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Current Trends and Future Directions in Sea-Land Segmentation for Remote Sensing Images

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ABSTRACT

Nowadays, sea-land segmentation for remote sensing images has a valuable role in water resources monitoring, maritime safety, and coastal zones management. However, it has faced many challenges such as the complicated distribution of land area, noise, poor contrast between sea and land regions, different weather conditions, the development of sensors, and high-resolution images provide more information. Consequently, there are considerable efforts have been made to develop various methods to overcome these challenges. Therefore, this paper introduces the description of the main steps of the sea-land segmentation procedure and the main characteristics of each step. Also, the paper focuses on the taxonomy of the current sea-land segmentation methods. These methods are broadly categorized into six main groups namely thresholding-based methods, region-based methods, energy minimization-based methods, machine learning-based methods, watershed transformation-based methods, and hybrid methods. Finally, this paper also shows and discusses the common challenges which are facing the sea-land segmentation. Besides, the paper introduces promising future research directions in the sea-land segmentation field.

General Terms

Survey

Keywords

Sea-land segmentation, Remote Sensing, Coastline/shoreline Extraction, Machine Learning, Energy Minimization.

1. INTRODUCTION

Remote sensing technology particularly provides a large amount of information. Also, it can easily capture the features in a large area of interest. Therefore, it has a vital role in a broad range of applications, especially in water resources monitoring, maritime safety, and coastal zones management. Sea-land segmentation has a vital role in remote sensing image analysis, target detection, coastline extraction, and object classification in many maritime and coastal applications for monitoring the changes in coastal zones and maritime life. Currently, sea-land segmentation is considered a very hot research area in the field of remote sensing images (RSIs) segmentation and classification. The goal of sea-land image segmentation is to separate RSI into two uniform regions called the sea and the land according to specific criteria. The result of sea-land segmentation has a great role in a broad range of remote sensing applications. It also provides valuable information for decision-makers towards national development and environmental protection.

For marine target detection, sea-land segmentation has a great role in the development of maritime monitoring systems such as control maritime traffic, detect illegal smuggling, protect sea resources, and protection of the coastal environment [1]. For ocean monitoring systems, sea-land segmentation is a crucial step in ocean surveillance, oil leakage detection, and ship target detection and classification [2]. Besides, dynamic natural processes like coastal erosion, accretion, sediment transport, and environmental pollution have a negative influence and cause horrible changes in the coastal zones. These coastal zones are considered the main socio-economic environment in most parts of the world. The coastal changes lead to loss of life, decrease coastal land resources, the security of harbors, economy, tourism, and environmental protection [3]. Therefore, sea-land segmentation has an effective role in coastal zone monitoring and coastline detection.

Sea-land segmentation of RSIs often faces many increasing challenges and difficulties which can affect on the performance of segmentation results such as (1) different weather conditions (e.g. rains, clouds with different kinds and sizes, waves, and wind), (2) illumination and shadows of mountains and buildings, (3) the complex environment of sea and land, (4) the quality of the image sources and poor contrast between sea and land areas, (5) the complicated distribution and complex texture of land area, wharves, and isolated isles, and (6) ships are causing problems close to the border between sea and land. (7) The development of sensors and high-resolution images provide more information about sea and land objects and show a large diversity of texture and spectral features. Therefore, significant efforts have been recently made to develop various segmentation techniques that take into considerations all these challenges for sea-land segmentation of different types of RSIs. These challenges have a negative influence on the efficiency and the accuracy of sea-land segmentation algorithms.

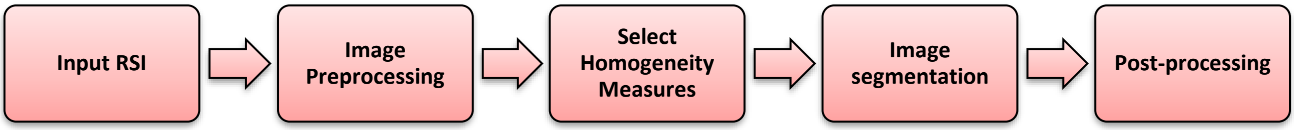

Figure 1. The basic steps of sea-land segmentation procedure.

In the past decades, the manual sea-land segmentation has been possible based on prior geographical information of the research area as a standard reference. It has been faced many problems like take much time, need substantial efforts and it is difficult to obtain accurate geographical information about some areas [2]. Consequently, the implementation of an automatic sea-land segmentation approaches can provide precise results about research cases and do not take much time compared to manual segmentation.

While many methods exist, there is not a deep literature review to focus on the general procedure of sea-land image segmentation and the taxonomy of sea-land segmentation methods for RSIs and the current challenges. Therefore, this paper presents a description of the main steps of the sea-land segmentation problem. Also, it introduces a review of the current progress and different methods in sea-land segmentation of RSIs and their various applications. Besides, it describes the main current challenges and limitations which are facing sea-land segmentation problem as well as the future directions in that field.

The remainder of the paper is organized as follows. In the beginning, Section 2 shows the basic steps of sea-land segmentation procedure in general. Section 3 discusses the taxonomy of the different sea-land segmentation techniques and related works which are associated with each sea-land segmentation taxonomy. Also, it shows their results, the advantages, and limitations of segmentation techniques. Section 4 presents current trends and future promising directions in sea-land segmentation. Finally, the conclusion is presented in Section 5.

2. THE GENERAL PROCEDURE OF SEA-LAND IMAGE SEGMENTATION

As aforementioned, sea-land image segmentation converts an RSIs into a simple format for making an image that is easy to understand and analyze to be helpful in various applications. The goal of this section is to generally explain the basic steps of the sea-land segmentation procedure that helps in achieving such a goal. The sea-land image segmentation procedure consists of some steps. For the sea-land segmentation of RSIs, there are some considerations when each step is implemented. Figure 1 shows the basic steps included in the sea-land segmentation procedure.

2.1 Input RSI

The first step in the sea-land segmentation procedure is to obtain RSI which has been acquired from different remote sensing system platforms. Satellites and aircraft are considered the most common platforms for remote sensing of the earth and its natural resources [4]. In general, the RS system acquires images in different wavelengths of the electromagnetic spectrum including visible, infrared and microwave bands. Thus, there are various types of RSIs including optical RSIs (e.g. panchromatic images, natural color images (RGB), infrared images, false-color images, and thermal images), synthetic aperture radar (SAR) images, and aerial images. Every category of these RSIs has specific characteristics, advantages, and limitations in different applications. Also, RSIs have been acquired in different resolutions (e.g. low, medium, high, and very high resolution) which could affect the amount of information about the scene and object segmentation. For more details about RS systems principles, visit the following web page [5]. The sea-land segmentation has been utilized for different categories of RS images in different resolutions as shown in the following sections.

2.2 Image Preprocessing

As explained in the introduction section, there are a set of factors that could affect RSIs during the acquisition process including the sensor's noise, poor contrast, blurring, Illumination, weather conditions, and so on. Therefore, sea-land RSIs must be preprocessed before analyzing and feature extraction step. The preprocessing step corrects the distorted image and enhances the image structure contrast to produce a more faithful representation of the original image. Besides, it increases the image details.

Many image preprocessing methods have been applied in the sea-land images. In [3], the authors enhanced the contrast of the coastal NIR image by applying the clipped histogram equalization method. Gaussian blurring in [2], [6] was applied to the infrared images to suppress noise and speckles reduction [7], [8]. Another method called edge-preserving filter was applied in [9] to reduce the influence of the image noise and make it smooth while preserving the image edge structure. Due to the large size of RSIs, there are some methods including image cropping [8], [10], image down-sampling as in [1], [9] and divide the image into small blocks or patches as in [11] to enhance processing speed and utilize spatial features. Geometric correction [7], [8]. Transforming an image to another color space to discriminate well the characteristics of an image as in [12].

2.3 Select Homogeneity Measures

As previously defined, the aim of sea-land image segmentation is dividing RSI into two consistent regions called sea and land according to homogeneity criteria. Here, appropriate homogeneity measures are determined to describe the image features. Thus, the possible measures are comprising spectral, texture, spatial, size, shape, edge, and temporal features. Spectral and textural features are the most primitives of homogeneity measures. The integration of one feature with other features can provide accurate segmentation results.

