Research proposal under PhD program of Mumbai University
Academic year 2019-20

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Research Title	**:**Hyperspectral Image Segmentation using Deep Neural Networks
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Abbreviations and Symbols

DNN	Deep Neural Network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
DCNN	Deep Convolutional Neural Network
RBM	Restricted Boltzmann Machine
LSTM	Long Term Short Memory
FCN	Fully Convolutional network
VGG	Visual Geometry Group
CRFs	Conditional Random Fields
FPN	Feature Pyramid Network
MLPs	Multi-Layer Perceptrons
PSPN	Pyramid Scene Parsing Network
ResNet	Residual network
R-CNN	Regional Convolutional network
GRUs	Gated Recurrent Units
AVIRIS	Airborne Visible/Infrared Imaging Spectrometer
ROSIS	Reflective Optics System Imaging Spectrometer
GPU	Graphics Processing Unit
FAR	False Acceptance Rate
FRR	False Rejection Rate
ERR	Equal Error Rate
CCR	Correct Classification Ratio
MVCC	Multi Version Concurrency Control
PPA	Per Pixel Accuracy
MCA	Mean Class Accuracy
MIOU	Mean Interview over Union

Abstract:

Modern Remote sensed imaging systems produce huge hyperspectral images having very high spatial resolution and spectral information. These are widely used in many applications like land-use mapping, weather forecasting, environmental study, natural hazards study, resource exploration, prevention of natural disasters and population growth etc. The rapid accumulation of gigabytes worth of remote sensing data on a daily basis has rendered a need for robust and automated tools, designed for their management, search, and retrieval, for effective exploitation.

Different from natural images, hyperspectral images (HSI) often viewed from a high altitude angle Thus, the range of imaging is wide, and the background is complex and diverse. Moreover, the images of the same area are acquired after every particular time period with different swath angles depending on the sensor's instantaneous field of view; hence the same image is acquired many times with different angles. However, different issues such as the high dimensionality of the data, the presence of noise and mixed pixels, presents several challenges for image analysis. The size of the objects present in the remote sensed scene is varying in nature and also the classification of such objects in various Landuse classes is quite difficult and challenging task.

Combining the visual information with textual information can build a powerful and effective model for semantic understanding of the HSI images. A collaborative approach of Deep Convolutional Neural Network (DCNN) with Deep Clustering is proposed by subdividing the original HSI image into segments/regions that ideally represent real-world objects of interest. Deep spectral and spatial features can be extracted using DNN and captions can be generated using RNN or LSTMs. This requires huge amount of time to get the outcomes, making retrieval of huge, sensitive and target specific data in a mixed environment a challenging task.

The proposed research work aims to improve semantic segmentation results by using efficient clustering approach. Secondly LSTMs based image captioning task can be improved using multi-level attention and multi-label attribute module. In order to quantitatively evaluate the accuracy of segmentation results, Per Pixel Accuracy (PPA), Mean Class Accuracy (MCA), Mean Interview over Union (MIOU) and Cohen's kappa can be used as evaluation criteria.

1. Introduction

1.1 Topic area

With the advancement of remote sensing imaging technology, the spatial resolution of hyperspectral images has been continuously improved. In low- and medium-resolution hyperspectral images, the problem is that different objects may share the same spectral response curve, but the same object may have different spectral response curves, thus making the classification methods at the pixel or object level show many limitations. Using the highly informative image segments as the basic unit for conducting image interpretation can make effective use of the spatial context information to eliminate the ambiguity of interpretation. As a basic unit of hyperspectral image interpretation, the segment is a combination of multiple objects, environments, and semantics.

Image segmentation sub-divides an image into homogeneous segments on the basis of some similar characteristics like color, intensity, and texture that ideally represent real-world objects of interest. It is mainly used as a pre-processing step in any problem of image analysis and computer vision. It plays a central role in a broad range of applications including medical image analysis (e.g., tumor boundary extraction and measurement of tissue volumes), autonomous vehicles (e.g., navigable surface and pedestrian detection), video surveillance, satellite imaginary and augmented reality to count a few. There are many different techniques available to perform image segmentation. Mainly, image segmentation is of two types: semantic segmentation and instance segmentation. Also, there is another type called panoptic segmentation which is the unified version of two basic segmentation processes. Figure 1 shows different types of segmentation with examples.

