Semantic Segmentation of Satellite Images Using SegNet: An Evaluation of Performance and Application Potential

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Abstract:

In the satellite image segmentation numerous techniques are given the better results for segmentation of images into different regions and objects. One of the approaches is Semantic segmentation which applies on satellite images using deep learning models. The segmentation of satellite image is a complicated task in various applications of satellite image like geospatial classification, classification of land cover areas, planning of urban area, and environmental monitoring. In this paper we explore the architectural design and use of SegNet, a kind of deep learning architecture, for the application and results of semantic segmentation of satellite images. This paper presents a detailed and comprehensive performance evaluation of SegNet's, the performance in segmentation of high-resolution satellite imagery and discuss its potential applications. The paper also highlights the challenges associated with satellite image segmentation and suggests future directions for research in this area.

***Keyword**: Satelite Image, Masking, Convolution Network, Pooling, SegNet*

Introduction:

In today's era, the Earth's surface is observed and analyzed by different ways using satellite image analysis through fasten development in the technology related to remote sensing data. The satellite imagery, with its broad and vast varieties in terms of high-resolution capabilities and extensive coverage, has become a performing tool in various areas of satellite image processing like urban planning, agriculture, environmental monitoring, and disaster management. However, the larger volume with variety and complex nature of satellite images facilitates the valuable techniques for extracting and accessing meaningful information. Although, numerous approaches have been extensively applied and used for satellite image segmentation. These approaches are largely used the basic phenomenon of behavior of swarm of various insects or nature optimized algorithm, which has provided a significant analysis of satellite image segmentation. The major problem associated with swarm intelligence technique and nature base optimized algorithm is only the larger complexity and higher noise in the process of segmentation. Also, the multi-thresholding techniques was associated with these algorithms, provides a tremendous outcome but the larger complexity problem has been there in these algorithms, other techniques also explored during research to overcome above issues For this this specific challenge has generated the requirement of deep learning-based approaches, especially semantic segmentation [1], which applies the process to classify each pixel in an image into different predefined categories. Out of numerous models defined and developed for this segmentation, SegNet has prominently seeking significant attention for its effectiveness and accuracy in processing high-dimensional data like satellite images [2].

The semantic segmentation, as a field of research has evolved very rapidly in previous years. It incorporates the dividing of an image into different required segments [3], where every segment corresponds to a specific object or region of interest. Although, traditional image classification which already used in different applications, assigns a single label to an entire image, in compare to that the semantic segmentation [4] provides a pixel-level understanding, making it highly correct for tasks that require detailed spatial information. The swarm intelligence is also used for segmenting images where different swarm optimization algorithms used to optimize the swarm behavior [5]. The process of deep convolutional neural networks (CNNs) has tremendously improved and enhanced the performance of semantic segmentation models, activated them to learn complicated features and patterns in a very easy way from raw data. Among all these CNN-based models, SegNet proven its suitability due to its unique architecture, which is particularly designed for effective pixel-wise labeling [6].

The SegNet, was introduced by Badrinarayanan et al. in 2015, which is a type of deep learning model especially designed for semantic segmentation problems. It is described by its encoder-decoder architecture, where the encoder network is provided the functionality for capturing spatial features through a sequence of different convolutional and pooling layers, and the decoder network is provided the functionality to reconstructs the map for segmentation from these features. The different feature of SegNet is its strength to store the spatial information through the use of max-pooling layer indices in the duration of decoding process. This method not only enhances the accuracy of the segmentation but also reduces the computational complexity by carrying the structural integrity of regions and objects within the image. The network's capability to train hierarchical features from data makes it suitable for the semantic segmentation of satellite images.

The application of SegNet in semantic segmentation of satellite image presents both opportunities and challenges [7]. As opportunity, the model's strength is to process high-resolution images efficiently makes it a suitable technique for real-time analysis of satellite images. This is especially benefits in scenarios where the time for decision-making is crucial, like in disaster response or environmental monitoring [8]. As challenge, the similarity and high dimensionality of satellite images forces data in significant complexity to the model's performance. Different kind of satellite images often contain a collection of features, including buildings, roads, vegetation, water bodies, and bare land, each with different spectral and spatial characteristics. Accurately segmenting these diverse features requires a model that can generalize well across different contexts and scales.

