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A NOVEL SATELLITE IMAGE SEGMENTATION USING VGGNET

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Abstract:
The Satellite image classification technique is included the grouping of values of image pixels within the substantial groups. However, satellite image segmentation have involved various kinds of procedures and approaches. Three types of techniques of satellite image classification are automatic, hybrid, and manual which are having individual advantages and disadvantages. In the 1st group, most of the methods of satellite image classification are made classified. By relying on the requirements of the satellite image classification, the suitable technique of classification is to be chosen. To assess the remote sensing measurements frequently out of a space platform, a plain graphical indicator is developed that assists in evaluating the target which is identified with live green vegetation is called as normalized difference vegetation index (NDVI). Based on pixel feature extraction and classification using VggNet. According to color and texture, the satellite image is segmented into small regions and these segments are further made into classification of different regions with the use of VggNet.

1. Introduction

Wetlands are relevant to the fields of peatland, fennel, Marsh, or stream whether permanent or temporary, natural or artificial with brackish, fresh, or salt water that is flowing or stagnant, including areas of sea water with a depth not exceeding six metres at low tide. The transitional regions between deeper ecosystems of water such as lakes and rivers and dry lands are also existed. Wetlands have inundated land or waterlogged soils permanently, intermittently, or seasonally. They consists of an essential resource for humans and for plants and animals of wetland. The essential components of the human diet are fish, eggs and birds found in wetland ecosystems. For the purposes of medical and food, 51 edible species of wetlands detected by seven major wetlands based on the studies conducted between 2003 and 2006 in Norteast India. They found that at least 27 species were traded, generating revenue for the communities. Humans, particularly in developing countries, have a strong relationship with wetlands.

The elixir of life is water. Since the origin of civilization and the fact that early civilizations first emerged along rivers in the floodplains' fertile soils, man has been connected to the wetlands. The distribution of human populations and early ancestors of hominid are controlled by the most significant element known as the water. For the purpose of fulfilling the basic requirements of humans including from water for drinking to fertile soils for crops cultivation, first signs of civilization are traced to the wetland areas. Historically, they facilitate plants such as reeds, and bulrushes as raw materials for baskets, thatching, bedding, and caning.

Wetlands include the environments which are active biologically and host a diverse and distinctive variety of animals and plants that are well adapted to the habitats and unique to them. For acting as nutrient transformation sites and their beauty, they are also appreciated as leisure areas. Additionally, they are playing an important role in reduction of floods' affects and storing of flood water temporarily. It leads to the tremendous economic advantages, biogeochemical cycling and nutrient cycling, maintaining the environment integrity, natural sewage treatment and recharging aquifers, and regulation of contamination by removing all nitrate virtually from the wetlands with fresh water making these habitats.

Wetland health is significantly impacted by the processes and events that occur inside and around these ecosystems. Water, animals and plants are entangled in their life. Both plants and animals are a complex of ecosystem interactions and anthropogenic, biological, and land-surface processes interact on numerous spatial and temporal scales in ecosystems to create distinctive patterns. Therefore, human activities influence and affect the transformation of wetlands in their habitats, affect the balance and dynamics of ecosystems, and also alter the microbial activities of soils that mediate essential processes such as nitrification, denitrification, and methanogenesis that regulate the functioning of ecosystems. This in turn influences rates of decomposition of organic matter and products of decomposition in soils.

2. LITERATURE REVIEW

The collection of physical information relevant to the surface of earth from some distance including an aircraft or an equipped satellite with remote sensors involve in the remote sensing science. To collect the data on different resources and phenomena on the surface of earth, it has become a very effective instrument by relying on how representing the electromagnetic radiation falling on them. Owing to the advantages of remote sensing like measuring and mapping of essential parameters at global and regional levels, it has proven to be important for ecologists (Roller and Colwel et al., 1986).

A powerful conservation tool is also considered as remote sensing data from earth observation. It's crucial to working with satellite imagery by conservationists. To use the technology, working together by conservationists, and turn the findings into the action of a conservation, the experts have been made some investigations. In Green et al., 2011, the remote sensing methodologies with recent improvements have been demonstrated and mentioned how they implemented for conservation involving the data detection that conservation and practitioners need remote sensing data from the observation of earth.

