higher sensitivity in detecting intra structures

CT disadvantages imaging are [3]:

- Soft tissues has no enough contrast compared to IRM images
- Based on X-ray
- Contraindications related to the possible injection of contrast medium
- Extra radiation dose exposure

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IV. Features Selection and Extraction for Segmentation

Selecting the relevant features to use and extracting them are crucial steps in any image processing task. In image segmentation features can be resumed to three types: Intensity-based Features, Probability-based Features and Spatial information.

4.1 Intensity-based Features

Image intensity features is one of the simplest features to process, the most intensity used is the pixel or voxel color (gray or three channels color). Intensity feature is relevant for region segmentation based on color similarity. But individually is not good enough for distinguishing different structures since most of them share similar intensity patterns in medical imaging. To address such a problem, in addition to image intensity values, probabilistic and spatial information are often used.

4.2 Probability-based Features

Probability based features are spatial probabilistic distribution maps for the different structures. They analyze the likelihood of a voxel to belong to a determined structure. The higher the value of a structure at a given location, the more likely the voxel at that location to be the structure. Probability maps generated for machine learning based systems can be seen like a sort of probabilistic atlases, but with more relaxed registration constraints.

4.3 Spatial Information

In images, individual spatial objects can be defined as a set of contiguous cells, which are known as regions. Spatial information can aid in segmentation in several ways, for example the structures occur in a characteristic spatial pattern relative to one another.

Once the adequate features are selected for the task on image, next step consists on the choice of image features representation, the image data, can often be represented in different ways, for example, an edge can be represented as a boolean variable in each image point that describes whether an edge is present at that point. We can also use a representation which provides a certainty measure instead of a boolean statement of the edge's existence and combine this with information about the orientation of the edge. Similarly, the color of a specific region can either be represented in terms of the average color (three scalars) or a color histogram (three functions). Those features can be computed and deducted then in different ways, either by local features witch focus on image regions result of subdivisions on regions or by global features which rely on subspace learning for whole image patches. In addition, generic techniques in feature representation has been proposed such as: (i) Dimension reduction: Dimension reduction aims to generate compact low-dimensional features from high-dimensional ones, in order to reduce computational complexity and noise. (ii) Feature combination: Feature combination motivates the fusion of the information of multiple visual cues in order to generate more comprehensive feature representation.

V. Medical Segmentation Approaches

Segmentation is the process of dividing an image into regions that belong to same structure, segmentation is often based on properties such as gray level, color, texture, brightness or contrast. Segmentation has many roles like the subdivide of the objects in an image; in case of medical image segmentation the aim is to:[3]

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- Detect and study anatomical structure.
- Identify interest regions i.e. locate tumor, lesion and other abnormalities.
- Measure growth of tumor or decrease in size of tumor with treatment, by measuring tissue volume.
- Treatment planning help prior to radiation therapy; like in radiation dose calculation.

Automatic segmentation of medical images is a difficult task as medical images are complex in nature and rarely have any simple linear feature. Most medical images appear as weak quality affected by artifacts, the sources of artifacts can be physiological, the instrumentation used or the environment of the experience. Further, the output of segmentation algorithm is affected due to: [3]

- Partial volume effect.
- Intensity inhomogeneity.
- Presence of artifacts.
- Closeness in gray level of different soft tissue.

An example of artifacts that can be present in CT images: [4]

- Motion artifacts
- Noise artifact
- Non-sharp edges

On basis of artifact's rectification techniques in CT images, we can divide artifacts into three categories : (i) artifacts needing filtering techniques, such as noise artifact, susceptibility artifact and presence of non-sharp edges in the image (ii) artifact needing restoration techniques, such as motion artifacts and (iii) artifact needing other specific algorithm are; partial volume, intensity inhomogeneity [3].

Although the big number of algorithms proposed in the field of medical image segmentation, the segmentation task continues to be a challenging and complex problem. We have done the classification of segmentation techniques in one or another way. At present, from the medical image processing point of view we have done the classification of segmentation techniques on the basis of computational techniques. Thus, the proposed works approach can be classified, considering their techniques, on two classes:

- Hand-crafted methods
- Machine learning approaches

In the next sections, we will discuss the relevant related works on the both approaches and demonstrate the advantages and cons of each one. We will focus specially on deep learning-based methods.

