Machine Learning for Object Recognition — Systematic Literature Review

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Abstract

In recent years, remote sensing technology has developed rapidly, and the spatial resolution of remote sensing images is getting higher and higher. Remote sensing images are used in various fields, such as land resource management, autonomous driving technology, medicine, etc. Many image analysis techniques based on remote sensing images have been proposed. We attempts to discuss the important branches of image analysis, object recognition and image segmentation techniques. Due to the rise of machine learning technology in recent years, great breakthroughs have been made in the accuracy of object recognition and image segmentation. This research aims to summarize and analyze the development trend of this field through a systematic literature study, focusing on object recognition and image segmentation.

1 Introduction

1.1 Motivation

With the development of remote sensing technology, the spatial resolution of images taken by sensors is getting higher and higher, and remote sensing data is therefore used in various fields. The application of remote sensing images relies on image analysis technology. Due to the rise of artificial intelligence technology, image analysis has been automated by machines. In addition, machine learning algorithms play an increasingly important role in the field of object recognition and image segmentation.

Object/region recognition technology and image segmentation technology realized by machine learning and remote sensing images are widely used in methods of acquiring semantic information in images. There are already some popular platforms, such as Landsat, Worldview and Quickbird, which provide remote sensing images with different spatial resolutions that can be used for object recognition tasks with different granularities. However, it is difficult to achieve very high accuracy for object/region recognition tasks, so many studies are currently trying to find a method to improve the segmentation accuracy. This study aims to summarize the relevant researches, discuss the advantages and disadvantages of various ways, and try to find a feasible and effective image segmentation method.

1.2 Machine Learning

Machine learning, as an important branch of artificial intelligence technology, has experienced the development process from focusing on ”inference” to focusing on ”learning”. Machine learning has been widely used in various fields, such as computer vision, expert systems, intelligent robots, natural language understanding, automatic reasoning, etc. In essence, the purpose of machine learning is to generate and continuously improve the ability to distinguish the same type of data through the calculation and learning of the data provided in advance. The currently proposed machine learning algorithms have their own suitable application fields and situations. For example, when the data dimension is high, the random forest algorithm is usually selected, while when the amount of data is large, the performance of the neural network is often better.
The popular algorithm in recent years, deep learning, is a branch of machine learning. Deep learning, as the name suggests, is to achieve high-precision extraction of complex features of data by building a deeper network structure (building more layers). The deep learning model is built on a neural network, but it has more layers and deeper depth. Specifically, it has more hidden layers. Deep learning is widely used in image and speech recognition technology, and has achieved considerable results. In addition, benefiting from the increase in data volume and the substantial improvement in machine computing capabilities, deep learning was able to play a role in various tasks that were once considered impossible.

1.3 Machine Learning for Image Analysis

The acquisition of image information currently mainly depends on the interpretation of remote sensing images, which is essentially the extraction of semantic information from images. In the process of acquiring image information, because the information extracted at the pixel level and the visual level does not completely match, there is often a problem of semantic gap [11]. In order to better address the semantic gap problem, image analysis methods based on objects/regions are proposed, and object recognition and image segmentation are its branch technologies.

According to recent research, it can be found that deep learning has achieved satisfactory results in the field of object recognition and image segmentation. There are already some built deep learning models, such as vgg, resnet, unet, etc., which reduces the cost of image segmentation and improves the speed of building deep learning networks. These models are all derived models based on Convolutional Neural Networks (CNN). Their essence is to learn some simple image features in a shallow convolutional layer, while deep convolutional layers are able to extract some abstract features of graphs. Many current studies have used CNN to achieve automatic segmentation of remote sensing images, and reached an accuracy rate of more than 90% at the pixel level. In order to achieve high precision at the regional level, that is, higher precision detection of boundaries, some studies have proposed a method of combining CNN with other algorithms or using remote sensing data from multiple sources at the same time. According to these attempts, we have seen the potential of machine learning in the field of object recognition and image segmentation.