To understand the ecosystems (De Roeck et al., 2008), the integration of spreading RS awareness and ecology for more ecologists has been used. It becomes one of the most promising and powerful techniques of investigating the planet due to its applications in different fields of science and national economy, and accessibility, stability, authenticity, efficacy, and capacity to research vast territories (Dolinets and Mozgovoy et al., 2009). In different fields of ecological research in the climate parameter estimation, community biodiversity assessment, landscape ecology metrics formation, environmental process estimation, land use status and change, modelling, organism distribution, and vegetation mapping, RS has been involved (Rocchini et al., 2010).

From woody tissue, the determination of total biomass and discerning green vegetative tissue and separating from the water in plants are allowed to perform by RS techniques. To track the changes in the environment, indicators can be produced from remote sensing data and information on changes in land cover or land use can be generated by the systems. It allows the evaluation and comparison of patterns that can be helpful for environmental monitoring (Tiner et al., 2004). The exploitation environment and an efficient data protection are represented that replicates the overall environment. It helps to contribute the better management of ecosystems and to improve the decision-making because of its GIS contributions for modelling of geographic space and wealth of data.

In the field of GIS, principles and methodologies involved in the processing of spatial information were studied. The remote sensing benefits optimization will focus on technical advances and changes in approach for requirements of information and the information systems' development. This will be helpful for detecting the priority areas that should allow particular environments of interest to be characterized (Sanchez-Azofeifa et al., 2003), and meet the requirements (Biovin et al., 2003). Without neglecting any area and bias, continuous scientific research on natural resources including wetlands is required. To improve the RS benefits (Junk and Piedade et al., 2004), a growing number of scientists are working in the RS field are expected with the increased funding for classification and inventory of wetland. The developments in wetland science should be compatible with increasing needs, accelerated economic growth and rapid progress in human colonization. Therefore in wetland studies, there is an urgent need to speed up science. Furthermore, future research should focus on the integration of new and new space-borne sensors, the wider integration of usable passive and active spatial-scale image data, and the collection and high-quality field data with distribution (Gillespie et al., 2011).

Many conventional optimization approaches concentrate more on addressing only one appropriate solution. Thus, these methods were to be utilized often, hence there were no chances of producing the intended solution. Therefore, the issue of multimodal optimization has to be considered. So, to reduce the difficulties by the clustering and further, it followed by the optimization technique. Here, the variety of real-time and artificial techniques is used. Using the FCDP-Fast Clustering with Density Peak, we calculate the density values after determining the centre with the help of objective function. Then, the fuzzy clustering is applied to form the clustered groups with the density and centre values. Finally, we optimize the data using the CDE-Crowding Differential Evaluation methodology. Performance analysis is then proceeded with some existing methods by using the performance metrics like NMI and ARI. After validation, it concluded that the proposed method was superior to the existing method (Kamakshaiah et al., 2020).

2.1 Remote Sensing of Wetlands

To collect the data for wetland surveys, an easier and reliable alternative is considered as RS field. Here, the wetland surveys are enabled to undertake the process with a systematic evaluation and monitoring and vulnerable for logistical challenges (Silva et al., 2008). In the wetland vegetation, different plants occupy the information on patches that can be obtained, which results in providing of information on ecosystem services, wetland health, micro habitat patterns, and succession of species (Zlinszky et al., 2012). Sustainable use and conservation of essential ecosystems in studies, RS and GIS are necessary and excellent resources. Long-term research, both retrospective and predictive, will incorporate RS technology and other scientific instruments, In order to take successful ecosystem conservation steps at the early phases of their depletion (Dahdouh-Guebas, 2002). To deal with the emerging remote sensing technologies utilization and make research in the GIS climate, more systematic techniques require to be improved.

Since the first Landsat series of remote sensing satellites launch in 1972, earth observation with a continuous record for nearly 40 years has been retrieved. The advancements have been done in the tracking and inventory of wetland approaches in terms of precision (Wulder et al., 2008). A variety of factors, as we know today, have contributed to the advancement of remote sensing. In utilization of these tools (Botkin et al., 2004), improvements in scientific interests, the development of stable high-altitude aircraft and sensor-carrying satellites, developments in computer processing and its remote sensing applications, and the invention and production of digital data producing multi-spectral scanners are included. Owing to the advantages of broad on-board capacities, robust geometric and radiometric requirements, well-known and defined spatial, radiometric, spectral temporal image features in land cover mapping and dynamic studies, the program of Landsat is succeed. In Melesse et al., 2007, different sensors were improved for data acquisition and mapping of natural and environmental resources. Accordingly, new tools have been created by such advances in both computer technology and remote sensing systems for ecologists to understand and track the changes in the biota of the Earth. Geologists, foresters, geographers, agriculturalists, and engineers are currently using remote sensing to assess natural and agricultural resources (Greegor, 1986).