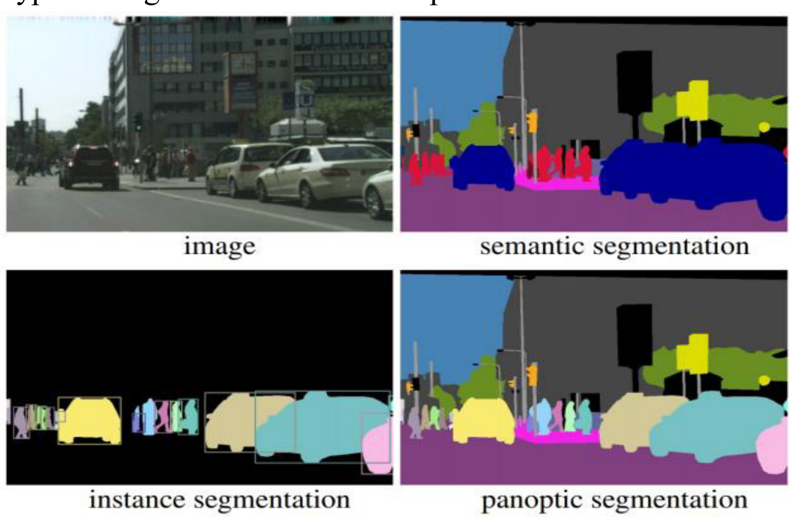


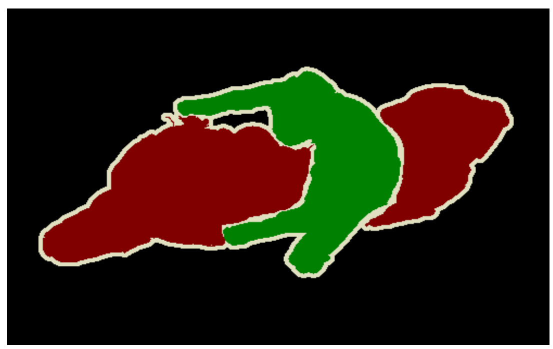
Figure 1.1: An example of different types of image segmentation

1.2 Hyperspectral Image Segmentation (HSIS):

With the advancement of aerospace technology, more and more hyper spectral images are obtained from satellites, aircraft, unmanned aerial vehicles (UAVs), and other satellite platforms. HSIS is the task of performing pixel-wise classification in images. Semantic segmentation is an important field in remote sensing and is used for tasks such as environmental monitoring, forestry, disaster monitoring, agriculture and urban planning and many more [1]. Hence, HSI is being actively used in a range of areas, including precision agriculture, military, surveillance, and more [1].

Hyperspectral images are different from natural images in terms of size, complexity, multimodal, multi-feature, multichannel data [2]. The difference is illustrated in Figure 2, which shows a typical image that can be encountered in remote sensing and an image that represents the type of image that has received most focus in computer vision in the recent years.