Here, the first three measures are explained. The first one is the spectral feature. It refers to the gray intensity of pixels values of an RSI. Spectral features cannot reflect the spatial information. Therefore, the image segmentation methods only based on spectral features (e.g. thresholding methods) cannot provide accurate results and produce more false-alarms due to sea waves, noise, and weather conditions as presented in sea-land RSI [2],[13],[14].

The second one is the texture feature. It is considered an important feature to identify textural objects since it represents the variability of local intensity and patterns inside the surface of objects [15],[13]. Also, it represents fine-scale spatial arrangement information in images. For the sea-land image, texture features describe more surface properties of sea and land [2].

There are various texture feature descriptors have been used to express the texture characteristics of the sea and the land areas. Liu et al. [9] adopted the local entropy to express sea and land texture features because of its computational efficiency and stability. Xia et al. [13] expressed the texture features by using local binary pattern (LBP) descriptor. LBP has several advantages like its immunity against illumination changes, less computational time, ability to encode fine details, and edge-preserving. Gabor filter has been widely applied as a texture descriptor because of its sensitivity to the edge of images and has a wide adaptation to illumination variation as a result, Cheng et al. [16] and Wang et al. [13] were applied Gabor texture to the optical RSI to express regional arrangement information of the sea and the land. Seixas et al. [17] applied texton, another texture descriptor, to explore the image texture of the sea and the land from the SAR image. Texton can acquire the spatial features of textured regions more effectively. In [18], texton features have been defined as clustering centers of high-dimensional points of filter responses.

The last one is the Spatial feature of the objects. Morphological profiles (MPs) and morphological attribute profiles (APs) [19] are considered efficient methods to capture the spatial features of objects in RSIs. Cheng et al. [42] used MPs and APs to extract spatial features of sea and land objects from the natural colored image.

2.4 Image Segmentation

Here, sea-land segmentation has been applied to partition an image into sea and land regions based on the selected homogeneity measures from the previous step. The result of segmentation is a set of contours (boundaries) of objects or a set of regions that cover the entire image. Furthermore, RSIs contain a lot of complex information. Therefore, the image segmentation techniques are utilized to convert an image into a simple format to make an image that is easy to understand and analyze.

Generally, segmentation techniques are partitioned into two main groups based on the similarity and the discontinuity (edges) detection. In the first one, an image is segmented into regions that are homogenous according to a set of a priori defined criteria (e.g. intensity, color, shape, size, and texture). Thresholding methods, region-based, and clustering approaches belong to this group. In the second one, an image is segmented based on sudden changes in the intensity of the pixel such as edge detection-based and active contours approach. In this paper, sea-land segmentation techniques are categorized into different categories, as illustrated in Figure 2.

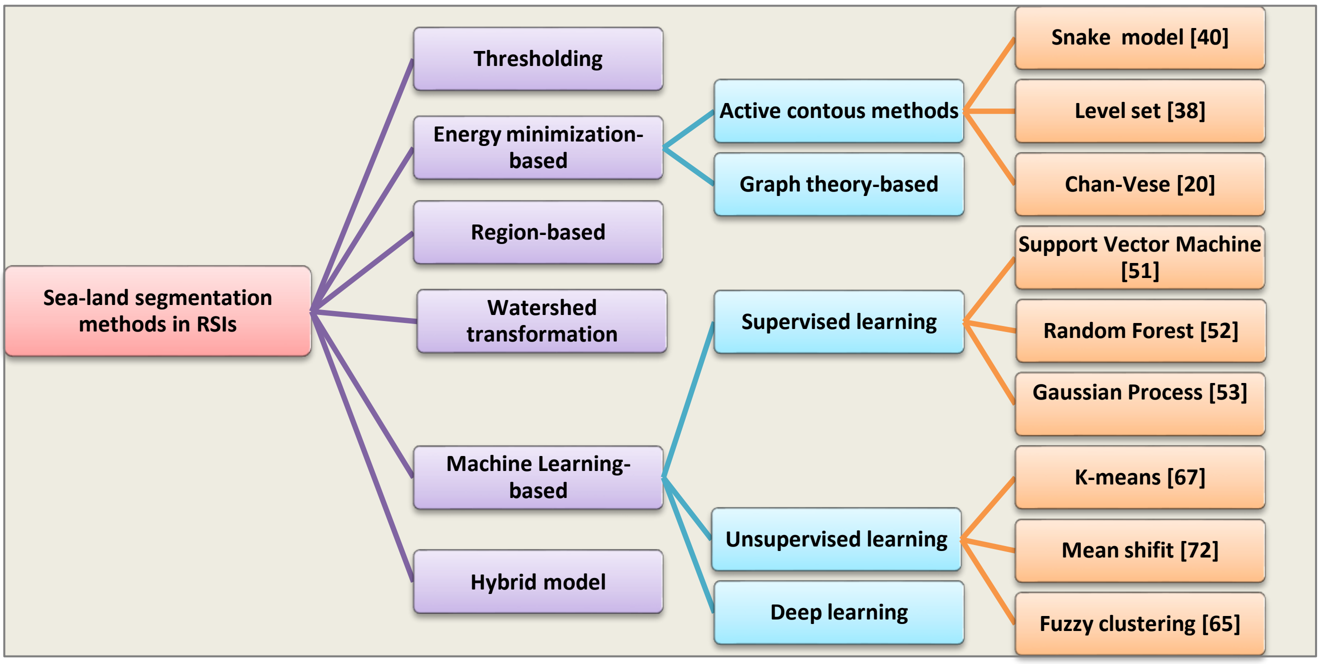

Figure 2. Taxonomy of sea-land segmentation techniques

2.5 Post-processing

There are perhaps still a few holes in the land or the sea regions after the sea-land segmentation step. Thus, the holes filling methods are considered the main approaches to solve these problems. The most used methods in holes filling are contours information-based [21], corrosion-expansion, morphological operations, and scan line polygon filling. Also, upsampling was applied when downsampling was applied in the preprocessing step. In general, the post-processing step has not been applied to all segmentation methods, as shown in Section 3.

3. BASIC CONCEPTS AND RELATED WORK

Over the last few years, various range of techniques has been developed for sea-land segmentation for aerial and satellite images. Generally, sea-land segmentation techniques are divided into six main categories: thresholding-based methods, region-based methods, energy minimization-based methods, machine learning-based methods, watershed transformation-based methods, and hybrid methods. Figure 2 shows a taxonomy of current sea-land segmentation techniques that have been applied to different types of RSIs. The goal of this section is to define the terminology and basic concepts of image segmentation techniques. Besides, it shows the related researches of each taxonomy, its performance, and the limitations.

3.1 Thresholding Methods

Thresholding methods are the simplest and earliest techniques in image segmentation, which depend on the idea that there are irregular objects are placed in a uniform background [14]. Based on the selected appropriate intensity value which is called the threshold, the image can be classified into the object and the background. All pixels with intensity greater than the selected threshold are classified into object class and all other pixels are classified into background class [22]. The selection of threshold value can be considered a crucial step in image segmentation. Therefore, thresholding methods are generally grouped into three broad categories: global, local, and adaptive.

In the global thresholding method, a single threshold value is applied to the whole image. Also, this method does not capture the spatial features of objects in an image. However, this method fails when the background illumination is irregular because of the shadow or the direction of illumination [23], [24]. Therefore, it is not immune against the noise and intensity non- homogeneous intensities which can occur in RSIs. There are many global thresholding techniques such as Otsu [25], histogram analysis [26], iterative thresholding [27], and maximum correlation thresholding [28].

In the local thresholding method, the image is partitioned into $m \times m$ sub-images. Then for each sub-image, an appropriate threshold value is selected based on many local image features of neighboring pixels such as mean or variance. This local method can be applied when the gradient effect is small for the chosen sub-image [24].

In the adaptive threshold, different thresholds for different local areas are utilized. Also, objects of the image and background are separated depending on the difference in pixel intensities of each region. The computational time is considered a drawback of this method. Therefore, it is not appropriate for real-time applications [24].

Because of the simplicity of thresholding methods, many studies were published in sea-land image segmentation. Nevertheless, it has been faced a set of challenges as illustrated in Section 4. They also provided acceptable segmentation results as shown in the following related work for example:

Raju et al. [3] applied an automatic method based on clipped histogram equalization that used in the preprocessing step as previously explained. Also, the adaptive threshold was determined based on the mean and standard deviation of the equalized histogram for sea-land segmentation. This method achieved high performance on extracting the shoreline from infrared images. However, this method still faced some limitations because of the complicated distribution of intensity and complex scene.