3. Existing System

Block diagram

Figure 1 show the existing block diagram, which has input image, preprocessing, convolution neural network and patch based image labelling blocks.

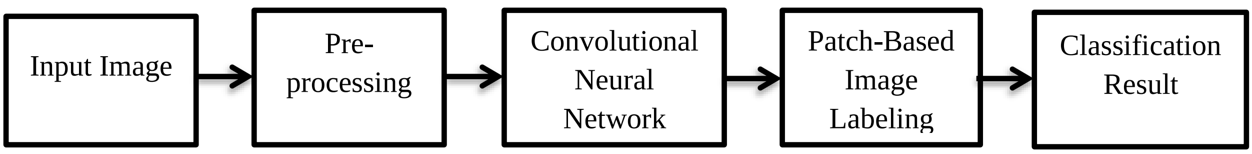


Figure 1. Existing method

Pre-processing:

The aim of pre-processing is to improve image data that removes unwilling distortions or improves some image features essential for further processing, while geometric image transformations (e.g. rotation, scaling, translation) are classified here as similar techniques are used by pre-processing methods.

Convolution Neural Network Network

CNN is one of the deep learning models that processes the data with a grid pattern like images. This is developed by taking an inspiration from an arrangement of animal visual cortex and designed for learning the spatial hierarchies of features from the patterns ranging from low to high-level automatically and adaptively. Three different layers includes in CNN which is usually a mathematical construct such as convolution, pooling, and fully connected layers. The extraction of features is performed by first two layers whereas the third layer is responsible for mapping of extracted features into the final output like classification. A stack of mathematical operations such as convolution and a linear operation with a specialized type have been included in a convolution layer of CNN. In digital images, the storing of pixel values is as a two-dimensional grid i.e. an array of numbers. For an optimizable feature extractor and each image position, a small parameter grid is applied called as a kernel which makes CNN as most efficient one and used as a feature that can occur in the image anywhere. The extraction of features become more complex because one layer embeds its output into the next layer progressively and hierarchically. To reduce the difference between ground truth tables and outputs, the method of optimizing parameters like kernels is called planning which is processed based on an optimization algorithm i.e. backpropagation and gradient descent, among others.

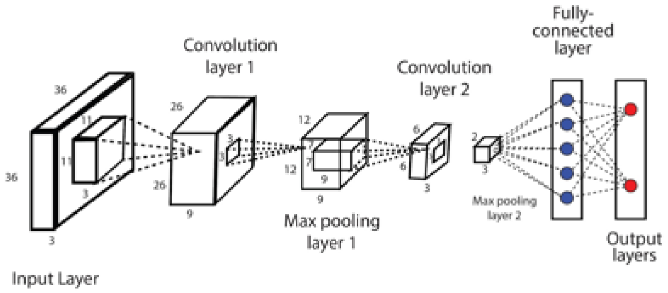


Figure 2. CNN architecture

Patch-Based Image Labeling (PBIL)

Finding a specific mark for an input image is the primary objective of a typical convolutionary network. The objective of processing the information from remote sensing is not possible even though this is a great approach for images categorization. For most of the remote sensing applications including each imaging pixel (ex, classification and segmentation), a clear mark should be defined specifically. For making CNN compatible with remote sensing applications, the categorization problem is transformed to classification by introducing PBIL methods. A label is assigned to the each patch's center and an input picture is categorized into several patches in these techniques. The whole issue is considered as a probability strategy for a given image patch S and the corresponding target M. here, the image patch contribution over the mark is illustrated as follows:

$$P(n(M,i,w_m)|n(S,i,w_s))$$

Where n(I, I w) is indicated a centered patch on pixel I with the scale of w*w from the image I. The problem is also indicated in a feature form. The problem is formulated for a given path in a multi-class classification from pixel I in the input image to the output unit 1:

$$f_{il}(s) = \frac{exp\ (a_{il}(s))}{Z} = P(m_i = l|s)$$

Where ail represents the total input for the lth output and the pixel I is displayed by fil to mark 1 for the expected mapping of probability. The network should be educated to determine the feature which utilized by reducing the predefined function's residuals.