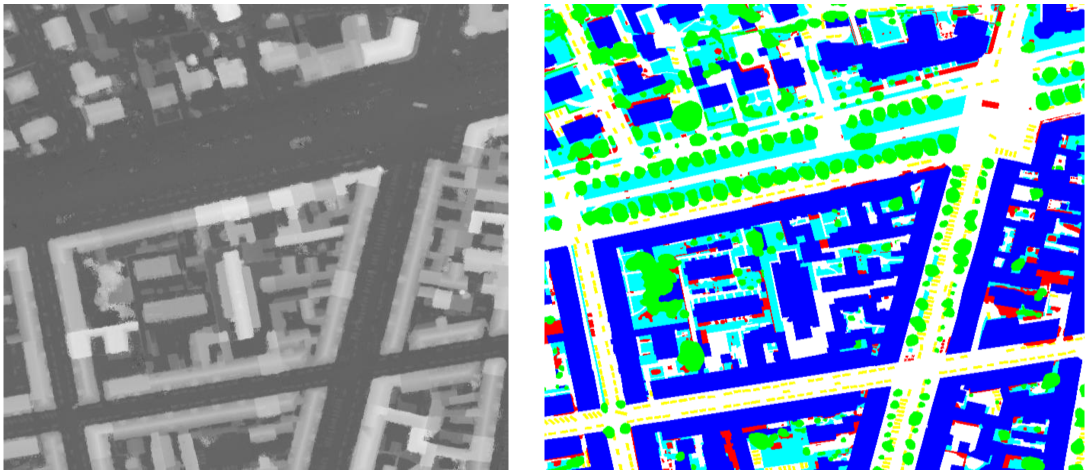
a)an normal RGB image



b) the segmentation ground truth

c)Remote sensed RGB image

d)Remote sensed Infrared (IR) image



e) Digital Surface Model (DSM) f) ground truth

Figure 1.2: Different types of images and its segmentation ground truth

The first row displays an image and the segmentation ground truth from the Pascal VOC dataset [3] and represents the typical images considered in computer vision. The second and third row show a more typical remote sensing image. From left to right, top to bottom: RGB image, Infrared (IR) image, Digital Surface Model (DSM) and ground truth. The image has been taken from the ISPRS benchmark dataset provided by the German Association of Photogrammetry and Remote Sensing [4] and illustrates the difference in image size (500 × 342 compared to 6000 × 6000 pixels), the importance of small objects, and the availability of multiple modalities in remote sensing. Not accounting for these differences in image properties has, for instance, led to poor performance on classes that contain only a small number of pixels [5]. Effectively addressing these differences in order to design more accurate and fitting approaches is a promising direction.

1.3 Traditional Image Segmentation Methods:

There are two categories of image segmentation techniques, i.e., classical and non-classical approaches. Classical approaches define the filtering and statistical techniques. Some classical approaches are edge detection based or boundary based techniques, thresholding based techniques, region-based techniques, morphological techniques, normalized cut-a graph-theoretic approach, k-means algorithm based approaches etc. The non-classical approaches define the fuzzy-neuro-genetic paradigm or its content is used with features for real-time application [6].

Thresholding techniques:

It is a simple and one of the most important techniques for image segmentation that deals with the pixel value of the image like a grey level, color level, texture etc. [6]. The aim of this technique is to determine the threshold value of an image. The pixels whose intensity values exceed the threshold value are assigned in one segment and the remaining to the other. There are three types of basic thresholding techniques [8] named global thresholding, variable thresholding, multiple thresholding.

Edge detection or boundary based techniques:

In these techniques, edges between two regions in the image are considered immediately by the pixel value. Some edge detection operators are Sobel, Roberts and canny operator has been applied in these techniques. Most of the edge detectors are obtained by derived discontinuous or over-detected edges [6]. However, it is described that the output of the actual region boundaries should be closed curves. The closed region boundaries can be prevailed by some post procedures like edge tracking, gap filling, smoothing and thinning [6].

Region based techniques:

In these techniques, an image is segmented into various regions having similar characteristics. There are two techniques based on this method [7] namely Region growing and Region splitting and merging methods. Region growing methods rely on the assumption that neighboring pixels within common segment share some common properties. These kinds of methods generally start from seed points and slowly grow while staying within semantic boundaries. The regions are grown by merging adjacent smaller regions based on some intra-region variance or energy. Many common algorithms such as Mumford-Shah or Snakes algorithm other variants of such methods depend on the lambda connectedness and grown on the basis of pixel intensities. In Region splitting and merging methods, Splitting is used for iteratively dividing an image into regions having similar characteristics. Merging techniques are used to combine the adjacent similar regions.

Morphology based techniques:

Morphology modifies the images based on shapes can be applied for analyzing and representing the geometric structures inherent within an image such as boundaries, skeletons, and convex hulls. Watershed algorithms [6] assume the gradients of an image as a topographic surface. Analogous to the water flow lines in such a surface, the pixels with the highest gradients act as contours for segmentation.