Dejan et al. [6] presented a locally adaptive threshold and the Canny edge detection method for coastline extraction. A locally adaptive threshold was applied to classify the image into sea and land regions. Then, the boundary between land and water areas was detected as a coastline by Canny edge detection. The results proved that this method was fast and accurate. However, the weather conditions and the poor contrast between water and land areas influenced the extraction of an accurate coastline.

Xia et al. [13] used the Local Binary Pattern (LBP) to express texture features and highlight the edge pixels with gray intensity features of an image. The sea-land segmentation was taken place by thresholding method based on the extracted features. The experimental results showed that this approach could minimize the false alarm rate compared to traditional methods. However, this method did not consider the cloudy images. Post-processing was needed, and LBP was sensitive to noise.

Ma et al. [29] developed a fast and hierarchical segmentation method via integrating modified Otsu's method with intensity and texture features to obtain the initial segmentation. Then, modified Otsu's method was applied to extract the sea-land boundaries. The results proved that this method was robust and computationally efficient compared to other state-of-the-art methods under various complex background conditions.

Zhuang et al. [30] proposed an approach based on the integral image reconstruction and coarse texture areas. Firstly, a gradient feature map (GFM) was calculated to form the sum area table (SAT) and reconstruct an integral image. Secondly, an adaptive threshold of texture and structure information was used to segment the textural integral image into sea and land regions. Finally, the morphological operations were applied to fill the holes of the binary pattern. The results proved the effectiveness of this approach. However, noise could influence GFM.

You and Li [31] proposed an automatic method for sea-land segmentation based on an adaptive statistical model of the sea region (SMS). Firstly, Otsu's method was utilized to extract the sea area. Then, SMS was applied to segment the image into the sea and land. At last, the misclassified land regions were eliminated based on the difference of the variance in SMS between sea and land. The experiments demonstrated that this method was better performance, robustness, and less computation complexity compared to other different methods. However, there were problems of misclassification in the sea area and the optimization of complexity.

Wang et al. [32] presented a method to solve the problems for Middle wave infrared remote (MWIR) in sea-land segmentation. This method integrated gradient feature map (GFM) and pyramid integral image reconstruction on a different scale to enhance structural and texture information. Then, the adaptive threshold method was applied to the multi-scale integral image to obtain sea and land regions. The results proved that this method was robust and stable at the day and night scenes.

3.2 Energy Minimization-based Method

The energy minimization methods are broadly utilized in many computer vision problems. The Image segmentation aims to label each pixel in an image into two sets, object, and background. Therefore, the image segmentation problem can be defined as a pixel labeling problem that assigns a label from the label set **L** to each pixel in an image **P**. The goal is to find a labeling function that maps from (**P** → **L**) and minimizes the energy function. In general, energy functions express the constraints of the problem to be solved [33]. Graph theory-based and active contour models are the most popular approaches used to minimize the energy function.

3.2.1 Graph Cut- Based

Let's an image is viewed as an undirected weighted graph and defined as **G = (V, E)** where **V** is a set of vertex or nodes which correspond to image pixels, and **E** is a set of edges. Each edge connects every two adjacent pixels and has a corresponding weight which is a nonnegative measure of the dissimilarity between adjacent pixels. A cut is a subset of edges by which the graph **G** will be partitioned into two disjoint sets **A** and **B**. So, the cut value is usually defined as:

$$cut(A,B) = \sum_{u \in A, v \in B} w(u,v) \qquad (1)$$

where **u** and **v** refer to the vertices in the two different components. ***w*** refers to weight of edge between ***u*** and ***v*** vertices.

As previously defined, image segmentation is defined as a labeling problem, where a set of labels **L** is assigned to a set of pixels of an image in **P**. In the case of two-class segmentation (e.g. sea-land segmentation), for example, the problem can be formulated as assigning a label $\mathbf{L_i}$ from the label set **L**= {object (land), background (sea)} to pixel **i ϵ P**. Figure 3 [34] illustrates an example of two class segmentation based on s/t graph cut and cut of the graph corresponds to the minimal energy function. In other words, image segmentation based on graph theory, a graph is partitioned into several sub-graphs such that each of them represents a meaningful object of interest in the image.

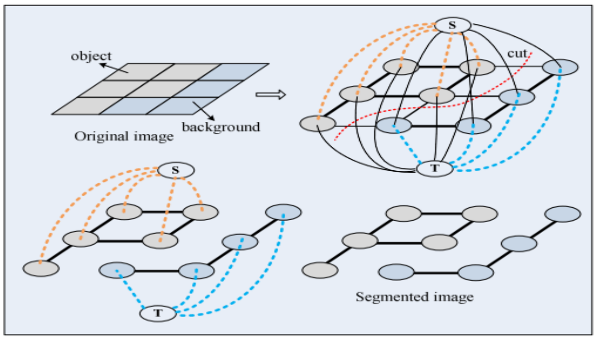

Figure 3. s/t graph cut for image segmentation

There are several techniques for graph partitioning, which are classified into five classes: the minimal spanning tree-based methods, graph-cut based methods with cost functions, graph-cut based methods on Markov random field models, the shortest path-based methods and the other methods that do not belong to any of these classes. More details about each category can be found in [35].

Recently, graph cut-based methods have been considered the most important methods for image segmentation problems. Due to their accuracy and good robustness, many studies were done by a lot of researchers in sea-land segmentation, for example:

Cheng et al. [16] developed a supervised method by incorporating a multi-feature descriptor and edge-directed graph cut (GC). This method solved the sea-land segmentation problem for high spatial resolution natural colored images. The image was pre-segmented into superpixels to reduce information redundancy and use the local relationship in GC. Then, the SVM classifier was trained to select the seeds of GC. The results showed that this method was robust and achieved high accuracy. Also, the final segmentation was spatially consistent. But this method suffered from under segmentation for some thin and fine-structured objects, such as wharves.

Cheng et al. [36] developed an automatic and hierarchical method for sea-land segmentation of natural colored images. At first, the image was firstly pre-segmented into superpixels to reduce information redundancy. After that, superpixels were merged to extract the Maximum Area of the Sea Region (MASR) based on the hierarchical graph merging method. In the end, an edge-directed graph cut was utilized to achieve the final segmentation. Due to the presented edge constraints, the result was smooth and spatially consistent. Experiments proved the effectiveness of this method compared with other methods. However, there were a few errors in the results near the edges of the sea and the land.

She et al. [37] developed a new method based on graph cut (GC) to solve the sea-land segmentation problems for PolSAR images. The multi-polarization features were utilized for automatic seed selection for the sea and land to build a graph model for GC. To reduce the speckle effect and avoid the under- segmentation for some thin and elongated structures, the edge constraint for formulating the boundary term in GC was extracted by a ratio of an average operator. Comparative experiments were executed, and the results proved that this method was effective and robust.

Ferreira [1] presented a sea-land SAR image segmentation based on energy minimization via graph cut (GC). The data terms were modeled via a finite mixture of gamma distributions and estimated based on manually selected land and sea samples. A Markov Random Field was utilized to model the prior probability, which imposed local continuity between neighboring pixels of the image. The proposed method provided good results. But there were some regions were not segmented well and time-consuming. Also, the selected seeds depended on user intervention.

Ding and Li [7] presented multi-scale normalized cut segmentation to extract coastline from SAR images. Firstly, the image was divided into many regular sub-blocks to capture local and spatial characteristics and speed the processing step. Secondly, each sub-block was segmented into regions using multi-scale normalized cut segmentation. Finally, the coastline edge pixels were automatically delineated. For estimating the accuracy of the sea-land boundary extraction method, two experiments were done and showed that this method was effective and efficient. However, post-processing was performed, and the coastline extraction is still an open research task in SAR images, due to the speckle noise and other factors.

3.2.2 Active Contour Models

In the active contour models, the problem is considered as an energy minimization one. In an image domain, a curve is defined by energy function and moves toward the contours (edges) of objects under constraints from image forces. There are internal forces that are coming from within the curve itself and external constraints which are calculated from image data. Once energy function reached the minimum, object contours are achieved [38],[39]. There are two main categories of active contour methods: parametric active contours and geometric active contours. In recent years, the active contour is considered an important method for feature extraction and boundary detection of sea-land regions and provide accurate segmentation results. Active contour models are still an active research topic.