The negative log probability which formulated below for the training protocol in this analysis.

$$L(s,m) = \sum_{all\ patches} \sum_{i=1}^{w_m^2} \left(m_i\, ln\, ln(f_i(s))\right) + (1-m_i) ln\, (1-f_i(s))$$

The optimization is carried out with mini-lots using stochastic gradient descent. By tuning certain hyperparameters like the weight decay, learning rate, and momentum. Additionally, the optimization speed is also improved. AlexNet, the 2012 winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), is used for artifact identification.

4. Proposed System

Block diagram:

Figure 3 show the proposed block diagram, which contains input satellite image, preprocessing, feature extraction, and VggNet segmentation blocks. The input satellite image segmented into different blocks and preprocessed for feature extraction. VggNet has several number of layers, one of the layers are feature extraction layers. These layers good for feature extraction and all the features are trained, then classified into different regions.

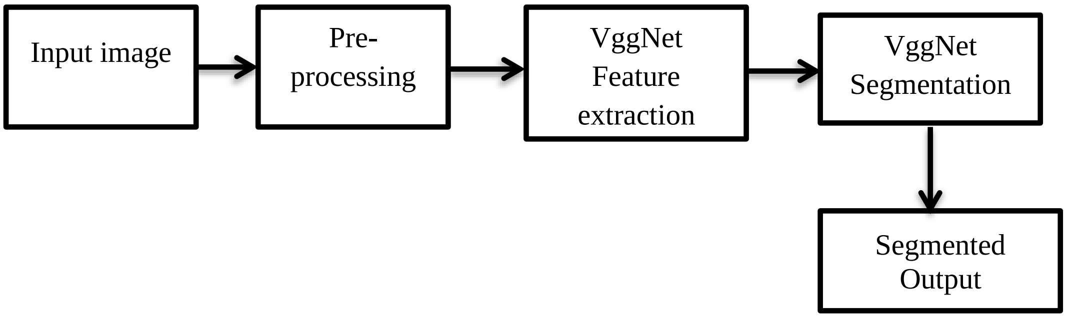


Fig 3. Block diagram of the proposed method

In the block diagram of proposed system, the steps are given below:

Pre-processing

In the experiment, the basic pre-processing techniques are used. The cropping and resizing of images is done with the use of suitable schemes of cropping (NDVI image) in order to fulfil the needs. To provide uniform intensity, the image is normalized later. The filteration of an image is also accomplished based on low pass filter.

Color feature extraction

Color is an important attribute that people experience when viewing an image and is the most straightforward one. The human vision system is more sensitive than gray levels to color details, so color is the first candidate used for extracting features.

In three-dimensional color spaces, colors are broadly known. As hardware-oriented and user-oriented, color space models can be distinguished. The hardware-oriented color spaces are based on the three-color stimulus principle, like RGB, CMY, and YIQ.

The method for manipulating colors is given by color spaces. A color space is defined in terms of intensity values as a model for representing color. In a color image retrieval system, the following four models are used.

- The model of the RGB color
- The color model of the HSV
- The color space of HMMD
- The CIE color space in the lab

The most popular color space used for computer images is the RGB color space, since the computer display uses the primary color combination (red green, blue) for displaying each received color. There are three points in each pixel on the screen which are stimulated separately by red, green and blue electron arms. The space of RGB is not standardized perceptually that means the color distance doesn't contribute to the perception of color dissimilarity in the RGB color space. Before extracting the features, the transformation of image data to other perceptual uniform space in RGB color space is preferred.

VGGNet

A dimensional picture (224, 224, 3) is the input for a network. The channels with the 64 3*3 filter-size and same padding have included in the first two layers. Two layers have included the filter size layers (3,3) and 256 filter-size convolution layers after a maximum stride pool layer (2,2). As similar to the previous layer, this is accompanied by the max stride pooling layer (2,2). Hence, the filters of 256 and two filter scale convolution layers (3,3) are involved. Then, a max pool layer and 2 sets of 3 convolution layers are existed. 512 (3,3) filters with same padding size includes in each channel which transformed to the stack of convolution of two layers. In these max pooling and convolution layers, the size of 3*3 is used instead of 7*7 in ZF-Net and 11*11 in AlexNet. In some layers, 1 pixels is also utilized for manipulating the number of input channels. A 1-pixel padding (same padding) is considered after each convolution layer for restricting the image's spatial feature.