K-Means Clustering based techniques:

Clustering methods [6] like K-means can cluster images into than one class. It is quite a simple process which can yield excellent results for images where objects of interests are in a high contrast with respect to the background. Other clustering approaches are combined with fuzzy logic or even multi-objective optimizations.

Histogram-based methods: Histogram-based methods provide a more global perspective when it comes to semantic segmentation. By analyzing the peaks and troughs of the histogram the image can be appropriately segmented into an optimal number of segments. Unlike clustering algorithms like k-means number of clusters need not be known beforehand.

Graph based approaches: Graph partitioning algorithms can be used to consider context of locality by treating pixels or groups of pixels as nodes thus converting an image to a weighted undirected graphs. Graph cutting algorithms may be efficiently used to obtain the segments. Probabilistic graphical models such as Markov random Fields (MRF) can be used to create a pixel labeling scheme based on prior probability distribution. MRF tries to maximize the probability of correctly classifying pixels or regions based on a set of features. Probabilistic graphical models like MRF or other similar graph based approaches can also be seen as energy minimization problems .Simulated annealing can be an apt example in this regard as well. These approaches can choose to partition graphs based on their energy.

Table 1.1 Comparative Analysis of various traditional image segmentation techniques

Segmentation technique	Description	Advantage	Disadvantage
Thresholding based	The aim of this technique is to determine the threshold value of an image.	Simple to implement	It is very much sensitive to noise. So, when noise appears in the image to a great extent, then it becomes very difficult to find the threshold value.
Edge detection	In this technique, edges between two regions in the image are considered immediately by the pixel value.	Detected Edges make it easy to identify different objects clearly and distinctly.	Not suitable for such type of images which contain too many edges.

Region based	Region based techniques have generally been used to solve image segmentation problems through seed selection and neighbour growing paradigm	Segments the image into various regions having similar characteristics. So, homogeneity criteria is properly followed	A costly method in terms of time and memory.
Morphology based	Morphology is an extensive image processing operation that modifies the images based on shapes.	Considered to be one of the data processing methods for solving complex analytical study on medical images.	Over segmentation problem arises in most cases.
K-Means Clustering based	The aim of this technique is to group data in such a way that similar objects fall under one cluster and dissimilar object are in different clusters	A simple algorithm to classify or to group the objects based on the attributes or features into K groups, where K is a predefined value.	Difficult to predict the number of clusters (i.e. It is very hard to determine the K value.)

1.4 Deep Learning

Deep learning techniques are representation-learning techniques, accepting raw data as input and being trained to discover useful features, instead of relying on hand-tuned feature extractors. Deep learning architectures consist of multiple layers, each consisting of simple modules that are subject to learning, and learn representations, each layer yielding a slightly more abstract and "useful" representation. Recently, due to the success of deep learning models in a wide range of vision applications, there has been a substantial amount of works aimed at developing image segmentation approaches using deep learning models. Image segmentation can be formulated as a classification problem of pixels with semantic labels (semantic segmentation) or partitioning of individual objects (instance segmentation). Semantic segmentation performs pixel-level labeling with a set of object categories (e.g., human, car, tree, sky) for all image pixels, thus it is generally a harder undertaking than image classification, which predicts a single label for the entire image. Instance segmentation extends semantic segmentation scope further by detecting and delineating each object of interest in the image (e.g., partitioning of individual persons).

Deep Learning based image segmentation Models:

Modern image segmentation techniques are powered by deep learning technology. Here are several deep learning architectures used for segmentation

1.4.1 Fully Convolutional Networks:

Long et al. [9] proposed one of the first deep learning works for semantic image segmentation, using a fully convolutional network (FCN). An FCN (Figure 1.4.1) includes only convolutional layers, which enables it to take an image of arbitrary size and produce a segmentation map of the same size. The authors modified existing CNN architectures, such as VGG16 and GoogLeNet, to manage non-fixed sized input and output, by replacing all fully-connected layers with the fully-convolutional layers. As a result, the model outputs a spatial segmentation map instead of classification scores.