- *Parametric Active Contours*

Parametric active contour also called a snake model which was firstly presented by Kass et al [40]. The basic idea of a snake model is described as follows: According to the energy minimization criteria, a curve or a surface evolves iteratively towards the desired features (e.g. lines or edges) of the objects under the external constraint forces and the internal smoothness constraint of the moving curve. The image is segmented when the energy function reaches a minimum. The snake model has some shortcomings. The first, this method is susceptible to initialization and should be defined near the contours of desired objects. The second, they cannot handle the topological changes because of the explicit parameterization of the model, and they failed to detect non-convex objects [39],[41].

There are many proposed methods based on the snake model, which were applied to sea-land segmentation of different RSIs. The results showed the efficiency of these methods, as shown in the following paragraphs.

Kun et al. [42] presented an improved snake active contour method for a coastline extraction from high-resolution RSIs. Water segmentation and boundary tracking were utilized to detect the coastlines. They also optimized an initial contour through an improved snake model. Due to the limitations of the original snake model, two new energy functions were developed to make snakes more effective. The internal energy minimized problems which were produced by convergence to local minima. The external energy could extremely increase the acquired region around the features of interest. The experiments proved that the proposed model was accurate for coastline detecting. However, it took a long computational time.

Liu et al. [43] offered a study with two basic contributions in sea-land segmentation. The first one, RSI was separated via an active contour model based on a novel energy function. Then, the global optimization method iteratively used to minimize the energy function. The presented energy correctly worked on the various intensity distributions between the sea and land compared with other traditional methods (e.g. Otsu's method). The other one, according to the segmented image, context information and shape analysis were extracted to detect inshore ships. The results from Quick-Bird images showed the presented study was robust and precise. But, images with strong waves could affect the results.

- *Geometric Active Contours*

Geometric active contour models are depending on a speed function which related to evolving surface characteristics (e.g. curvature, normal direction) and image features (e.g. gray value, gradient). The evolving gradually reaches zero speed as the ideal value when it closes to the edges of the object and eventually stop [39],[44]. Geometric active contour models are grouped into two groups: models depend on boundary functional and models depend on region functional. A level set model belongs to the first category and the Chan-Vese (CV) model belongs to the second category.

Level Set Model

The level set is a numerical analysis method using partial differential equations to solve the problem of curve evolution [38]. The concept of this model is described as follows: the surface or curve is defined as the zero-level set of a function in a higher dimension in which the changes in the topology of the active contour can be handled implicitly during the curve evolution. The Speed function is defined to express the movement of the level set [39]. This model has many advantages such as applicable to any dimension space and it is stable and efficient to detect contours in an image, handles topology changes, captures dynamic interface and shapes successfully, solve the problems which are produced from of corner point, and curve breaking and combing. However, objects with a strong gradient are only segmented because the stopping function depends on the image gradient. This model does not well converge if the image edge information is very complex and weak. Also, it is sensitive to noise. Consequently, all these drawbacks could affect the accuracy of image segmentation [44],[45].

In RSIs, there are many papers that were published based on the level set methods especially in sea-land segmentation and showed that the level method was fast and provide accurate results, as shown in the following paragraphs.

Song et al. [22] presented a new level set algorithm based on cross-entropy. Firstly, the region term of the presented model was calculated by the measurement of the probability distribution based on cross-entropy. Secondly, to accelerate the global minimization of an objective function of this model, the edge term was incorporated into the geodesic active contour model. The experiments showed that this algorithm was fast and accurate.

Wang et al. [46] presented a novel coastline detection using a level set model for infrared remote sensing images. The proposed model utilized the template initialization to improve level set initialization according to Global Self-consistent Hierarchical High-resolution Shorelines (GSHHS) data. GSHHS could minimize the number of iterations and numerical errors. Besides, local energy minimization was optimized. The results showed that this model could achieve acceptable results and minimize computational complexity. Nevertheless, this model had limitations when applied in optical remote sensing images due to complex conditions such as noise, etc.

Yu et al. [47] proposed a powerful methodology to recognize and extract a shoreline from satellite images. First, the proposed method detected singularities in an image using a non-separable wavelet. The singularities that were utilized to locate shoreline should be given more high-frequency components. Then, Distance Regularized Level Set Evolution (DRLSE) could be applied to extract the shoreline. The experiments showed that this algorithm was efficient and applicable for different satellite images and it was robust to noisy and blurred images. Nevertheless, a non-separable wavelet would be improved to be self-adaptive to acquire more singularities. In addition to adopting other creative methods was still an open challenge.

Silveira and Heleno [48] developed a method for SAR image segmentation. This method utilized the level set method and a mixture of lognormal densities which were used as the probabilistic model to express the pixel intensities in both land and water regions. Also, the probability density functions for each class were estimated by the expectation-maximization technique. Compared to other different methods, results showed that the presented method provided good performance. Here, this method relied on the manual initialization of the level set which was sensitive to contour initialization and could take much time.

Chan-Vese Model

The Chan-Vese (CV) model was presented by Chan and Vese [20]. It depends on the region homogeneity instead of edge information, as explained in the previous active contour models for stopping curve evolution. The main concept of the CV model is defined as follows. It depends on an image is segmented into two classes, one representing the background and the other one representing objects to be detected [44]. The curve moved to the edges of the object by computing the difference between grayscale values of pixels inside the object and background regions. Furthermore, the segmentation of the image is achieved by minimizing the within-class variance. But, the CV model has some drawbacks such as the convergence rate is reasonably slow and the iteration number is to some extent large [45],[22]. CV model has been applied for sea-land segmentation. The results have proved that it has been effective, accurate in the image segmentation, as shown in the following paragraphs.

Mao et al. [49] improved CV via integrating the edge information which was extracted based on the Dual-Tree Complex Wavelet Transform (DT-CWT). Then, an active contour evolution was implemented via an improved CV model. After that, the contour was modified based on the extracted edge information over the full evolution. After evolution, the final segmentation of the water and land was achieved. The experiments proved the presented model was accurate and effective compared to some existing methods.

Han et al. [45] presented an improved CV model that replaced the within-cluster variance with the median absolute deviation to define the constraint terms of external energy. Also, it could eliminate the effect of the interference regions. The regional energy weights were calculated to speed up the model evolution. These weights were obtained from information of within-cluster variances and median absolute deviations of grayscale values of a pixel inside the object and background regions. The experiments proved that the proposed model was highly efficient, accurate, and low false alarm rate compared to other active contour models. However, this model only based on the intensity features of the image which could affect the segmentation results.

3.3 Machine Learning- based Methods

Nowadays, machine learning has a vital role in the remote sensing field. It provides an automated procedure that is designed to learn and solve classification problems depend on the existing training data set. Image segmentation can be viewed as a classification problem. Generally, machine learning is defined as it has been built a classification model that can receive the input data and use statistical analysis models to predict the output within a tolerable range [50]. Based on the use of the labeled training dataset, machine learning classification algorithms are classified into supervised and unsupervised algorithms. Recently, researchers have moved to machine learning algorithms for the sea-land segmentation and coastline extraction. In this section, several machine learning algorithms and their accuracy are described in sea-land segmentation.

3.3.1 Supervised classification algorithms

Many latest methods considered sea-land segmentation as a classification problem and have achieved significant advances due to the strong representations of features and classification models. Therefore, supervised classification algorithms use labeled training dataset to build a classification model which able to generalize to the whole training data set and predict future instances. Figure 4 shows the framework of image segmentation based on supervised classification. In this figure, the segmented image is obtained by learning the classification model to capture the variation in the object (e.g. sea, land) appearances and views from a set of training samples in a supervised framework. To a large extent, the selected features and labeled dataset can affect the accuracy of classification algorithms [51].

There are many various supervised classification algorithms such as Support Vector Machines (SVMs) [51], Random Forest (RF) [52], Gaussian Process (GP) classification [53], Neural Networks (ANN) [54], K-Nearest Neighbors (KNN) [55] and Decision Trees [56]. Here, the basic concepts of the first three algorithms are described because they are utilized for sea-land segmentation of RSIs, as we illustrated in the following sub-sections.

- *Support Vector Machine*

SVM is considered one of the most usual and efficient classification algorithms for solving classification problems. It was proposed by Vapnik and Vapnik. Recently, it is widely applied to many different applications in RSIs such as object detection and classification [51]. SVM is a non-parametric supervised learning method. It was developed for classification and regression analysis based on statistical learning theory. With the presence of labeled training data instances, the basic idea of SVM is illustrated as follows. It is a linear binary classifier because it performs classification by building a hyperplane that optimally separates the dataset into two classes. The margin between the training samples is maximized via optimal hyperplane. Also, the support vectors are obtained through the vectors near this hyperplane [57],[58].