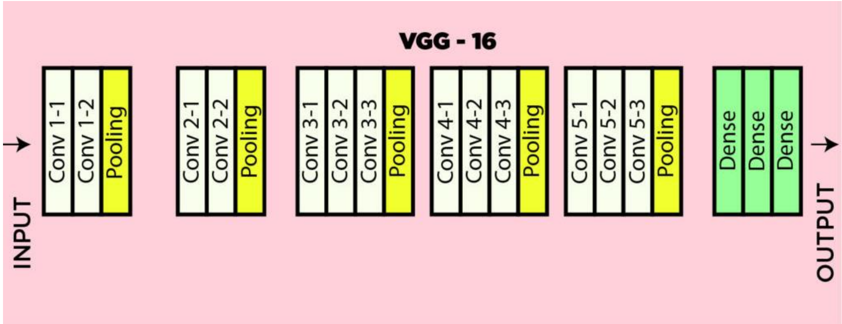


Figure.4 *VGG-16 architecture map*

A feature map of (7, 7, 512) is received after the stack of max-pooling and convolution layers. This output is flattened out to make a vector characteristic of (1, 25088). From the last vector function, an input is taken by the first layer and a vector of (1, 4096) is resulted as an output. A vector size of (1, 4096) is also provided as an output by the second layer where the third layer is provided an output of 1000 channels for challenge groups of 1000 ILSVRC. To evaluate the performance, the third layer i.e. fully connected layer transfers the output to softmm Top-5 groups. All secret layers used the ReLU as its activation function due to its effectiveness in computation that leads to the faster reading and reduction of disappearing of a gradient problem probability.

Configuration:

In the below-mentioned table, different architectures of VGG are demonstrated. Here, 2 versions of VGG-16 can be viewed (C and D). These two doesn't have much differences except for one i.e. the convolution of (3, 3) filter size is used rather than for some convolution layer (1, 1). However, 134 million and 138 million parameters are contain in these two layers respectively.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 5. Configuration

5. Results

A series of the following is the fundamental building block of classic CNNs: (ii) a nonlineary like ReLU, and (iii) For maintaining a resolution, a pooling layer such as a convolutional layer and a max pooling layer with padding. A series of convolutional layers and a max pooling layer have included in one VGG block for spatial down-sampling. The kernels of 2-22-2 max step 2 pooling and the convolutions of 3-33-3 kernels with padding 1 (keeping height and width) were utilized in the original VGGG (having the resolution after each block). A function called vgg block is described in the below code for implementing one VGG block.

Two different parts such as LeNet and AlexNet are categorized by the VGG Network. The first part includes the convolutional and pooling layers and the second one consists of fully connected layers.

The training process includes generally two graphs which are accuracy and loss. If the training process reaches to maximum epoch the accuracy graph reach to 100% and the loss graph reaches to 0%.

In the both accuracy and loss graphs consists 3 lines. The thick line represents the training(smoothed). Thin line with dots represents the training and the dash line represents the validation.

The figure 7 shows the training process for face images using semantic segmentation.