VI. HAND-CRAFTED APPROACHES

The works in computer vision offered a rich toolbox of handcrafted methods for the segmentation task, the field is still active, and several relevant operators was proposed in the last decade. The main approaches have been classified in four categories: intensity-based, edge-based, region-based and deformable models. An additional technique that has recently achieved surprising results is the atlas-based segmentation.

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6.1 Methods based on Gray Level features

6.1.1 Thresholding Segmentation

Thresholding is the simplest segmentation methods, based on histogram features, the methods consist of pixels partition depending on their intensities.

Several thresholding techniques have been previously proposed using global and variable techniques. Global methods apply one threshold to the entire image while variable thresholding methods apply different threshold values to different regions of the image, if the threshold depends on neighborhood of (x,y), it's a local thresholding, or it's adaptive thresholding when the threshold is a function of (x,y)[5]–[8].

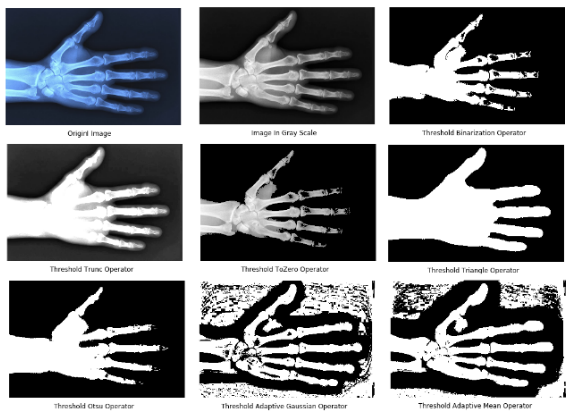

Figure 1: Thresholding Algorithms

Limitations

The big challenge for this category is the proper selection of values of threshold that is quite difficult, in addition performance of result is affected in presence of artifacts. To overcome this limitations several works try found the optimal thresholds values, by coupling the thresholding algorithms and an optimization algorithm [6], [7], [9]–[11].

6.1.2 Edge based Segmentation

In edge based segmentation we generally 1)-apply the derivative operator to detect edges of the image to 2)-measure the strength of edges by measuring amplitude of the gradient, then we 3)-retain all edge having magnitude greater than threshold T (removal of weak edge), after we 4)-find the position of crack edges; the crack edge is either retained or rejected based on the confidence it receives from it predecessor and successor edges, step 3 and 4 are repeated with different values of threshold so as to find out the closed boundaries; segmentation of an image is achieved [12].

Limitations

The limitations of edge-based method are:

Performance is affected by the presence of noise, fake edges and weak edges may be present in the detected edge image which may have a negative influence on segmentation results. For a complete segmentation, edge detection techniques are often required to be used in conjunction with region-based technique.

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6.1.3 Region based Segmentation

Region based segmentation method is founded on measuring similarity criteria between the pixels, pixels with similar properties are clustered together to form a homogeneous region. The similarity criteria varies depending the nature and complexity of image, and it can be specified by following conditions R1 U R2 U R3 U .... U Ri=I where R1, R2, R3, …Ri are the region in the image I, and further, R1 ∩ R2 ∩ R3 ∩ ... ∩ Ri=0 This is as per the set theory of homogeneity. For instance, region-based methods give successful results in bone and soft organs segmentation. Based on the principle of region growing, region segmentation is divided into three types:

- Region merging
- Region splitting
- Split and merge

Region Merging

Known also as Region Growth, this method requires the initial selection of a representative pixels, known as seed points. Then the neighbor pixels with similar properties are then clustered together to form bigger and bigger regions. This process is continued until all pixels are assigned to their respective regions as per merging criterion [13], [14].

Region Splitting

In opposition to region merging, that start by seed pixels to create regions, in Region splitting algorithm we follow the opposite sense, we consider the whole image as a single region and subdivide the regions that do not satisfy the similarity criteria. The process stops when the properties of a newly split pair do not differ from those of the original region.