For a multi-class classification problem, there are modifications are made to the simple SVM binary classifier to operate as a multi-class classifier by using methods such as one-against-all and one-against-others [51]. Also, SVM can be used as a non-linear classifier by mapping the non-linear training data into a higher-dimensional feature space via kernel function. Nevertheless, non-linear SVM is affected by the selected kernel. When the convenient kernel is selected with optimal parameters, SVM can achieve a perfect classification result. SVM was applied in many studies of sea-land segmentation, as shown in the following examples.

Lei et al. [2] developed a novel method that used superpixels and multi-scale features for supervised learning based on SVM. Firstly, the image was partitioned into superpixels based on the graph segmentation method. Then, multi-scale features were extracted from superpixels to train SVM for sea-land segmentation. This model was applied to the infrared images. The results illustrated that the developed technique was accurate and very robust compared to traditional methods. But, superpixels segmentation affected by the selected parameters which could affect the results.

Su et al. [59] proposed a method for Polarimetric SAR sea-land segmentation based on SVM learning. Polarimetric features were obtained from polarimetric decomposition and texture features based on first-order statistics which were extracted for training the SVM classifier. The results proved that the proposed study achieved satisfying results in the image segmentation. However, new features and increasing the number of training data could improve the performance of the classifier.

Amr and Khan [60] proposed a novel method based on the fusion of different remotely sensed data sources including LiDAR DEM data and aerial images using a genetic algorithm to maximize the mutual information. Then SVM classifier was utilized for water and land segmentation of the fused image. Eventually, a Gaussian kernel was utilized to extract and smooth the shoreline. The results showed that the presented method was accurate and efficient compared to other related methods. However, the fusion of other data sources would further improve the accuracy.

- *Random Forest method*

The Random Forest is a supervised method. It can be utilized to solve the classification and regression problems. The main concept of the RF method is described as follows. From its name, it randomly creates a forest in some way. RF builds a group of individual decision trees models and combines them. Then, the class with the majority over all these trees in the ensemble is being returned. Sometimes, RF is trained by the " bagging " method. In general, the bagging method is a combination of learning models that increases the overall accuracy. In other words, merging results from individual models can improve classification accuracy [52],[61]. RF is scalable, fast, do not overfit, robust to noise, easy to interpret, and visualize with no parameter to manage. But, the more increased the number of trees, the slower the method in real-time classification [62]. RF methods were applied in sea-land segmentation and provided accurate and efficient results, as illustrated in the following paragraphs.

Bayram et al. [63] presented a study for shoreline extraction based on the RF method from Landsat-8 and Gokturk-2 images. RF was utilized to divide the NIR image into sea and land regions. After the image classification, shoreline could be extracted clearly. The results proved that the presented study is accurate and efficient in both medium and high-resolution images. However, an automation selection of RF parameters could lead to better performance instead of manual selection.

Demir et al. [8] proposed an integrated method for shoreline extraction based on RF method classification and fuzzy clustering from the SAR image to enhance the quality of results. Firstly, an image was classified into land and sea regions by using the RF method. Secondly, the previous results were utilized as training samples to compute fuzzy parameters for shoreline extraction from the SENTINEL-1A SAR image. Experiments proved that this method was accurate compared to the manually digitized shoreline. However, the presented method was sensitive to the speckle noise.

- *Gaussian Process*

GP is a non-parametric flexible supervised method based on statistical learning theory, especially the "Bayesian" theory. It assumes some prior distribution on the underlying probability densities that achieves some smoothness properties. Besides, it can adapt well to deal with complex problems such as non-linear, high dimensions, and small samples [53],[64]. In GP classification, given a set of **N** training input samples **S= [s$_1$, s$_2$, ..., s$_N$]** and their corresponding class labels **L= [l$_1$, l$_2$, ..., l$_N$]**. For classification a new test point, a variable can be identified to assign a GP prior. The class labels are not suitable for this purpose. Therefore, a latent function **f(x)** can be defined whose value is then mapped into **[0, 1]** interval through the probability function. This function can assign a GP prior and use a regression treatment to model **f(x)**. This function then can be "squashed" by passing it through the logistic response function [65],[66]. For the sea-land

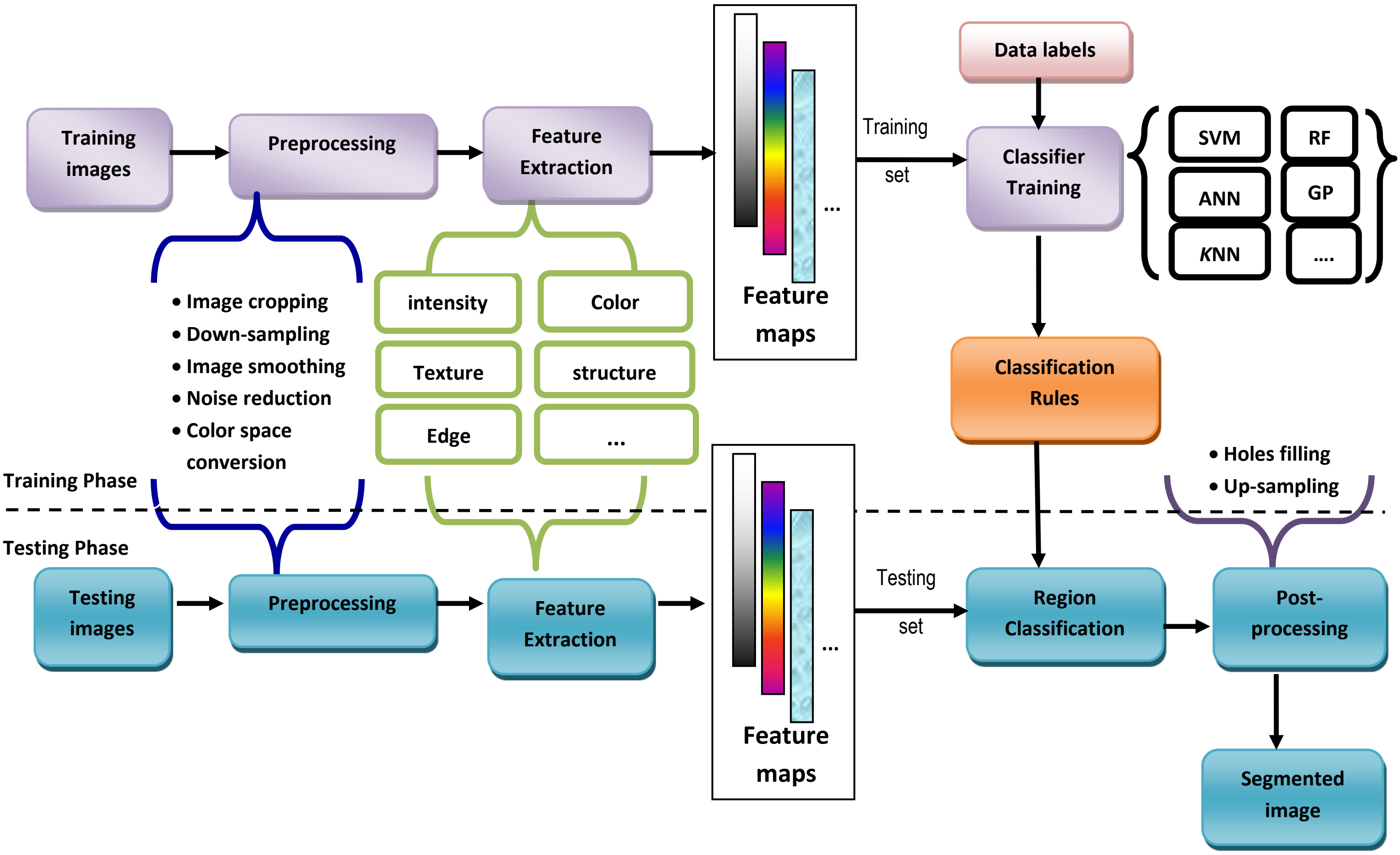

Figure 4. The framework of supervised classification-based segmentation

segmentation problem, there are little studies have been done based on GP, as shown in the following paragraphs.

