

Satellite Image Segmentation and Classification for Environmental Analysis

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Abstract— Image segmentation is a challenging task in computer vision. This process includes the classification of visual input into segments to simplify image analysis. There are many types of methods for image segmentation some of the common methods are edge detection-based method region-based methods, clustering-based method, partial differential equation-based, watershed-based method, and neural network-based methods. This research work is focused on image segmentation. Satellite images are given as the input of the proposed system. Machine learning techniques play a key role in various domains. Here the remotely sensed data can be segmented by using the K-Means clustering method. Compared with other traditional methods this clustering technique yields better results. This system can be implemented by using the MATLAB software tool. Machine learning concepts drastically decrease the time needed to arrange an exact map.

Index Terms— MATLAB, K-means clustering, Segmentation methods.

I. INTRODUCTION

In remote sensing images, a lot of predictions can be made without any intervention from the human being. Remotely sensed images are digital representations of the Earth. By using this, places that cannot be accessed are reviewed by remote sensing images, which will encourage the process of those interior parts. Each pixel in remotely sensed image data represents a specific area of the Earth. A pixel is considered to meet a particular set of requirements if it is assigned to the class that meets those requirements. Image classification is the term used to describe this process. Currently, image classification techniques fall into two main categories based on the image primitive: object-based and pixel-based techniques.

Methods based on pixels classify individual pixels without considering the pixel's neighborhood or spatial information. High-resolution images can be overseen by object/region-based methods as well, which makes the classification process more difficult for most pixel-based methods. Classes will be distinguished from the existing features based on the type of information extracted from the original data. A land cover map showing vegetation, bare land, pasture, urban areas, and so on is an example of a classified image. A pixel in remote sensing imagery might represent a mix of class covers, variability within classes, or other intricate surface cover patterns that cannot be accurately described by one class. To learn more about the used lands and agricultural levels in each area, it is crucial to determine the level of vegetation indices. A remote sensing image must be processed to accomplish this; This work uses the LANDSAT image to identify the utilized land. During processing, the noise-freeness of the LANDSAT image is checked first. The necessary highlights are extracted from this image. This feature extraction considers various features, such as vegetation indices, unused land, and forests. After the features of the image have been extracted, classification algorithms are used to obtain the various classification groups, and the classified image is obtained using KNN, SVM, and fuzzy algorithms.

These outcomes were contrasted and the MOKNN and MOSVM. When compared to the algorithms that are currently in use, modified algorithms produce superior outcomes. Different metrics, such as user accuracy, producer's accuracy, omission error, and commission error, are used to predict the algorithms' overall accuracy.

The earth's images have been archived by satellite remote sensing programs, making them an increasingly useful data source for studying land cover and changes in land use. The Landsat program, which has been in operation since 1972, is the most prominent example. Time-series data for most of the world can now be accessed by the public thanks to the free availability of the entire Landsat archive. However, interpreting these images remains difficult. The results of a temporal signature extension have been better than those of a spatial signature extension, especially when year-to-year variation is reduced by radiometric normalization (or rectification). However, the general validity of the conventional signature extension method has not been extensively researched, and alternative methods, like combining data from multiple images, have not been taken into consideration.

II. METHODOLOGY

SAR Image Land Cover Datasets for Classification Benchmarking of Temporal Changes Corneliu Octavian Dumitru ET.AL IEEE 2021.

The increased availability of high-resolution synthetic aperture radar (SAR) satellite images has led to new civil applications of these data. In particular, the detection and quantification of temporal changes, as well as the systematic classification of land cover types based on the patterns of habitation or agriculture observed by SAR imagers, are some of them. An orderly (re)classification will permit the task of persistently refreshing semantic substance marks to nearby picture patches. Because of this, the image data that need to be trained and validated must be carefully chosen to contain categories that are clearly defined and can be seen. These steps are well-known for optical images, but SAR sensors' unique imaging characteristics frequently prevent a similar approach.