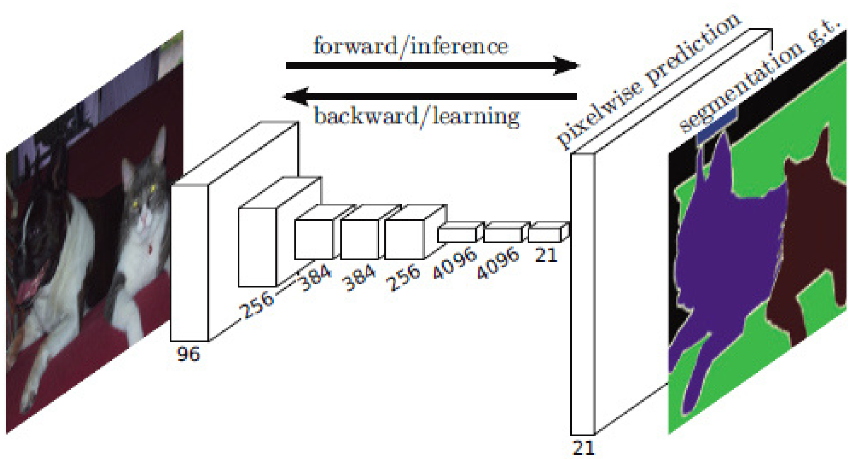


Figure 1.4.1: A fully convolutional image segmentation network.

FCN can be trained for semantic segmentation in an end-to-end manner on variable sized images. However, despite its popularity and effectiveness, the conventional FCN model has some limitations—it is not fast enough for real-time inference, it does not take into account the global context information in an efficient way, and it is not easily transferable to 3D images. FCNs have been applied to a variety of segmentation problems, such as brain tumor segmentation [10], instance aware semantic segmentation [11], skin lesion segmentation [12], and iris segmentation [13].

1.4.2 Convolutional Models with Graphical Models:

FCN ignores potentially useful scene-level semantic context. Chen et al. [14] proposed a semantic segmentation algorithm based on the combination of CNNs and fully connected Conditional Random Fields (CRFs) (Figure 1.4.2). They showed that responses from the final layer of deep CNNs are not sufficiently localized for accurate object segmentation (due to the invariance properties that make CNNs good for high level tasks such as classification).To overcome the poor localization property of deep CNNs, they combined the responses at the final CNN layer with a fully-connected CRF. They showed that their model is able to localize segment boundaries at a higher accuracy rate than it was possible with previous methods.