Split and Merge

Split and merge, is an iterative algorithm that consists on subdivision of the image in homogeneous regions (split phase), then joins of the adjacent homogeneous regions (merging), we continue the split and merge until no further split and merge of region is possible.

Limitations

The limitation of region-based segmentation can be resumed to (i) over segmentation of regions in the image when two adjacent regions share same similarity criteria. (ii) under segmentation of regions in the image when borders affected by artifacts.

However, to reduce the effect of this problem we can: (i) Optimize selection of the criterion for segmentation, using artificial intelligence techniques as example. (ii) combine region-based approach with other approaches like edge based.

6.2 Methods based on Texture Features

The regular repetition of an element or pattern on a surface it is called as texture. Features based on texture are mostly used in image classification and segmentation. Segmentation based on texture consists of subdividing image into regions that differ on texture properties, the result of segmentation can be used to perform the classification task. We distinguish:

- Statistical approach
- Syntactic or structural approach
- Spectral approach
- Transform approach

Texture based methods are best suited for segmentation of medical image, it includes the local spatial pattern, scale and magnitude of brightness variations, smoothness or roughness of the image. The output image then used as the basis for further image analysis. Therefore, methods based on texture struggle with noise as well as the weak boundaries of medical images.

6.3 Model based Segmentation

Medical experts are still able to delineate the object because they know what it is supposed to look like and they have a model of the object in their mind, the brain have information of its shape and appearance. The model-based approach is defined as the assignment of labels to pixels or voxels by matching the a priori known object model to the image data. Model-based segmentation methods try to model smart algorithms that have a prior knowledge about the structures of interest. Proposed methods can be categorized in:

- Model based methods of segmentation involve active shape and appearance model,
- Deformable models
- Level-set based models.

Several relevant model based work was proposed for different segmentation tasks, with a promoter results [15], [16].

Limitations

Those methods can offer a high accuracy result; however, they require manual user interaction to choose appropriate parameters and place an initial model, also standard deformable models can also exhibit poor convergence to concave boundaries.

6.4 Atlas based Segmentation

Atlas and recently multi-atlas based segmentation approaches are the one of the most powerful methods used on medical images segmentation. In Atlas segmentation a database is populated with labeled images, and when an input image is given for segmentation, a registration algorithm is applied to retrieve the best similar image by establishing spatial correspondence between images. Image registration involves deforming (or warping) one or more images to maximize an objective function that combines a metric of spatial alignment with a regularizer that quantifies the plausibility of the deformation [17]–[19].

Limitations

The registration between two images struggles for complex structures and variable shape, size and orientation. Also, the building of database requires expert knowledge which make the task expensive.

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VII. Machine Learning Approaches

Another approach for medical images segmentation includes several artificial intelligence algorithms, specially machine learning algorithms, that has been approved for many other imaging applications. In this section we will overview the most relevant works already done on medical imaging segmentation using machine learning, in which methods will be organized into two categories, Traditional Learning and Deep Learning methods.

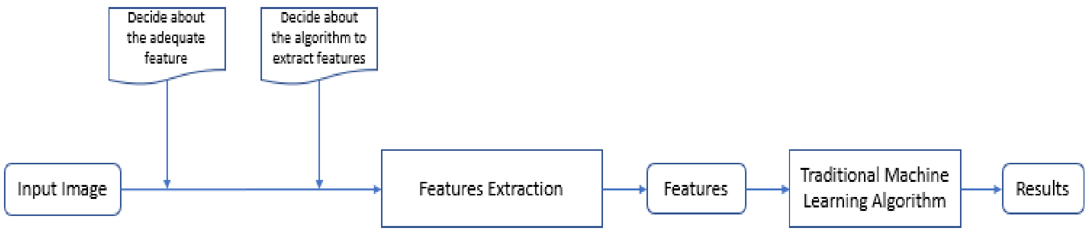

Figure 2: Traditional Machine Learning Workflow

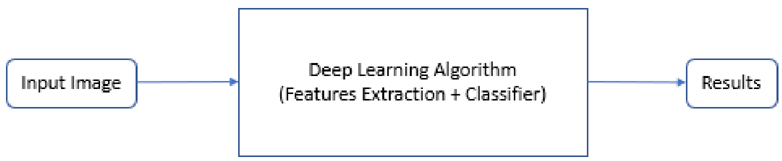

Figure 3: Deep Learning Workflow

In each category we distinguish two classes: the supervised and unsupervised learning. In a supervised learning task, the dataset consists of a set of training samples where each one contains the input object and the desired output, which is often known as label or target. The algorithm is responsible for analyzing the data, extracting significant features from it and producing a function which can make predictions on new, previously unseen data.