2 Study Design

2.1 Research Goal

The goal of this study is to have an overview of current object recognition and image segmentation algorithms through literature research and learning in recent years. On this basis, the research will analyze and classify the literature, and try to summarize the current development trend of object recognition and image segmentation technology.

2.2 Research Questions

In order to achieve the research goals, this research proposes and attempts to solve the following research problems:
RQ: What is the development trend of object recognition and image segmentation technology in recent years?

Sub-questions

Several sub-questions, as shown in the following part, are proposed in this section to address the main research question.

Sub-RQ1: Is the classification method used in the study at the pixel level or the object/region level?
Sub-RQ2: What technologies are used in object/region recognition and image segmentation?
Sub-RQ3: Which remote sensing data is collected and used for object/region recognition and image segmentation?
Sub-RQ4: What objects can be used as recognition targets?

2.3 Search Process

There are various sources of literature available for the search process. The literature database selected in this study is Google Scholar, VU LibSearch, Semantic Scholar, China HowNet and the literature mentioned by the expert. The detailed search process is shown in Table 5.

Data source	**Database name**	**Date of search**	**Search content**
Electronic database	Google Scholar	20-3-2020	Title, abstract, keywords
Electronic database	VU LibSearch	20-3-2020	Abstract
Electronic database	Semantic Scholar	20-3-2020	Title, abstract, keywords
Electronic database	China HowNet	20-3-2020	Title, abstract, keywords
Expert‘s references	Dr. Anna Bon	Continuous	-

Table 1: Data sources

The criteria for choosing databases for research are as follows: first, to ensure the reliability of the data source, and second, to obtain the most comprehensive data possible (so the literature selects four databases). In addition, the literatures mentioned by the expert is more professional and informative, so it is used as an important data source for the research.

2.4 Search Query

The purpose of the search query is mainly to filter the documents in the database, to select and research relevant documents in a targeted manner. According to the strength of the association with our study, the following concepts and keywords that should be used in the search query are determined, find in Table 2. The principles for generating the above concepts and keywords are as follows:

i Concepts included in the research question

ii Synonyms of the concepts generated in the previous step

iii Extract keywords from a few literature related to research

iv Group the keywords extracted in the previous step according to the relevance of their source documents

v Take the intersection between keywords of each literature that belong to the same group

Category	Concept	Keywords
ICT	Artificial Intelligence	Artificial Intelligence Machine Learning Deep Learning CNN
Technical	Image Analysis	Image Analysis Object Identification Image Segmentation Region Recognition
Subject	Satellite Image	Satellite Image Remote sensing Remotely sensed

Table 2: Concepts and keywords

The keywords listed in the table are applied to the search query in the form of permutations and combinations. It should be noted that at least one keyword included in each ”Category” must be selected to form a set of query keywords. In other words, the query must contain at least three keywords, such as ”Artificial Intelligence”, ”Satellite Image” and ”Region Recognition” is a valid query keywords collection.

2.5 Paper selection process

The articles are selected to enter the next process after a selection process. The operation steps of the selection process are as follows:

1 Initialization: Enter query keywords in the four selected databases to search and get the initial dataset.

2 Deduplication: Delete duplicate documents based on the article title.

3 Filtering: Filter the articles retained in the previous step according to the inclusion and exclusion criteria.

4 Assessment: Select articles of higher quality according to quality assessment rules.

5 A total of 29 articles in the final collection are considered high-quality and can be used for our research.

The flow chart of the selection process is shown in Figure 1.