The variety of local targets and the extensive range of SAR imaging parameters have an impact on the characteristics of the image product and require special attention. How to get accurate results for image patch classification from time series data using only a small amount of information is explained in the following sections, along with some concrete examples. Several given training data. " We show that by breaking down the classification problem into physically significant subsets of defining target attributes and critical imaging parameters, one may avoid creating fake training data." Benchmarking of SAR Image Land Cover Datasets for Classifier ")

Deep Self-Paced Residual Network for Multispectral Images Classification Based on Feature-Level Fusion Jiaqi Zhang ET.AL IEEE 2021.

The fusion of multisource multispectral (MS) images has long been the subject of research into classification methods. Nevertheless, it may be challenging to classify these data at the feature level while avoiding data inconsistency brought on by multiple sources and cities or regions. To classify multisource MS data based on feature-level fusion, we propose a deep learning structure called 2-branch SPL- ResNet that combines self-paced learning with the deep residual network. Multiscale features and a sparse representation of MS data are first obtained by employing a discrete wavelet in two dimensions. Then, a 2-branch SPL-ResNet is laid out to remove the individual qualities of the two satellites. Finally, we classify the integrated feature vector after putting the feature-level fusion into action by cascading the two vectors of features.

Supervised and Adaptive Feature Weighting for Object-Based Classification on Satellite Images Ya'nan Zhou ET.AL IEEE 2021.

The object-based image analysis (OBIA) technique has been representing an evolving paradigm of remote sensing applications, along with more high-resolution satellite images available. However, too many derived features from segmented objects also present a new challenge to OBIA applications. A supervised and adaptive approach to ranking and weighting features for object-based classification is presented in this paper. The feature weight maps for each land type produced by previous thematic maps and the satellite images of the study areas that correspond to them form the basis of this approach. First, the spectral, shape, and texture features of the objects in the segmented satellite images are calculated using an adaptive multiscale algorithm for classification. Second, to generate feature weight maps, we derive distance maps and feature weight vectors for each land type from the preceding thematic maps and satellite images.

Learning Multiscale Deep Features for High-Resolution Satellite Image Scene Classification Qingshan Liu ET.ALIEEE 2021.

In this paper, For the classification of scenes in high-resolution satellite images, we propose a multiscale deep feature learning approach. We first wrap the original satellite image across a variety of scales. The pictures in each scale are utilized to prepare a profound convolutional brain organization (DCNN). However, it takes a long time to train multiple DCNNs simultaneously. To resolve this issue, we investigate DCNN with spatial pyramid pooling (SPP-net). Since various SPP nets have a similar number of boundaries, which share indistinguishable beginning qualities, just tweaking the boundaries in completely associated layers guarantees the viability of each organization, accordingly, enormously speeding up the preparation cycle. The multiscale deep features are then extracted by feeding the multiscale satellite images into their respective SPP nets. Finally, a method for learning the best combination of these features automatically is developed using multiple kernels. Comparing the performance of the proposed method to that of another current method on two difficult data sets, experiments demonstrate that the latter performs better.

Convolutional Neural Network-Based Land Cover Classification Using 2-D Spectral Reflectance Curve Graphs With Multitemporal Satellite Imagery Miae Kim ET.AL IEEE 2021.

To make it easier to use improved picture goals in precisely identifying and observing area cover, analysts are always looking for more efficient discovery methods. Recently, convolutional neural networks (CNNs) have demonstrated high-performance levels that are as good as, if not better than, those of popular machine learning techniques. The purpose of this study is to investigate how CNNs can be used to classify land cover using two-dimensional (2-D) spectral curve graphs from multispectral satellite images. To classify the land cover in Concord, New Hampshire, the United States, and South Korea, multispectral images from 30-m Landsat-8 and 500-m Geostationary Ocean Color Imager were utilized. To create CNN-specific input data, two seasons of multispectral bands—winter and summer—were transformed into 2-D spectral curve graphs for each class. Support vector machines (SVMs) and random forests (RFs) were compared to CNNs' land cover classification results. In both study sites, the CNNs model performed better than RFs and SVMs.