7.1 Traditional Learning Methods

7.1.1 Unsupervised Methods

Many segmentation methods were proposed in last year based on unsupervised algorithms, specially researches have been done in this area using clustering approach. The main idea is to create groups of objects (clusters). A cluster is a set of pixels that satisfy some similarity criteria. The most used algorithms are k-means and PCA for their high accuracy [20].

Limitations

The major disadvantage of clustering techniques can be resumed to the prior need image enhances, the results remains unclear and doesn't work for ill-defined edges, it requires apriori specification of the number of cluster centers and two highly overlapping data cannot resolve into two clusters.

7.1.2 Supervised Methods

Based on labeled images, the supervised methods try to classify pixels in classes (the result of segmentation) using delineation with learning images. Several works in literature was proposed, the K-nearest-neighbors (KNN) and neural networks stay the most discussed [21].

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Limitations

In addition to the need of big account of labeled data often expansive to prepare, those methods are very sensitive to spatial deformation like rotation and scale, still struggle with noise presence, and affected by normalization step.

7.2 Deep Learning Methods

In the last years deep learning based methods have been successfully applied to many medical imaging tasks. It's applied for classification, detection, registration, content-based retrieval and more. In the next paragraph it is briefly described how we overview the most relevant methods that succeed in medical images segmentation, and we take a study about advantages and disadvantages of each of them.

7.2.1 Unsupervised Methods

As there is a huge manual effort involved in creating the labels for supervised deep algorithms, unsupervised algorithms offer another alternation that derives insights directly from the data itself, several works was proposed using Sparse Coding Model, Deep Boltzmann Machines [22], etc.

Limitations

Despite the relevant result obtained by unsupervised deep algorithms, they stay seen as black box, because the difficulty of understanding exactly how they learn from data.

7.2.2 Supervised Methods

Two major architectures types dominate medical segmentation tasks in deep learning, a type of architectures based on Convolutional Neural Network (CNN) with and without transpose convolution and a type of architectures based on Encoders/Decoders.

Convolutional Neural Network} (CNN): is the most known deep architecture. Its structure has inspiration from the natural visual mechanism of the living creatures. Published by LeCun in 1990, the CNN consists of stat of art in image recognition and features extraction. Numerous variants of CNN architectures in the literature [23]. However, their basic components are very similar.

It consists of three types of layers, namely convolutional, pooling, and fully connected layers. (i) The convolutional layer aims to learn feature representations of the inputs. It's composed of several convolution kernels(operators) which are used to compute different feature maps, the complete feature maps are obtained by using several different kernels, many type of convolutions was proposed recently, as example Tiled Convolution, Transposed Convolution, Dilated Convolution, Network In Network and Inception Module [23]. (ii) The pooling layer is an important concept of CNN. It lowers the computational burden by reducing the number of connections between convolutional layers, several pooling layers was proposed in literature, as Lp Pooling, Mixed Pooling, Stochastic Pooling, Spectral Pooling, Spatial Pyramid Pooling and Multi-scale Orderless Pooling[23].