2.6 Inclusion and exclusion criteria

Inclusion criteria

- Articles published in the year 2000 or later (due to the rapid development of the field of computer science, articles in recent years have more research significance)

- Literature is a paper or book

- Literature should be applicable to general scenarios

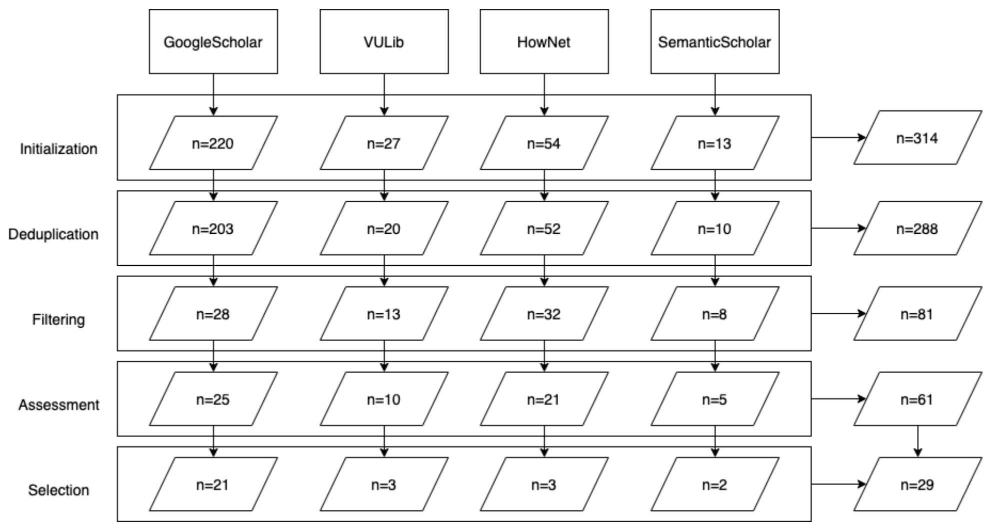

Figure 1: Selection Process

Exclusion criteria

- The language of the article is not English or Chinese
- Inaccessible literature
- The application mentioned in the article is limited by the scenario

2.7 Quality assessment

Articles screened by inclusion and exclusion criteria need to go through a quality assessment process to evaluate the quality of the article, and select the high quality to enter the next process. The quality assessment rules are carried out as follows:

1 Does the dataset used in the article mainly consist of remote sensing data?

2 Is machine learning algorithm the main technology used in the article?

3 Are object recognition and image segmentation the research focus of the article?

According to the quality assessment rules, the articles which are marked as high quality (satisfied all the rules) are selected and sent to next procedure.

2.8 Data extraction

In this step, we extract data from the article collection to study these documents systematically. The extracted data is divided into two categories, one is metadata and the other is information-rich data.

Metadata:

- Article Source
- Year of publication
- Author(s) name
- Research problem

Information-rich data:

- Research technology
- Research dataset
- Study focus more on pixel-level or object/region-level classification (classification method)
- Research focus (a certain type of object or multiple types)

2.9 Data analysis

In this step, the extracted information will be classified according to information-rich data, such as region-based or pixel-based classification, focus on tree or crop or all categories, use CNN or watershed or combination, Landsat or Worldview or Quickbird data. Author has re-read and analyzed the article according to the results of the classification.

3 Results

After reading and analyzing the data according to the data analysis process, we classified it in four ways according to our understanding of the literature collection, and listed the following

Table 3, Table 4, Table 5 and Table 6 . The four tables constructed answer the four sub-research questions raised in the previous chapters in detail.

Among the selected 29 documents, 16 documents study pixel-level classification methods, and 18 documents study region/object-level classification methods (some of which study both pixel-level and object-level methods). Then, 20 out of 29 articles involved machine learning algorithms, while the remaining 9 articles studied some other algorithms or used software, respectively. In addition, in 29 studies, eight popular data sources were mentioned and used, and the other data used mostly came from some constructed data sets. Moreover, it can be found that more objects in the field of object recognition are agriculture, vegetation and urban objects.