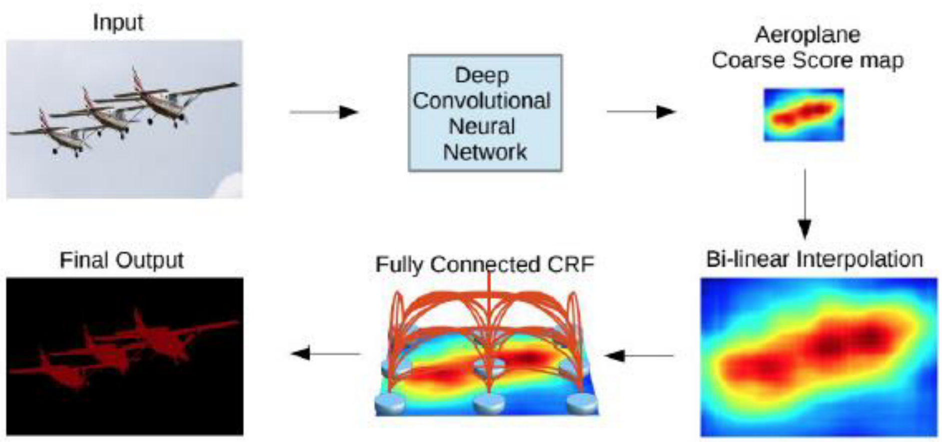


Figure 1.4.2: A CNN+CRF model

1.4.3 Encoder-Decoder Based Models:

Noh et al. [15] published an early paper on semantic segmentation based on deconvolution (a.k.a. transposed convolution). Their model (Figure 1.4.3) consists of two parts, an encoder using convolutional layers adopted from the VGG 16-layer network and a deconvolutional network that takes the feature vector as input and generates a map of pixel-wise class probabilities. The deconvolution network is composed of deconvolution and unpooling layers, which identify pixel-wise class labels and predict segmentation masks. This network achieved promising performance on the PASCAL VOC 2012 dataset, and obtained the best accuracy (72.5%) among the methods trained with no external data at the time.

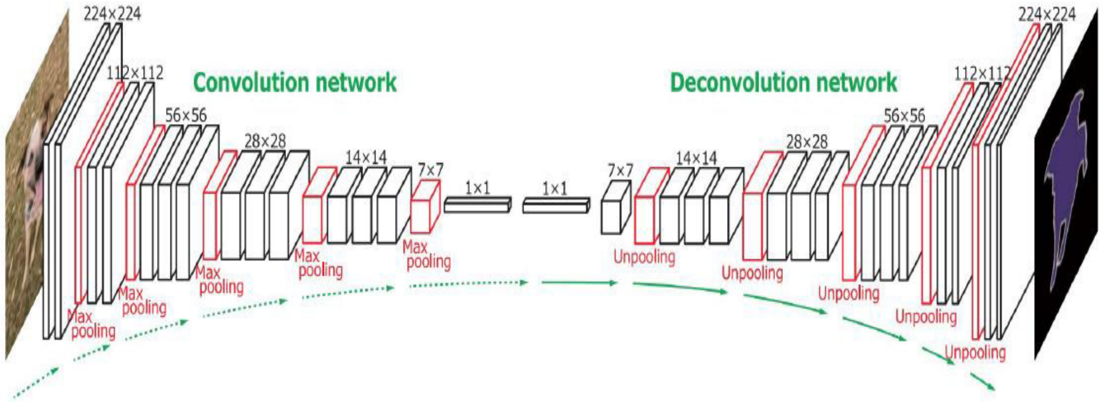


Figure 1.4.3: Deconvolutional semantic segmentation

Badrinarayanan et al. [16] proposed a Segnet: a convolutional encoder decoder architecture for image segmentation (Figure 1.4.4).Similar to the deconvolution network, the core trainable segmentation engine of SegNet consists of an encoder network, which is topologically identical to the 13 convolutional layers in the VGG16 network, and a corresponding decoder network followed by a pixel-wise classification layer. The main novelty of SegNet is in the way the decoder upsamples its lower resolution input feature map(s); specifically, it uses pooling indices computed in the max-pooling step of the corresponding encoder to perform non-linear upsampling. This eliminates the need for learning to up-sample. The (sparse) up-sampled maps are then convolved with trainable filters to produce dense feature maps. SegNet is also significantly smaller in the number of trainable parameters than other competing architectures. A Bayesian version of SegNet was also proposed by the same authors to model the uncertainty inherent to the convolutional encoder-decoder network for scene segmentation.