Hu et al. [53] presented a study for coastline extraction based on GP classification. In the beginning, the water index feature was extracted from the remote sensing image via Normalized Difference Water Index (NDWI) which reflected the radiation in the green band and absorbed it in the NIR band. Once NDWI was calculated, the GP classifier was utilized to segment the image into the sea class and land class. After that, the coastline was extracted. The results showed that the GP classifier was effective and could distinguish the complex interferences. But, this classification based on only spectral features. Other features were ignored like shape, context information, and texture.

3.3.2 Unsupervised Classification Methods

Unsupervised classification also called clustering, unlike supervised classification, the class labels are unknown. In other words, clustering aims to find similarities in the presented data points and group similar data points together into a specific number of groups without any supervision or feedback from the environment. Therefore the image is segmented into homogeneous regions or clusters. Image segmentation can be defined as a clustering problem. The current clustering methods provided accurate and efficient results in sea-land segmentation for RSIs. In the following, the basic concepts of clustering methodology such as K-means, mean shift, and fuzzy clustering are described as well as their related works in the sea-land segmentation.

- *K-means*

K-means clustering is an iterative algorithm and a partitional clustering approach. It divides data points into a k number of nonoverlapping clusters based on their inherent distance from each other and each data point belongs to only one cluster. There are different distance metrics which have an important role in clustering methods. These metrics are used to define a distance between data points and each cluster centroid such as Euclidean distance, Manhattan Distance, Chebychev Distance, and Minkowski Distance. The basic steps of K-means are described as follows [67]:

1) Randomly select K initial clustering centroids.
2) Calculate the distance from each sample to each cluster centroid and return each sample to the nearest clustering centroid.
3) For each cluster, update cluster centroid by calculating the mean of all samples within it.
4) Repeat steps (2) to (3) until the cluster centroid no longer changes or reaches a predefined set number of iterations.

K-means has many advantages such as simple, easy to implement, and scalable for a large dataset. However, it has disadvantages. The first one is the selection of initial centroids, which affects the accuracy of the clustering results. Also, they lead to different results for different initial centroids. The other one is the computational complexity, which depends on the number of samples, the number of clusters, and the number of iterations. All these drawbacks must keep in mind while designing K–means [68]. Owing to the previous drawbacks and the complicated distribution of RSIs, K -means the method can be integrated with other segmentation methods to produce more accurate and efficient results especially in sea-land segmentation, as illustrated in the hybrid model in Section 3.6.

- *Fuzzy Clustering*

In fuzzy clustering, each data point can be assigned to different clusters at the same time with some weight or probability called a membership. This membership is associated with every data point. It represents the belonging degree of data sample $\mathbf{xi}$ to a cluster $\mathbf{cj}$. Membership weights belong to [0,1]. So, fuzzy clustering is a process of assigning these membership weights to data points [69]. In other words, membership weights donate how much the data point $\mathbf{xi}$ belongs to cluster $\mathbf{cj}$. Fuzzy clustering is flexible compared to hard clustering, which shows the natural relationship between the data points and clusters [23]. In the sea-land segmentation, fuzzy clustering approaches have been applied and provided accurate results. Furthermore, fuzzy clustering has been combined with other segmentation methods, as shown in the hybrid model in Section 3.6.

Demir et al. [70] proposed an unsupervised fuzzy clustering method to extract the coastline from the SAR images. At first, mean-standard-deviation Large membership function was utilized to calculate fuzzy memberships. The membership was utilized because the large amounts of land and ocean pixels dominate SAR image with large mean and standard deviation values. Then the clustered image was converted to a vector for the final coastline. In the end, the experiments showed that the presented method was accurate. However, the speckle noise of SAR images could affect the performance of the fuzzy clustering method. So, a noise reduction was necessary as a preprocessing step.

- *Mean shift*

Mean Shift has a role in different applications in computer vision such as clustering, tracking, filtering, and smoothing. Mean Shift (MS) is an iterative and a non-parametric feature space analysis technique based on the kernel density estimation. On the other hand, MS is utilized to find the modes of a kernel density estimation effectively. So, it is called mode seeking algorithm. The modes of a density estimation are corresponding to the location of the densest area in the data set [71]. MS procedure is defined as follows [72]:

1) MS starts at initial point $\boldsymbol{y1}$, and define a region of interest around the initial point by a spherical window of radius $\boldsymbol{r}$ which is called the *kernel*.
2) Find the center of mass which is like a centroid by calculating the mean of all data points within the kernel and shifts the kernel to the calculated mean. This shift is defined by a mean shift vector which points toward the direction of the more densely populated region [73].
3) Repeat the previous steps until it converges or when the mean shift vector is zero which means there is no more shift.

The method for calculating the mean relies on a choice of the kernel size which is called bandwidth. The results of MS highly depend on the bandwidth parameter. The inaccurate value of bandwidth will lead to under-clustering and over-clustering, which is considered a disadvantage of MS. The too-large value of bandwidth produces under-clustering and the too-small value of the bandwidth produces over-clustering [74]. MS has produced good segmentation results in sea-land segmentation. Moreover, combining MS with other segmentation methods can enhance segmentation results.

Aktaş et al. [75] presented an edge-aware segmentation method based on mean shift algorithm and steerable filter responses for shoreline detection. Firstly, the mean shift used to segment the image based on spectral features. Then, segments were merged based on edge information which extracted according to steerable filter. The experiments illustrated that the presented method worked well. But, shadows of ships or objects near-shore produced unexpected errors.

3.3.3 Deep Learning-based Methods

Recently, deep learning (DL) methods have achieved wide success in various computer vision problems such as image classification, semantic segmentation, object detection, image representation, etc. DL techniques rely on a set of neural network models that can be utilized to automatically extract features and learning informative representations of raw input data via multiple levels of abstraction without human intervention. [15]. The architecture of DL consists of more than two layers. Therefore, there are different types of layers. Each layer performs a specific task and trains a distinguished set of features based on the output of the prior layer.

Deep learning has various models including Generative Adversarial Networks [76], Convolutional Neural Networks (CNN) [77], Fully Convolutional Networks [78], and a Deep Convolutional Encoder-Decoder Architecture for image segmentation [79]. More details about DL models can be found in [15]. The architecture of CNN consists of several hidden layers including:

- Convolution layer which is considered as features extractor by applying 2D learnable filters (e.g. edge detection, sharpening, blurring, and identity filters) to produce feature maps.
- Pooling layer which is utilized to minimize the spatial resolution(dimensionality) of feature maps by dividing each map into equal-sized regions. Average pooling and max pooling, which are the most commonly used pooling operations.
- Relus, Tanh, Sigmoid Layer (Non-Linearity Layers), Relus (Rectified Linear Units) is an activation function for all convolutional layer and change everything negative to zero.
- A Fully connected layer is essentially the same as one within a traditional neural network, which interprets the feature representations and performs the function of high-level reasoning). The output maps of the last convolution layer or pooling layer are arranged into vectors, acting as the inputs to the first fully connected layer [15].
- Softmax, Cross-Entropy, Euclidean (Loss Layers) are commonly used learning classifiers which can be applied to accomplish classification operation by connection output of fully connected layer with it [72].

Figure 5 shows a simple framework of CNN for image classification. Feature extraction and classification steps are two steps in CNN. In the feature extraction step, the input image is passed to many convolution and pooling layers. In the convolution layer, ***n*** filters with different sizes are applied to the image to produce feature maps. In this example, the filter size is [5×5] with no padding. Red square refers to the convolution of the filter with the image. Then these feature maps are passed to the pooling layer by applying ***n*** filters. In this example, the filter size is [2×2]. After that, feature maps are passed to the convolution layer then the pooling layer, and so on. After the feature extraction step, features are passed to fully connected and Softmax layers for image classification.