III.K-Nearest Neighbor (KNN):

In remote-sensing images, the key features can be extracted only when the details of the image are properly classified. Classification of an image is especially important to extract the minute details for further processing. Many researchers were concentrated on identifying the best classification algorithm in recent years, active learning algorithms were used to find the best classifier in hyperspectral images and this work identifies that KNN algorithms were tested in the hyperspectral images. The k-nearest neighborhood algorithm the used vastly in the classification of images. An improved KNN for high-resolution remote sensing is used and it permits a combination of the locality using the maximum margin classification. KNN is used with an artificial immune B-cell network is used and it proves that reduction of data for processing. Later KNN is used with the maximal

margin principle and is proved with satisfactory results. KNN is applied in hyperspectral images, and it is used with the genetic algorithm and accurately produces good decision boundaries. The above rational work concludes that KNN gives satisfactory results in classification with the help of maximum marginal classification.

IV. Support Vector Machine (SVM):

Support Vector Machine is a novel method for supervised pattern classification that has been effectively used to solve a variety of pattern recognition issues. It also serves as the basis for some extremely effective and straightforward algorithms. Proposed System Advantages:

- All areas which we needed have been detected.

A method of learning from data is the classification and regression rules. Because of its strong mathematical foundation and ability to operate reliably and effectively in high-dimensional feature spaces, SVM is the most suitable.

- Time consumption is less.
- Less complexity.
- User-friendly model.