It should be noted that some of these studies are conducted on the subject itself, while some are discussions and summaries of related studies. There are only a few articles focus on only one type of object, most of the study aims to recognize multiple types of objects. Further, most of the articles mentioned and applied a variety of data sets and techniques at the same time

Classification method	**Study**
Pixel-based	Hofmann et al., 2012 [14]; Löw and Duveiller, 2014 [19]; Forkuor et al., 2015 [10]; Inglada et al., 2016 [16]; Forkuor et al., 2014 [9]; Adam et al., 2010 [1]; Herrmann et al., 2005 [13]; Brandt et al., 2018 [3]; Navalgund et al., 2007 [25]; Du et al., 2014 [24]; Melesse et al., 2007 [21]; Adjognnon et al., 2019 [2]; Chen et al., 2016 [18]; Chen et al., 2019 [4]; Iglovikov and Shvets, 2018 [15]; Dong and Zhang, 2019 [6]
Object/region-based	Cheng and Han, 2016 [5]; Vladimir et al., 2015 [17]; Forestier et al., 2012 [11]; Elmqvist, 2020 [8]; Adam et al., 2010 [1]; Maillot et al., 2004 [20]; Durand et al., 2007 [23]; Gould et al., 2009 [12]; Navalgund et al., 2007 [25]; Du et al., 2014 [24]; Melesse et al., 2007 [21]; Derivaux et al., 2010 [26]; Vetrivel et al., 2016 [27]; Monteiro and Campilho, 2008 [22]; Zhang et al., 2017 [29]; Dong and Zhang, 2019 [6]; Wang et al., 2018 [28]; Duarte et al., 2018 [7]

Table 3: Classification method

3.1 Classification method

In all the studies, it can be observed that the number of documents for object recognition and segmentation at the pixel level and the object/region level is basically the same. This phenomenon reflects that the popularity of the two classification methods is similar, and both can achieve ideal segmentation results.

3.2 Type of technology

Among the 20 studies involving machine learning algorithms, more than half of the articles discussed and studied deep learning algorithms, namely CNN algorithms. The model built based on CNN can achieve relatively good semantic segmentation accuracy (Chen et al., 2019; Durand et al., 2007;). It can be explored that the VGG model (Vladimir et al., 2015) is a good basic model. The DCNNs model based on VGG16 has outstanding performance in multi-category object classification tasks (Chen et al., 2016). The Unet model built with VGG11 as the basic model can also achieve better pixel-level classification accuracy (Iglovikov and Shvets, 2018). In addition, some studies have used the traditional watershed algorithm to achieve some image segmentation tasks (Derivaux et al., 2010; Monteiro and Campilho, 2008), while (Zhang et al., 2017) proposed a combination of CNN and watershed algorithm to achieve high-precision object-level segmentation. The improved Faster R-CNN algorithm based on CNN also achieved an average recognition accuracy of about 0.9 (Wang et al., 2018). Moreover, it can be observed that the random forest algorithm has a good effect on the identification of crops. In general, machine learning is a relatively important method of object recognition and segmentation.

3.3 Dataset

The most frequently mentioned data sources in the research are WorldView, Landsat, MODIS, RapidEye, GeoEye, Sentinel, QuickBird and TerraSAR-X. The sensor with low spatial resolution is MODIS. The sensor with medium spatial resolution is Landsat. Sensors with high spatial resolution include Sentinel, GeoEye, QuickBird, RapidEye, WorldView. TerraSAR-X is the source of radar remote sensing data. It can be known from analyzing the dataset that images with different spatial resolutions are suitable for segmentation tasks with different granularities.

Type of technology	Study
CNN	Cheng and Han, 2016; Vladimir et al., 2015; Zhang et al., 2017; Durand et al., 2007; Chen et al., 2016; Chen et al., 2019; Iglovikov and Shvets, 2018; Vladimir et al., 2015; Zhang et al., 2017; Dong and Zhang, 2019; Wang et al., 2018
K-means	Cheng and Han, 2016; Löw and Duveiller, 2014;
Random Forest	Cheng and Han, 2016; Löw and Duveiller, 2014; Forkuor et al., 2015; Inglada et al., 2016; Forkuor et al., 2014; Adjognnon et al., 2019;
AdaBoost	Du et al., 2014; Cheng and Han, 2016;
Knowledge Representation	Forestier et al., 2012; Maillot et al., 2004; Durand et al., 2007;
Software	Elmqvist, 2020; Herrmann et al., 2005; Navalgund et al., 2007; Melesse et al., 2007;
Regression Tree	Adam et al., 2010; Brandt et al., 2018; Melesse et al., 2007;
Inference Algorithm	Gould et al., 2009;
MLP	Du et al., 2014;
Decision Tree	Adam et al., 2010; Brandt et al., 2018; Du et al., 2014; Melesse et al., 2007;
Watershed	Cheng and Han, 2016; Zhang et al., 2017; Derivaux et al., 2010; Monteiro and Campilho, 2008; Zhang et al., 2017;
Other Algorithm	Cheng and Han, 2016; Hofmann et al., 2012; Forestier et al., 2012; Adam et al., 2010; Maillot et al., 2004; Durand et al., 2007; Navalgund et al., 2007; Derivaux et al., 2010;