For RSIs, deep learning techniques have a role in RS classification. Due to the different characteristics of RS data, (e.g. high dimensionality and available labeled samples are relatively small), classification of RS images faces a practical and a wide range of challenges, especially in sea-land

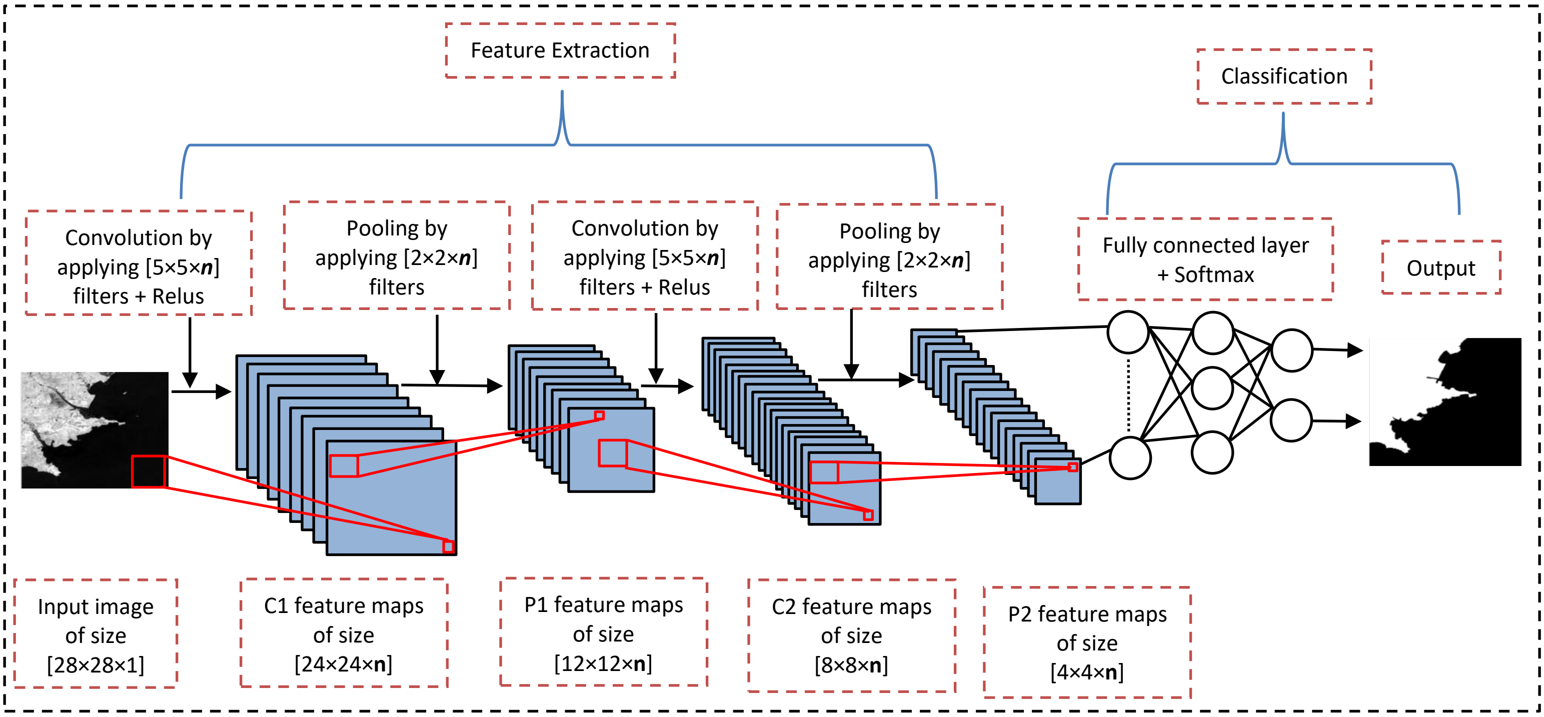

Figure 5. The framework of CNN with many convolutional layers

segmentation problems. Recently, there are DL models that are developed and can overcome the current problems in sea-land images. Besides, there are various studies that have been applied in sea-land segmentation. The results showed the efficiency of the current DL techniques, as illustrated in the following paragraphs.

Cheng et al. [80] proposed a Structured Edge Network (SeNet) for Sea-Land Segmentation based on the Deconvolution network (DeconvNet) framework. SeNet designed a multi-task way, so it could perform sea-land segmentation and edge detection at the same moment to obtain accurate edges. Also, it improved the segmentation results. A local smooth regularization term was proposed to produce segmentation results more spatially consistent. The results showed that the presented method was effective and accurate compared to other traditional methods. But, in high-resolution images with diversity details, the proposed network was not smart enough for good segmentation.

Cheng et al. [81] presented an edge-aware deep convolutional network called FusionNet which combined sea, land, and ship segmentation as well as edge detection in one task. FusionNet consisted of a segmentation network which produced a label for each pixel and the edge network produced the boundaries between different classes. An edge-aware regularization utilized the probability propagation among pixels within the same class to make the proposed model performed better for achieving spatially consistent results with good boundary located. Compared to state-of-the-art methods, the FusionNet model was effective. But this model limited only for ships that have a clear ship feature.

Li et al. [10] developed a new convolutional structure network named DeepUNet for pixel-level sea-land segmentation. The main idea behind DeepUNet was the two novel blocks with two novel connections were utilized to get more accurate segmentation results. These new blocks called DownBlock and UpBlock. Also, a new connection called U-connection and Plus-connection. Comparative experimental results showed that DeepUNet achieved a good performance rather than SegNet and U-Net. However, integration of the multi-task learning technique via DeepUNet could enhance accuracy.

Lin et al. [11] developed a multi-scale convolutional network for semantic labeling of sea, land, and ship segmentation. The proposed multi-scale provided feature information at a fine scale and focused on enlarge respective fields for a large scale at the same time with minimal parameter number increase. The results showed that the proposed structure improved performance compared with traditional semantic labeling. However, the proposed network limited only to large navy ships and oil tankers.

3.4 Region -based Methods

They are used to divide the image into disjoint regions. Each region is homogeneous based on some characteristics like intensity, color, and texture. They include a region growing method and a region split-merging method. Region-based methods have been applied in sea-land segmentation. Also, they have been combined with other segmentation methods to improve segmentation results, as shown in the hybrid model Section 3.6.

3.4.1 Region Growing Method

It is one of the simplest region-based methods, which firstly based on the initial selection of a seed point. Then, neighboring pixels of seed points are merged based on similarity criteria like intensity or color value. Repeats this method until no pixel satisfies the similarity criteria [82]. The initial seed points and time-consuming are considered the two drawbacks of this method. Different initial seed points lead to different segmentation results that can influence the stability of results [83].

3.4.2 Region Split-Merging Method

The concept of the region split-merging method is relying on the quadtree. Each node in the quadtree has four descendants. Also, it represents the subdivision of a node into four descendant nodes. In the image level, the root of the tree corresponds to the entire image. Initially, the whole image is considered a seed region. If it does not satisfy predefined similarity criteria, an image is split into four quadrants until homogeneous sub-region is obtained. After that, all subdivided similar regions are merged to obtain an image object according to similar characteristics until no further merging is possible [82]. One drawback of this method is producing the blocky segments, which can be reduced by splitting at a higher level, but this will increase the computation time [83].

3.5 Watershed transformation

Watershed transformation is an effective mathematical morphological approach for image segmentation. It relies on the gradient image, which is as a topographic surface. The gray value of each pixel at this location represents the altitude of the surface. The basic idea of this method based on a real-life flooding process concept. Imagine a topographic surface is flooded by water from the minima of the surface where catchment basins will fill up with water. If water from adjacent basins is merged, dams or watershed lines will be built to prevent the merging. This process is continued until the water level reaches the highest peak in the topographic surface. Catchment basins correspond to image objects, and watershed lines are boundaries of the adjacent basins. So, Watershed segmentation is used to find the watershed lines.

Due to noise, over-segmentation is a common drawback of the watershed method. Over-segmentation means that a single object is divided into several parts in the segmentation results. Therefore, the Marker Controlled approach is used to overcome the problem of over-segmentation [84],[85]. Watershed methods have been integrated with other segmentation methods. In sea-land segmentation, watershed methods have been utilized as a pre-segmentation step before applying another segmentation method to overcome the limitation of another method and provide accurate results as illustrated in the following hybrid model Section 3.6.

3.6 Hybrid model

The hybrid model is a combination of current image segmentation algorithms to produce more robust methods to deal with the limitations of individual image segmentation methods. Moreover, it improves the accuracy of segmentation results. In sea-land segmentation study, there are many hybrid methods were applied including:

Liu et al. [9] presented a coarse-to-fine sea-land segmentation method. This method combined Improved Multiscale Normalized cut (IMNcut) and Chan-Vese (CV) Model. IMNcut was used to segment the image into sub-regions. These regions were later merged based on the gray intensity and local entropy features to produce the spatially consistent coarse segmentation results. According to the coarse segmentation results, an improved CV model was used to generate a fine segmentation result. This model was effective and robust against complex conditions such as wave noise, shadows, and mist compared to other methods. However, the proposed study had high computational complexity and the convergence rate of the CV model was relatively slow.