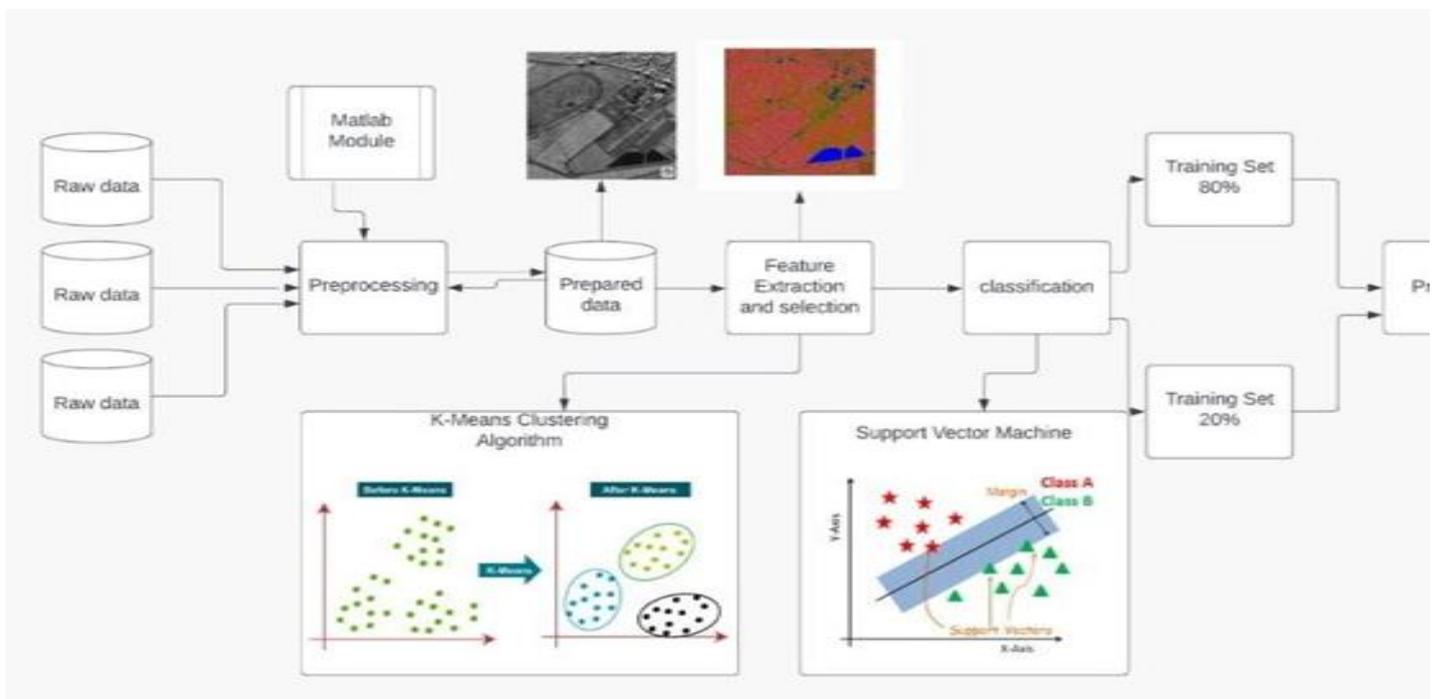


Fig1. System Architecture

V. MODULE DESCRIPTION

There are five components in the system. They are.

- (i) Acquisition of Images
- (ii) Image Preprocessing
- (iii) Image Segmentation
- (iv) Feature Extraction
- (v) Classification.

Google Maps' real-time satellite images are captured in Image Acquisition. A specific size is cropped from the captured images. Image Preprocessing converts the cropped RGB images to grayscale. Picture Division is the third part. It comprises sectioning the changed-over grayscale pictures utilizing K means separating. Backgrounds, light illumination, and other issues can all be eliminated with this. The process of extracting or displaying a portion of the segmented images makes classification simpler. The classification that makes use of Tensor Flow and Support Vector Machine is covered in the final module.

Image Acquisition

The process of gathering images is called acquisition. These images are obtained from Kaggle.com, an online dataset provider. A specific size is cropped from the captured images. Image Preprocessing converts the cropped RGB images to grayscale.

Image Pre-processing

As part of image pre-processing, RGB images undergo grayscale conversion. The original colors of an RGB image are shown. Grayscale images use only black and white. The conversion of RGB to grayscale improves the available dataset. The images are converted to grayscale, which improves the result's accuracy. Images in grayscale neutralize the background and reduce noise. Additionally, it enhances the brightness of the image. Data increment is a way to deal with making new data which has benefits like the ability to make extra data from limited data and it thwarts overfitting.