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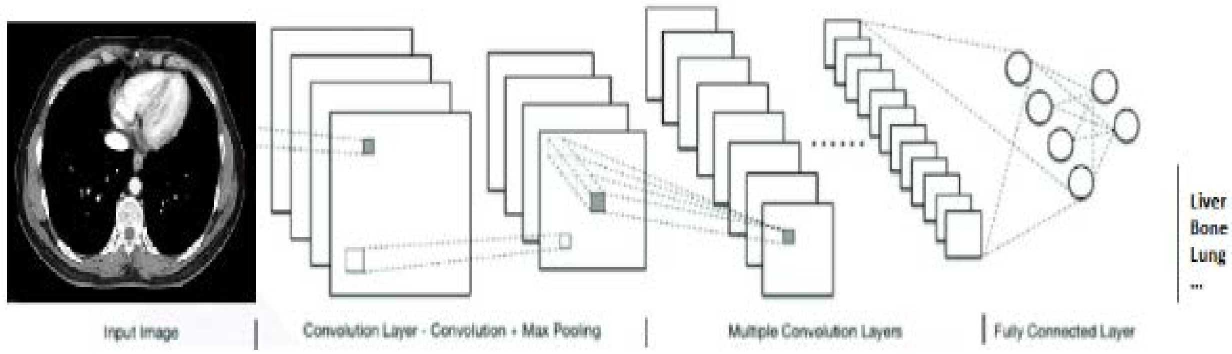

Figure 4: CNN Layers

CNN networks has been used in many different ways for segmentation task, the main intuition behind most of those methods is to trait segmentation as a classification problem, using the called wise pixel classification, it's a binary or multi-classes classification on which model calculates the likelihood of pixel belonging to some classes defined initially. However, this type of networks are high expensive on training step and need huge data to learn efficiently. To make faster the training of this architectures other variant has been proposed such as F-CNN that remove the last full connected neural and use instead a segmentation mask for learning. Learning time has been improved also by pre-detection of objects in R-CNN [24], Fast R-CNN [25], Faster R-CNN [26], Mask R-CNN [27] where process just some regions instead of the whole image, they create bounding boxes, or region proposals, using a process called Selective Search.

Table 1: CNN based Networks

Name	Year
AlexNet	2012
R-CNN	2013
Fast-RCNN	2013
Faster-RCNN	2013
Mask-RCNN	2013
ZF-Net	2013
Fully CNN	2014
GoogleLeNet	2014
DeepLab V1	2014
Dillated CONV CNN	2015
PSPNet	2016
DeepLab V2	2016
DeepLab V3	2017

Encoders/Decoders: In 1986, Rumelhart proposed the concept of auto-encoder and applied it to high-dimensional and complex data processing. The goal of the single-layer AE is to minimize the average reconstruction error between the input data X and the reconstructed data Z. The classical AE can be used to reconstruct the input data through minimizing the average reconstruction error between the input data X and the reconstructed data Z. In order to use the AE to complete semantic segmentation, a supervised learning layer is added to the classical unsupervised AE model.

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Table 2: Transpose Convolution based Networks

Name	Year
VGG	2012
ResNet	2012
SegNet	2015
VGG SegNet	2012
RefineNet	2012
Large Kernel Matter	2012
UNet	2015

Limitations

In order to increase the accuracy and avoid over-fitting, the supervised deep learning models require a large quantity of labeled data for training, and labeling data need expensive experts and time consuming, techniques such as data augmentation and transfer learning are used to increase accuracy.

VIII. CONCLUSIONS

The papers reviewed show how it's evident that deep learning has pervaded every aspect of medical image analysis, a large diversity of deep architectures are used for the task of image segmentation. To summarize the result of our work, a taxonomy has been developed that summarizes the most relevant categories of algorithms in the segmentation of medical images. Subsequently we present a comparative table of these different categories, according to several criteria of such fate that they help researchers to put themselves in the field of image segmentation in general and specially medical images.

The table below show that excepting the need of big quantity of data for training step, the deep learning algorithms perform the best result in segmentation task. That why research are oriented now to propose a new approaches that make deep learning less hungry to data without affecting the accuracy. We consider the use of Ensemble Learning and Multi-models Learning for future works.

Compared methods:

- HDM: Hand-Craft Methods
- T-ML: Traditional Machine Learning
- DL: Deep Learning

Table 3: Approaches Comparison Table

Criteria / Method	HDM	T-ML	DL
Don't Require manual interaction	No	No	Yes
No sensibility for algorithm initialization	No	No	Yes
No artifacts sensibility	No	No	Yes
Low computational time	Yes	No	No
Low implementation complexity	No	Yes	Yes
High Accuracy	No	Yes	Yes
Reliability	No	No	Yes
Manage Repeatability	No	Yes	Yes
Robustness	No	No	Yes
Least dependency on the operator	No	Yes	Yes
Don't need preprocessing	No	No	Yes
Easy Preserving Spatial information	No	Yes	Yes
Less Data Hungry	Yes	No	No