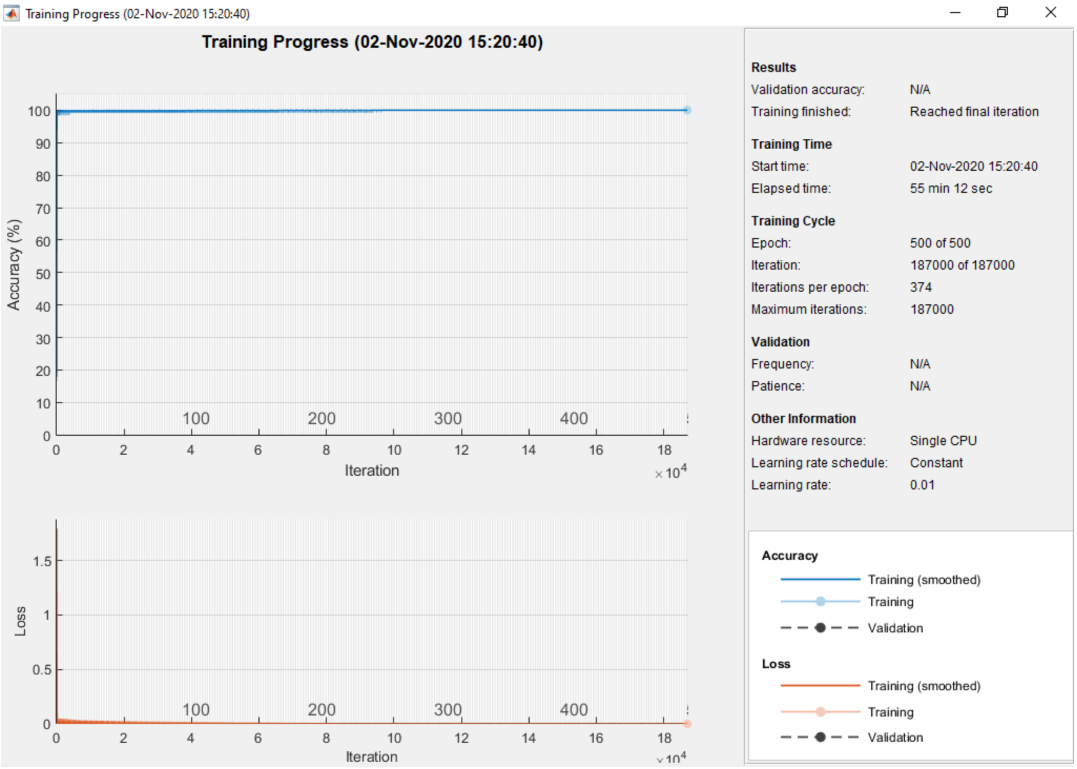


Figure 7. Training process

Figure 6 shows the different satellite images. In this satellite images have forest, agriculture, hill, water, and snow areas respectively.

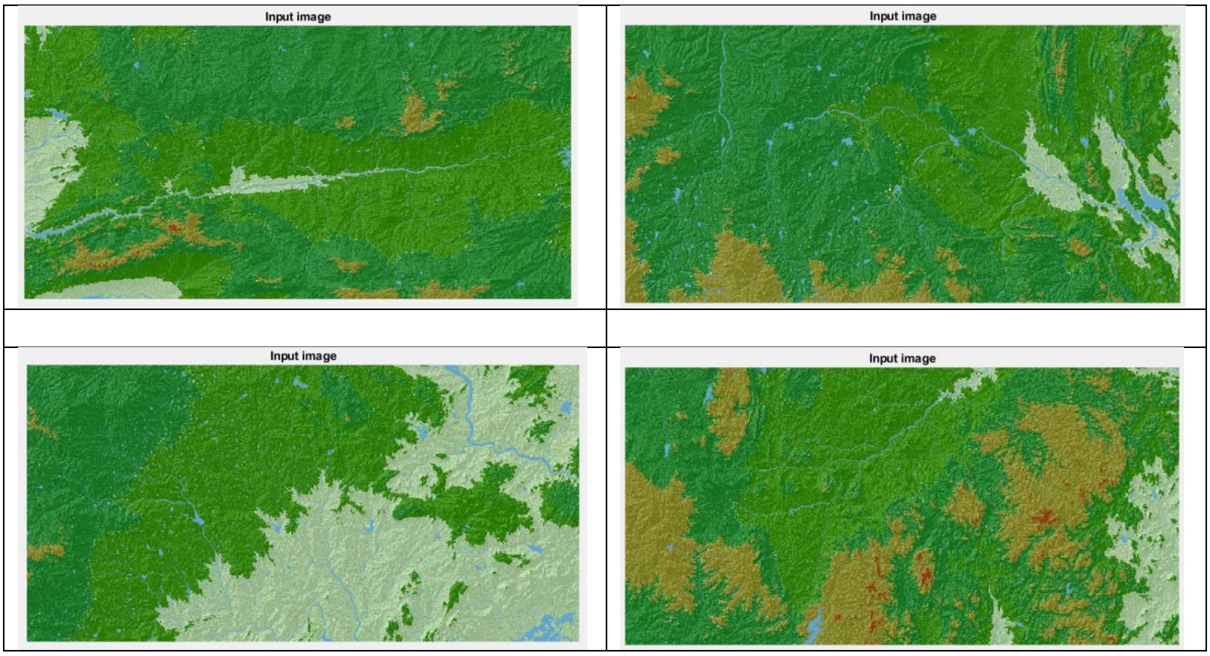


Figure 8. Input images

Figure 7 represents the segmented satellite image. Blue color represents the Forest area, Cyan represents the Agriculture area, red color represents the snow area, yellow color represents the hill area, greencolor represents the water area.