Table 4: Type of technology

For example, the segmentation of crops often combines images taken by medium-resolution (Landsat) and high-resolution (RapidEye, Sentinel) sensors (Forkuor et al., 2015; Inglada et al., 2016). In the segmentation task of urban objects, high spatial resolution image sources such as QuickBird (Forestier et al., 2012; Durand et al., 2007) are generally selected. When identifying some objects that may be affected by the atmosphere and air humidity, radar remote sensing data is sometimes combined with other dataset to analyze images (Forkuor et al., 2015; Forkuor et al., 2014). There are also some studies using constructed datasets, which is also a reliable source to get experimental data (Hofmann et al., 2012; Vladimir et al., 2015; Adam et al., 2010; Maillot et al., 2004; Herrmann et al., 2005; Gould et al., 2009; Chen et al., 2016; Chen et al., 2019; Iglovikov and Shvets, 2018; Monteiro and Campilho, 2008; Zhang et al., 2017; Wang et al. , 2018). [5]

3.4 Target object category

According to data analysis, it can be concluded that most researches on crop identification have occurred in the past five years. This phenomenon is closely related to the rapid development of remote sensing technology and the improvement of the spatial resolution of remote sensing images (Forkuor et al., 2015; Inglada et al., 2016). The identification of vegetation and urban objects has always been popular (Herrmann et al., 2005; Brandt et al., 2018; Melesse et al., 2007; Chen et al., 2019). It can be seen that the society pays more attention to the environment and urban planning and management. Image analysis for disasters and damage accounts for a small part of the total data set (Melesse et al., 2007; Duarte et al., 2018; Vetrivel et al., 2016). In addition, the recognition of vehicles has also achieved good results in recent years (Chen et al., 2016; Wang et al., 2018). In some other studies, the identification of indoor objects and animals is also involved (Chen et al., 2016). In short, it can be seen that most of the research is aimed at land coverage and use, which also reflects the importance of this task.

4 Discussion

Based on the results obtained above, this section will discuss and analyze the collection of articles.

Dataset	Study
WorldView	Brandt et al., 2018; Navalgund et al., 2007; Duarte et al., 2018; Dong and Zhang, 2019;
Landsat	Cheng and Han, 2016; Vladimir et al., 2015; Forkuor et al., 2015; Inglada et al., 2016; Adam et al., 2010; Navalgund et al., 2007; Melesse et al., 2007;
MODIS	Cheng and Han, 2016; Navalgund et al., 2007; Melesse et al., 2007;
RapidEye	Löw and Duveiller, 2014; Forkuor et al., 2015; Forkuor et al., 2014; Adam et al., 2010; Brandt et al., 2018; Melesse et al., 2007;
GeoEye	Elmqvist, 2020; Brandt et al., 2018; Melesse et al., 2007; Duarte et al., 2018; Vetrivel et al., 2016; Dong and Zhang, 2019;
Sentinel	Inglada et al., 2016; Adjognnon et al., 2019;
QuickBird	Cheng and Han, 2016; Forestier et al., 2012; Durand et al., 2007; Du et al., 2014; Derivaux et al., 2010; Dong and Zhang, 2019;
TerraSAR-X	Forkuor et al., 2015; Forkuor et al., 2014; Brandt et al., 2018; Melesse et al., 2007;
Other Structured Dataset	Hofmann et al., 2012; Vladimir et al., 2015; Adam et al., 2010; Maillot et al., 2004; Herrmann et al., 2005; Gould et al., 2009; Chen et al., 2016; Chen et al., 2019; Iglovikov and Shvets, 2018; Monteiro and Campilho, 2008; Zhang et al., 2017; Wang et al., 2018;