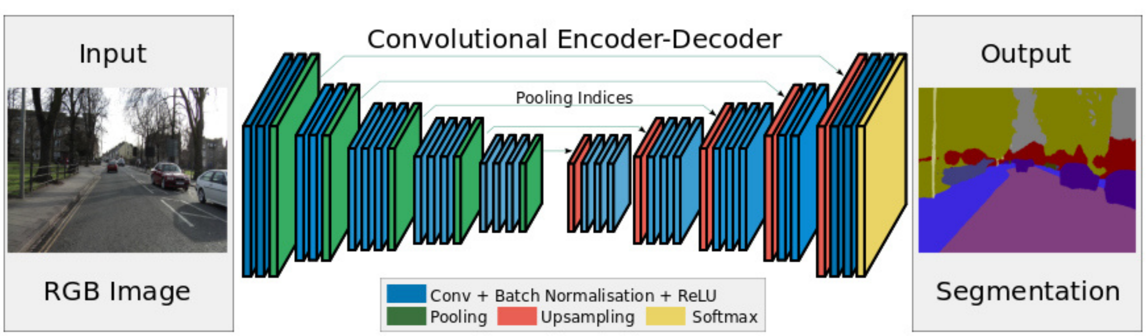


Figure 1.4.4: SegNet with no fully-connected layers

1.4.4 Multi-Scale and Pyramid Network Based Models:

Multi-scale analysis, a rather old idea in image processing, has been deployed in various neural network architectures. One of the most prominent models of this sort is the Feature Pyramid Network (FPN) proposed by Lin et al. [17], which was developed mainly for object detection but was then also applied to segmentation. The inherent multi-scale, pyramidal hierarchy of deep CNNs was used to construct feature pyramids with marginal extra cost. To merge low and high

resolution features, the FPN is composed of a bottom-up pathway, a top-down pathway and lateral connections. The concatenated feature maps are then processed by a 3X3convolution to produce the output of each stage. Finally, each stage of the top-down pathway generates a prediction to detect an object. For image segmentation, the authors use two multi-layer perceptrons (MLPs) to generate the masks. Figure 1.4.5 shows how the lateral connections and the top down pathway are merged via addition.

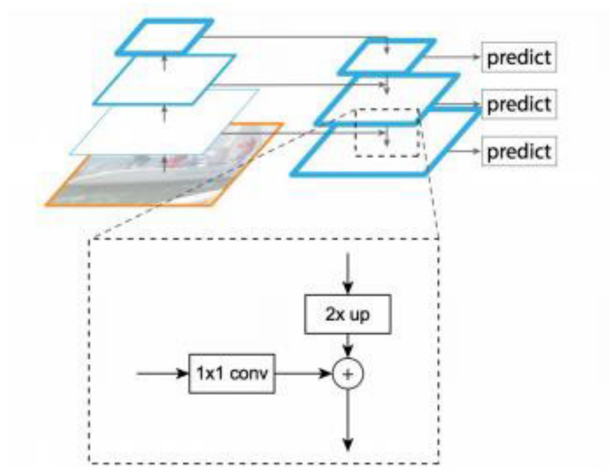


Figure 1.4.5: A building block illustrating the lateral connection and the topdown pathway, merged by addition

Zhao et al. [18] developed the Pyramid Scene Parsing Network (PSPN), a multi-scale network to better learn the global context representation of a scene (Figure 1.4.6).Different patterns are extracted from the input image using a residual network (ResNet) as a feature extractor, with a dilated network. These feature maps are then fed into a pyramid pooling module to distinguish patterns of different scales. They are pooled at four different scales, each one corresponding to a pyramid level and processed by a 1X1 convolutional layer to reduce their dimensions. The outputs of the pyramid levels are up-sampled and concatenated with the initial feature maps to capture both local and global context information. Finally, a convolutional layer is used to generate the pixel-wise predictions.