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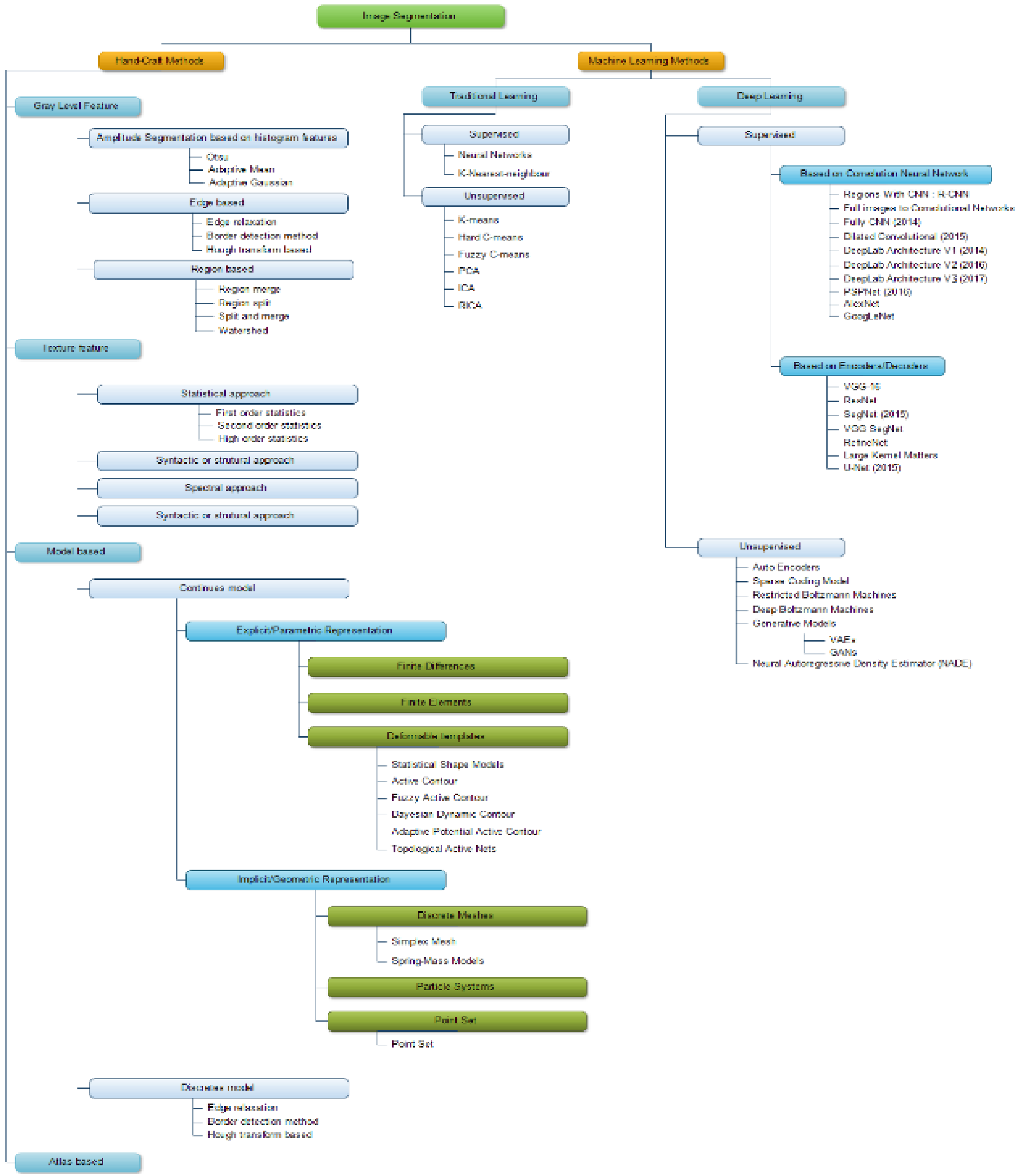

Figure 5: Segmentation Algorithms Taxonomy

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