Modava and Akbarizadeh [86] proposed a Level Set Active Contour method to extract coastline from high-resolution SAR images. The presented method utilized Spatial fuzzy -means clustering (SFCMC) technique to incorporate spatial constraints for segmenting the image into land and water areas. An active contour level set method was used to extract the coastline. Also, it was applied to refine the segmentation. The advantage of this method is not to require preprocessing for speckle reduction and reduced manual initialization. The results showed that the proposed approach could extract the coastline more precisely compared with the RD-LSA method in low and high-resolution images. Owing to the presented method was iterative, there was a trade-off between the speed and accuracy.

Zhang et al. [41] proposed an automatic and hybrid method for coastline extraction based on geometric active contour models and quadtree segmentation. The image was initially segmented to sea and land regions based on the quadtree method to detect initial contour which was close to the coastline. After that, the geometric active contour model evolved iteratively to get the boundaries of objects in an image. The results showed that the method was stable, reliable, and practical. However, there were limitations in the high complexity of active contour, and some noise was resulted because of the complexity of sea waves.

Li et al. [87] presented a novel method based on a combination of mean shift and modified Otsu's method for sea-land segmentation. After that, ship detection from a high-resolution remote sensing image. Firstly, the mean shift was utilized to segment image into homogenous regions. Secondly, the original image was divided into sea and land regions via modified Otsu's method. The mean-variance was replaced instead of maximum variance to improve adaptability in Otsu's method. Finally, results from both mean shift and modified Otsu's method were combined to get the final sea-land segmentation result. The results illustrated that this method was robust under complex texture, background noise, and sea waves. Also, it achieved accuracy over 90 percent compared to traditional methods.

Sheng et al. [88] presented a new approach for coastline extraction from SAR image by combining the watershed transformation and controllable Gradient Vector Flow (GVF) snake model. Firstly, gradient maps were produced by using the ratio of averages edge detector. Secondly, a watershed transformation was utilized to divide the gradient image into the sea and land regions. Also, it produced the initial contour for the GVF snake model. GVF was used to detect the boundary between the sea and land region as a coastline. The results showed that the proposed approach produced a better match between the detected coastline and the true one. However, automated markers would be selected for watershed transformation to improve the results and accuracy of the watershed transformation.

Liu et al. [89] proposed a novel approach based on an integration of modified K-means and adaptive object-based region-merging mechanism (MKAORM) for coastline extraction from the SAR image. Modified k- means was applied to produce the initial image over-segmentation. Then, an adaptive region-merging approach using sub-regions classification was utilized to provide an automatic selection of sea and land seeds. Finally, the final coastline was extracted. The results showed that the proposed approach reduced the high computation cost and provided a high accuracy. However, coastline extraction with high accuracy from SAR images was still a challenging problem due to speckle noise, complex sea condition, and land type.

Zhang et al. [90] proposed an integrating method based on the object-based region growing and edge detection (OBRGIE) for coastline extraction coastal zones with widely distributed aquaculture coasts. In this method, a new feature object merging index (OMI) was proposed to combine edge information into the processing step of the region growing. OMI was more effective than spectral attributes. The experiments showed that this method was robust to segmentation scale parameter and effective. But there were some limitations. For low resolution, the proposed method could not achieve satisfying results for detecting small changes along coasts.

Xiao and Hu [91] proposed two feature descriptors called Gray Smoothness Ratio (GSR) and Stripe Noise Intensity (SNI) for infrared RSIs which often suffered from low signal to noise ratio and weather conditions like clouds. SNI described the stripe noise. GSR descriptor eliminated the influence of stripe noise and described the intensity and texture features. After feature extraction based on new feature descriptors, the SVM classifier was trained for coarse segmentation. Then, Otsu's method was integrated to obtain fine segmentation. In the end, a coordinate projection method was utilized to fill the isolated holes. The results showed that the proposed method had a low computing complexity and produced better segmentation results compared to other traditional methods.

4. CURRENT CHALLENGES AND PROPOSED FUTURE RESEARCH DIRECTIONS

Recently, many studies have been presented in the field of sea-land segmentation for RSIs. The way is still open for moreover progress and improvement in this field particularly, with the presence of many challenges. These challenges can be divided into different categories due to the affecting factors. RS images and the applied methods/techniques are considered the main challenging categories in the context of sea-land image segmentation. The goal of this section is to discuss each of these limitations in certain details to illustrate the current challenges and future directions that arise in the context of sea-land segmentation problems which are recommended by the authors from literature reviews.

4.1 Remote sensing images challenges

As afore-explained, one of the major sea-land segmentation challenges is RS images. There are various types of RSIs that have been used in the sea-land segmentation process. Each type has been affected by many factors that can affect the quality and accuracy of sea-land segmentation algorithms and their results.

- SAR images have suffered from speckle noise and strong intensity variations. There are other factors that may cause strong scattering in the sea regions and lead to non-homogeneous characteristics of the sea surface coarseness such as wave, wind, clouds, and sea ice. Also, the lack of color information, the land regions are complex, and the poor discrimination of sea-land areas may produce discontinuous boundaries [37].
- Infrared RSIs usually suffer from main issues including low contrast ratios, complex scene information, and bipolar problem. Also, intensity inhomogeneity, weather conditions, high stripe noise, and blurred edges may limit the precision [91].
- Optical and Panchromatic RSIs have faced many issues such as the sunlight, altitude, shadow, and noise often present complicated texture and intensity distribution of

the land region. Illuminations and the different weather conditions may lead to poor contrast and produce a noisy image, respectively.

- ❖ The presence of Very High Resolution (VHR) images may lead to more complicated texture and intensity diversity. Also, the huge size of images, which can affect real-time monitoring.

4.2 Methods / technique challenges

The last factor of challenges is the applied methods/techniques. Due to the previously illustrated in RS image challenges, the applied methods have faced many difficulties to deal with these challenges.

- ❖ Traditional segmentation methods such as thresholding methods have only depended on the intensity value. Also, they cannot capture and utilize spatial context and texture information. Besides, they often misjudge between land and sea.
- ❖ Due to the improvement of the spatial resolution of RSIs, traditional threshold-based methods often fail because the complicated texture and intensity distribution may lead to misclassifications in land and sea regions [81]. Regarding the large SAR images, region merging-based methods would have a heavy computational load [89].
- ❖ Another presented limitation is the dependency on the initializations that can affect the performance of some methods and consequently affect the results. Besides, classification techniques provide better performance which greatly relies on large amounts of training sets. However, RSIs suffer from limited available labeled samples, thereby restricting classification techniques to obtain better performance [15].
- ❖ With the recent presence of VHR images, pixel-based approaches fail to deal with a complicated texture and spectral distributions of VHR images. Therefore, they produce inaccurate results.
- ❖ Finally, the most recent methods depend on handcrafted feature extraction, which affects the accuracy of results as well as the performance.

Because of the previously mentioned challenges, there are promising directions in the sea-land segmentation field to improve the efficiency of current methods and produce more precise results to overcome the current limitations.

Deep learning- feature representation is one of a promising direction in sea-land segmentation field because deep learning (DL) approaches can extract more powerful feature representation. DL leads to accurate results and improves performance. Nowadays, graph theory-based and energy minimization approaches attract attention in sea-land segmentation problems and provide accurate results. In the end, image fusion from different sensors may enhance the spatial resolution and provide more informative characteristics of sea-land segmentation. Also, feature fusion from different algorithms may produce more informative features as well as improve the performance of methods in this field. So, the fusion concept may open a new research direction in sea-land segmentation.

5. CONCLUSION

During the last years, sea-land segmentation had an effective role in many important applications such as coastline extraction, maritime, and coastal environment monitoring. Therefore, there are many efforts have been done to develop different approaches for sea-land segmentation. The presented paper introduces a description of the recent advancements in this field. Sea-land segmentation techniques are broadly classified into six main categories namely thresholding-based methods, region-based methods, energy minimization-based methods, machine learning-based methods, watershed transformation-based methods, and hybrid methods. Besides, this paper reviews these techniques exhaustively. The weakness of the presented studies in this field is also discussed. Finally, this paper shows and discusses the common challenges that have faced sea-land segmentation problem in RSIs. Also, this paper proposes a promising future research directions in the sea-land segmentation field to overcome the current challenges and produce more accurate results.

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