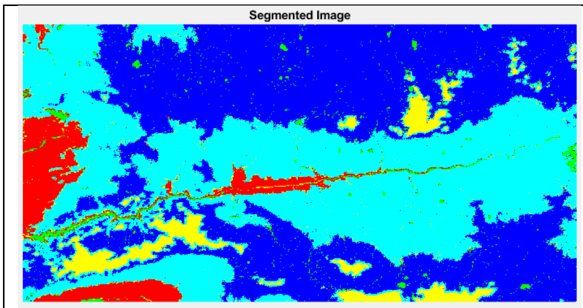
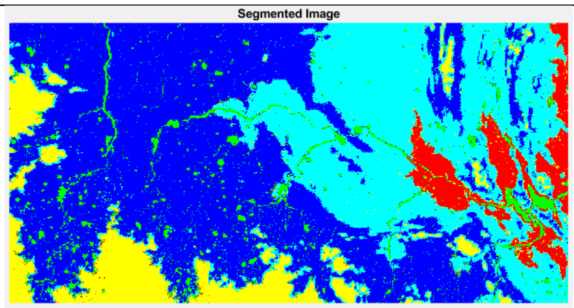
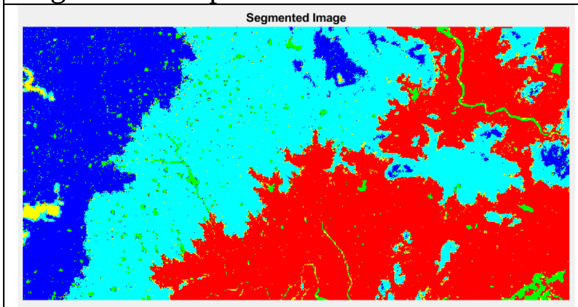
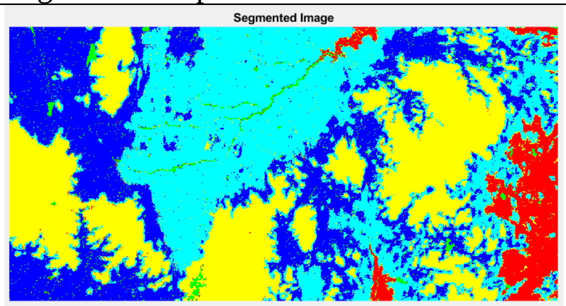
	
Segmented output 1	Segmented output 2
	
Segmented output 3	Segmented output 4

Figure 9. Segmented images

Conclusion:

In the conclusion with research findings and analysis of overall performance is demonstrated. Image segmentation is the most common method amid of various techniques of image processing such as image enhancement, image restoration, etc. Image segmentation is very challenging task in despite of it is very commonly used technique. The hard clustering is not the best solution for satellite images as they are covered with very large land area, non-homogeneous type of objects and associated with the large amount of uncertainty and imprecision. For initial clustering of image pixels, different types of segmentation regions are utilized. This analysis is being helpful in case of estimating the vegetation area from the NDVI images.

In the proposed method, satellite image segmentation implementation and classification technique is presented. For the purpose of classification, how pixel level segmentation and VggNet can be implemented for NDVI images is shown in paper. For determining the solutions for the segmentation and tasks of the object detection in the remote sensing data, the overall categorization and segmentation upon the specific sections of the map outcomes are presented by assuming the VggNet is a feasible technique. Based on the research work, the summarization of various overview upon the classification techniques of NDVI images and procedures is done. In this overview, the approach of suitable image classification is chosen. Many small regions are segmented from the image of NDVI (input image) based on texture and color. However, the classification of these smaller segments is made into various regions such as forest areas, hill, agriculture, and water. By comparing with the existing algorithms, the proposed technique is shown enhanced performance.

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