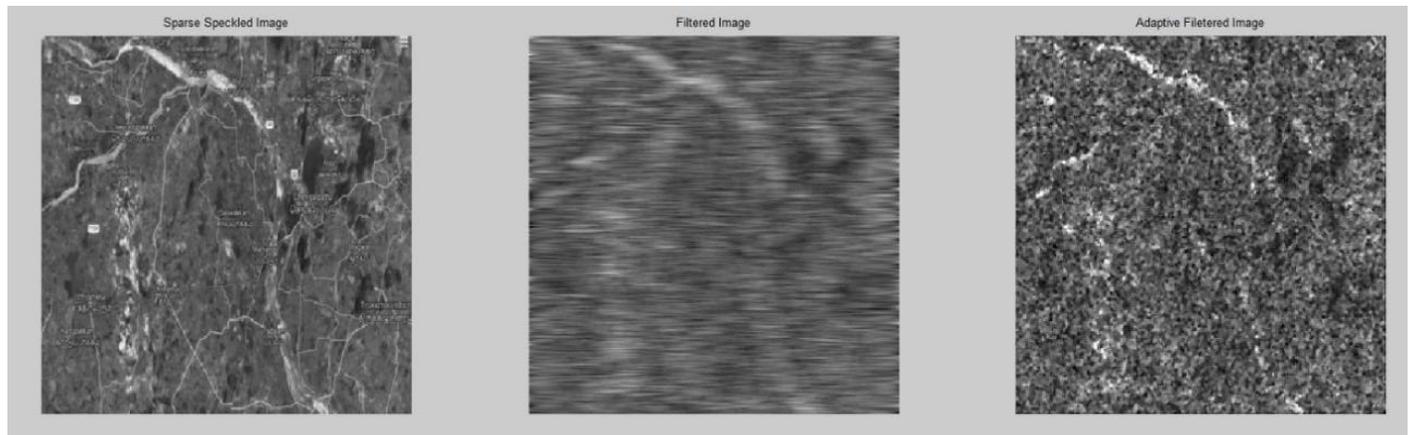


Fig2.Pre-processing

Image Segmentation

Image Segmentation Image segmentation divides an image into distinct areas. The digital image is broken up into multiple parts by this. The objective is to alter or simplify the representation. into and into a picture with more meaning. It distinguishes between the objects we want to examine further and the background or other objects. It comprises portioning the changed-over grayscale pictures utilizing K means division. among the images. All machine vision algorithms use feature extraction. Techniques for feature extraction and representation both aim to better describe the main features and attributes of segmented objects by transforming them into representations. different audits on satellite picture arrangement strategies and procedures. Based on the requirements, the summary assists researchers in selecting appropriate satellite image classification methods or techniques.

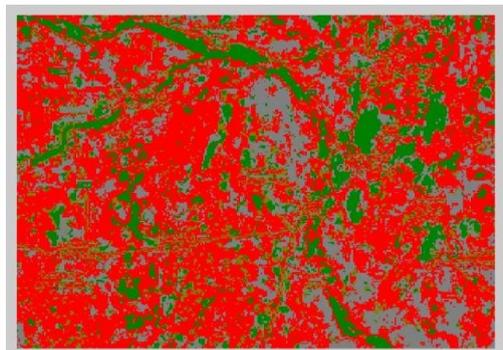


Fig3.Segmentation

Feature Extraction

The process of extracting or displaying the segmented portion of an image makes it simpler to classify it. To be effective, features are extracted.

The algorithm for machine learning will be used. TensorFlow is an open-source library for numerical computation that is compatible with MATLAB and makes machine learning faster and simpler. Dataflow graphs, or structures that describe how data moves through a graph or a series of processing nodes, can be created by developers using TensorFlow. Every mathematical process that makes up a node in a graph also makes up every edge connecting nodes, which is a multidimensional data array or tensor.

Classification

In this case, we employ the classification method concept. The classification that will make use of Tensor Flow and the Machine Learning algorithm is covered in the final module. Tensor Flow is a numerical computation open-source library for MATLAB that speeds up and simplifies machine learning. Dataflow graphs, or structures that describe how data moves through a graph or a series of processing nodes, can be created by developers using TensorFlow. Each edge or association between hubs in the diagram is a multi-layered information exhibit or tensor, and every hub in the chart addresses a numerical activity.

VI. CONCLUSION:

This project compares several reviews conducted by various researchers and provides a summary of automated satellite image classification methods. There are two types of automated satellite image classification methods: 1) supervised and 2) unsupervised. How pixels are categorized into meaningful groups varies between supervised and unsupervised satellite image classification techniques. The effectiveness of satellite image classification techniques in comparison to various datasets has been examined by researchers in literature. The various reviews on satellite image classification methods and techniques are summarized in this project. Based on the requirements, the summary assists researchers in selecting the appropriate satellite image classification method or technique.

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300

Percentage of Gray(Label1, Crops): 21.903333
Percentage of Blue(Label2, Water): 0.014444
Percentage of Red(Label3, Crop_other): 54.045556
Percentage of Green(Label4, Trees): 14.008889
Percentage of Yellow(Label5, Plants): 10.027778
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Fig4.Final Output

VII. FUTURE SCOPE:

The proposed method's outcomes will be useful in the future for flood impact prediction and analysis. It will make it easier for rescue teams to get too high-alert areas first so that there will be as few or no deaths as possible. The method can be improved to detect earthquakes, urbanization, deforestation, and coastlines in the future.

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