The SegNet's performance evaluation of satellite imagery [9] provides a complete analysis of different factors, including data quality, model architecture, and training statistics. Although, the quality and resolution of satellite images can prominently affect the segmentation results. The images contain high-resolution may have more detailed information, but they also exaggerate the computational complexity, providing more specified models and training techniques. In addition, the architecture of SegNet itself, includes the choice of convolutional layers, activation functions, and pooling strategies, also, plays a complex role in obtaining the model's capability to capture and reconstruct spatial features correctly.

Background:

The machine learning approaches like support vector machines and random forests, are initially used to apply the implementation of semantic segmentation, also, applied to handcrafted features extracted from satellite images [10]. However, the limitation with these methods is their reliability on feature extraction and their inefficient nature to capture complex spatial patterns [11].

The potential applications of SegNet in the field of satellite imagery are vast and varied. In urban planning, for example, semantic segmentation [12] can be used to automatically identify and categorize different land use types, such as residential, commercial, and industrial areas. This information can provide a background for the efficient allocation of various resources and the planning of architectural projects. In agriculture, SegNet can be used to observe the crop health [13] and forecast yields by analyzing the distribution and condition of vegetation over large areas. Environmental monitoring is another area where SegNet's capabilities can be used further, especially in observing changes in land cover, finding deforestation, and assessing the effect of natural disasters such as floods and wildfires [14].

Despite the promising potential of SegNet, it is essential to acknowledge the limitations and challenges associated with its application to satellite imagery [15]. One of the primary concerns is the model's generalization ability across different geographic regions and imaging conditions. Satellite images captured under varying weather conditions, lighting, and seasons may exhibit significant differences in appearance, making it challenging for a single model to perform consistently across all scenarios [16]. Additionally, the high dimensionality and complexity of satellite images often require extensive computational resources and time for training and inference, which may limit the scalability of SegNet-based solutions in practical applications.

This research paper aims to evaluate the performance of SegNet in the context of semantic segmentation of satellite images, with a focus on its application potential in various domains [17]. The study will explore the model's strengths and weaknesses, assess its accuracy and efficiency in different scenarios, and provide insights into the factors that influence its performance. By conducting a thorough analysis, this research seeks to contribute to the growing body of knowledge on deep learning-based semantic segmentation and its practical applications in remote sensing.

SegNet Architecture:

The below figure 1 shows the detailed architectural design of SegNet's architecture which consists of an encoder network pool [18], a corresponding decoder network pool, and a classification layer with pixel-wise details. The encoder network pool is having 13 convolutional network layers that are somewhere matched with the VGG16 [19] network. It gradually decreases the spatial resolution of the input image progressively rising the depth of the extracted feature maps [20]. The decoder network pool higher the samples, the encoded feature maps using pooling indices from the corresponding encoder layers, ensuring accurate spatial resolution in the segmentation output.

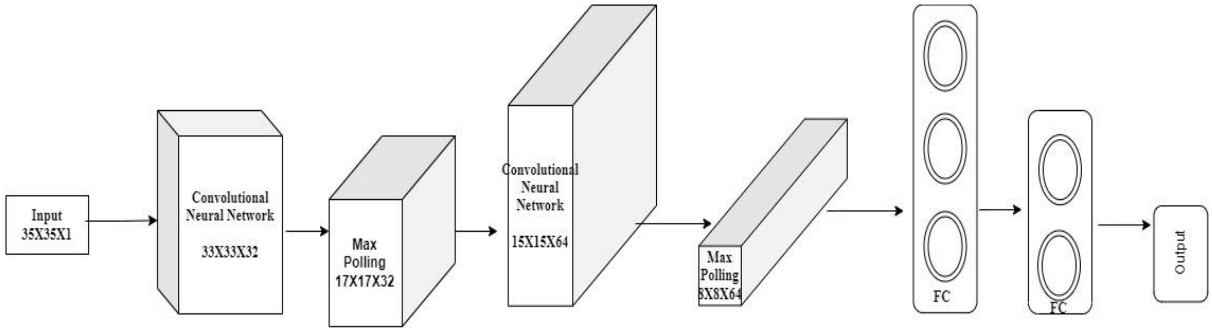

Figure 1 SegNet Architecture

Dataset and Methodology:

The data set in figure 2 consist of total 72 images split into 6 groups of high-resolution images. The categories of these images consist of diverse landscapes, including urban areas, forests areas, water bodies, agricultural lands etc. For this study, we utilized a high-resolution satellite image dataset containing 4 categories. The dataset [22] was preprocessed to standardize the image sizes and normalize the pixel values.

We trained the SegNet model using a subset of the dataset and evaluated its performance on a separate test set. The model was trained using categorical cross-entropy [21] loss and the Adam optimizer. Data augmentation techniques, such as rotation, flipping, and scaling, were applied to increase the robustness of the model.

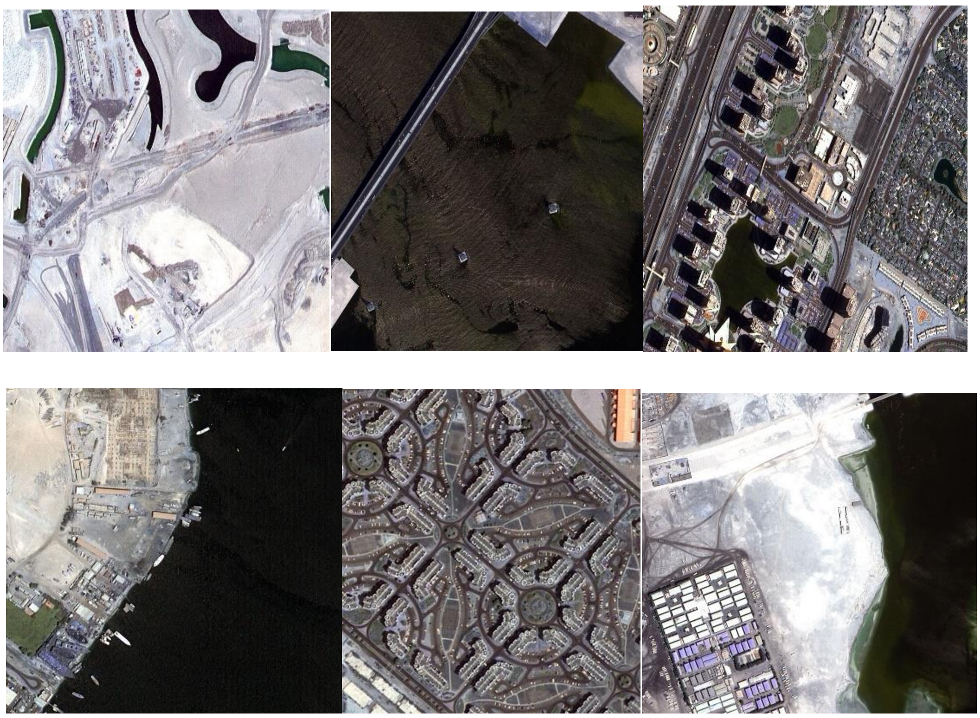

Figure 2: The dataset

Experimental Results:

The performance of SegNet was evaluated using metrics such as Intersection over Union (IoU), pixel accuracy, and F1-score. The results demonstrated that SegNet achieved high accuracy in segmenting different land cover types, with particularly strong performance in distinguishing urban areas and water bodies. However, the model showed some difficulty in accurately segmenting regions with complex vegetation patterns, which could be attributed to the limited spatial resolution of the 72 input images.