Table 5: Dataset

Target object category	**Study**
Agriculture	Cheng and Han, 2016; Vladimir et al., 2015; Löw and Duveiller, 2014; Forkuor et al., 2015; Inglada et al., 2016; Forkuor et al., 2014; Navalgund et al., 2007; Dong and Zhang, 2019;
Vegetation	Cheng and Han, 2016; Vladimir et al., 2015; Elmqvist, 2020; Adam et al., 2010; Herrmann et al., 2005; Brandt et al., 2018; Navalgund et al., 2007; Melesse et al., 2007; Adjognnon et al., 2019; Zhang et al., 2017; Dong and Zhang, 2019;
Urban Object	Cheng and Han, 2016; Vladimir et al., 2015; Forestier et al., 2012; Durand et al., 2007; Navalgund et al., 2007; Du et al., 2014; Melesse et al., 2007; Chen et al., 2019; Derivaux et al., 2010; Iglovikov and Shvets, 2018; Monteiro and Campilho, 2008; Zhang et al., 2017; Dong and Zhang, 2019;
Disaster/damage	Melesse et al., 2007; Duarte et al., 2018; Vetrivel et al., 2016;
Vehicle	Cheng and Han, 2016;Maillot et al., 2004; Vladimir et al., 2015; Gould et al., 2009; Chen et al., 2016; Wang et al., 2018;
Road	Cheng and Han, 2016; Vladimir et al., 2015; Elmqvist, 2020; Chen et al., 2019; Zhang et al., 2017; Dong and Zhang, 2019; Wang et al., 2018;
Soil	Elmqvist, 2020; Chen et al., 2019;
Water Body	Cheng and Han, 2016; Vladimir et al., 2015; Navalgund et al., 2007; Melesse et al., 2007; Zhang et al., 2017;
Other object	Cheng and Han, 2016; Hofmann et al., 2012; Chen et al., 2016;

Table 6: Target object category

First of all, according to the classification methods used by the collected literature, both pixel-level classification and object/region-level classification have achieved outstanding results in specific tasks. The popularity and accuracy of the two levels of classification methods are similar.

Secondly, from the perspective of the technology used in research, machine learning algorithms play an important role in image segmentation tasks. While, research using deep learning algorithms accounts for more than half of the research using machine learning algorithms. It can be concluded that deep learning algorithms are reliable in the field of image analysis. Moreover, in recent years, more and more studies have begun to use deep learning algorithms in combination with other algorithms, and have achieved impressive performance.

Furthermore, from the perspective of the dataset, whether the data comes from a remote sensing data platform (such as MODIS, Landsat) or an organized dataset (such as PASCAL), as long as the data source is reliable, the research can proceed smoothly. The choice of data source mainly depends on the spatial resolution required for the recognition task.

Finally, we discuss the target object category. In most object recognition tasks on land use and land cover, the most recognized object categories are crops, vegetation and urban objects. It can be considered that the trend of object recognition applications is for plant/crop management and urban planning.

5 Conclusion

This study systematically analyzes and studies the literature related to the topic. First, through the search process, the search database and search keywords are determined. Then, through a series of selection processes, the articles were screened and assessed (based on inclusion and exclusion criteria and quality assessment rules). Further, the structured data was obtained through two steps of data extraction and data analysis. Finally, according to the classification results of the data, the article collection is read and analyzed, the experimental results are obtained, as well as the results are discussed.

In summary, in the field of image segmentation and recognition, machine learning algorithms have played an increasingly important role. With the continuous development of remote sensing technology, the spatial resolution of images is getting higher and higher, which makes many fine-grained recognition and segmentation tasks possible.

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