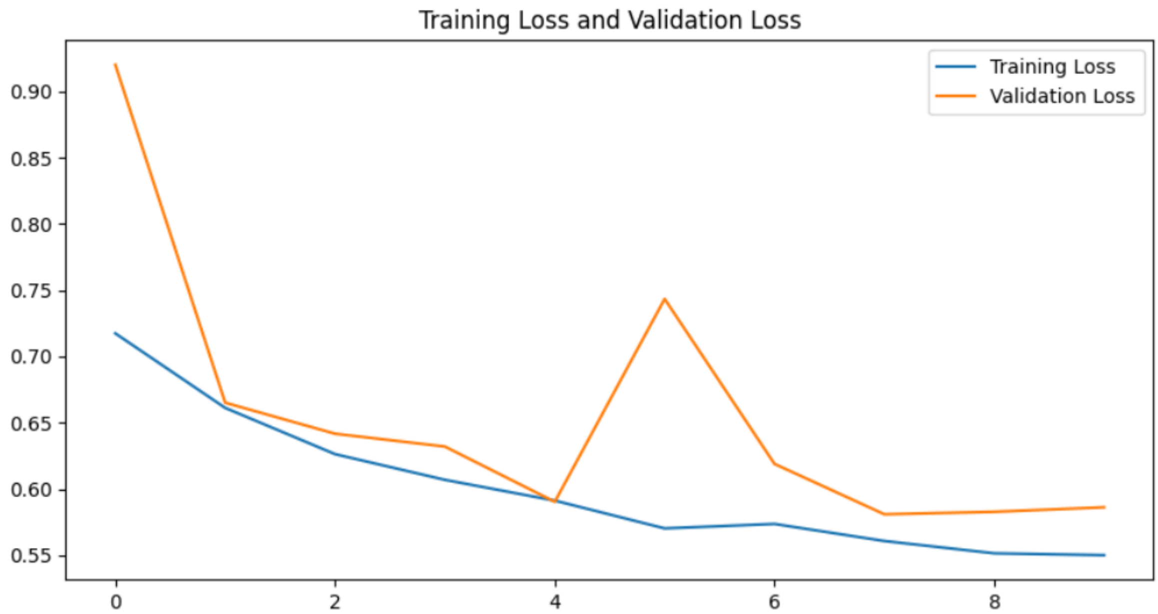

Figure 3 Loss Curve and Accuracy Curve at 10 epochs

Figure 4 Experimental Results after applying the mask

Table 1 Segmentation Accuracies

	RGB Features	RGB+Textural
Original Size (3000×4000)	83.3	85.1
Resized (512×1024)	82.9	84.7

The results indicate that SegNet is an effective tool for semantic segmentation of satellite images, particularly in applications requiring precise land cover classification. As shown in the table 1 the model accuracy in terms of RGB features and RGB features with textures. The model's ability to retain spatial information through its encoder-decoder structure is a significant advantage. However, the performance could be further enhanced by incorporating additional contextual information, such as elevation data or multispectral bands. *Precision is 0.77, Recall is 0.74* and *F1 Score is 0.75* for this model.

Challenges in semantic segmentation of satellite images include dealing with varying spatial resolutions, handling occlusions, and the need for large labeled datasets for training. Future research could focus on addressing these challenges by integrating multi-scale information, employing transfer learning techniques, and exploring unsupervised or semi-supervised learning approaches.

Conclusion:

In summary, the increasing availability of high-resolution satellite imagery has created a pressing need for advanced techniques that can extract valuable information from these data sources. In above analysis, initially contribution of previous approaches and problems has been notified and, the solution through the SegNet has been given in this paper. SegNet, is a tool with its efficient architecture and pixel-level accuracy, offers a promising solution for semantic segmentation tasks. However, the challenges posed by the complexity and diversity of satellite images highlight the need for further research and development. This study will provide a comprehensive evaluation of SegNet's capabilities and limitations, paving the way for future advancements in the field of remote sensing and geospatial analysis.

This study demonstrates the potential of SegNet for semantic segmentation of satellite images, highlighting its strengths and identifying areas for improvement. As the availability of high-resolution satellite imagery continues to grow, deep learning models like SegNet will play an increasingly important role in geospatial analysis. Future work will focus on optimizing these models for real-time applications and improving their generalization capabilities across diverse geographic regions.

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