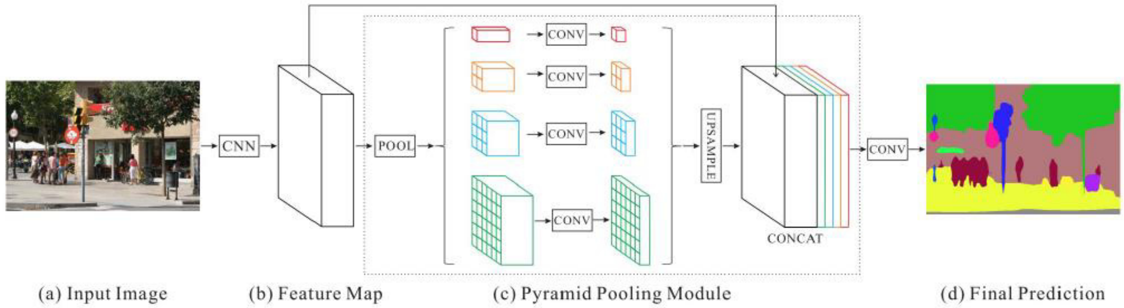


Figure 1.4.6: The PSPN architecture

1.4.5 R-CNN Based Models (for Instance Segmentation):

The regional convolutional network (R-CNN) and its extensions (Fast R-CNN, Faster R-CNN and Masked-RCNN) have proven successful in object detection applications. He et al. [19] proposed a Mask R-CNN for object instance segmentation, which beat all previous benchmarks on many COCO challenges. This model efficiently detects objects in an image while simultaneously generating a high-quality segmentation mask for each instance. Mask R-CNN is essentially a Faster RCNN with 3 output branches (Figure 1.4.7)—the first computes the bounding box coordinates, the second computes the associated classes, and the third computes the binary mask to segment the object. The Mask R-CNN loss function combines the losses of the bounding box coordinates, the predicted class, and the segmentation mask, and trains all of them jointly.

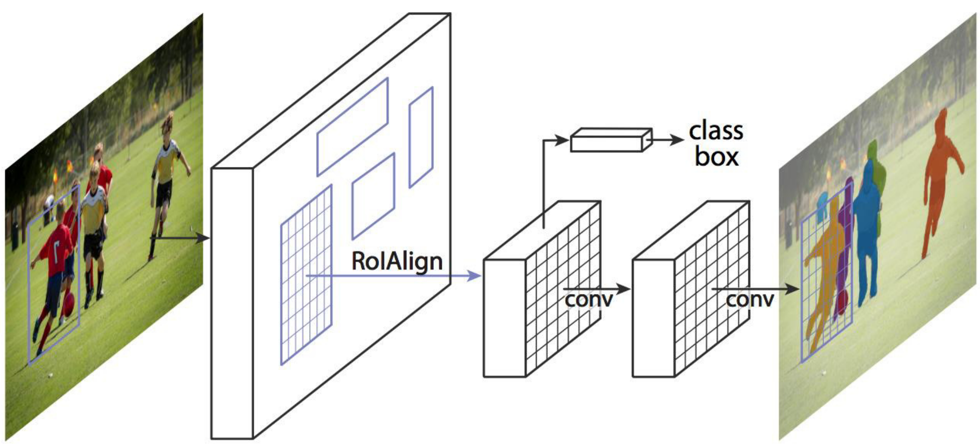


Figure 1.4.7: Mask R-CNN architecture for instance segmentation

1.4.6 Recurrent Neural Network Based Models:

RNNs are useful in modeling the short/long term dependencies among pixels to (potentially) improve the estimation of the segmentation map. Using RNNs, pixels may be linked together and processed sequentially to model global contexts and improve semantic segmentation. One challenge, though, is the natural 2D structure of images. Visin et al. [20] proposed an RNN-based model for semantic segmentation called ReSeg. This model is mainly based on another work, ReNet [21]

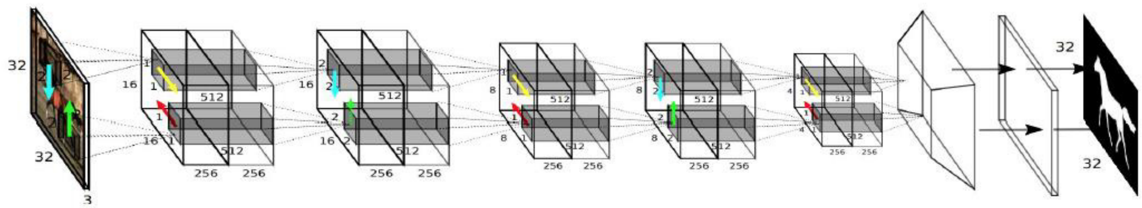


Figure 1.4.8: The ReSeg model

To perform image segmentation with the ReSeg model (Figure 1.4.8), ReNet layers are stacked on top of pre-trained VGG-16 convolutional layers that extract generic local features. ReNet layers are then followed by up-sampling layers to recover the original image resolution in the final predictions. Gated Recurrent Units (GRUs) are used because they provide a good balance between memory usage and computational power.

1.4.7 Attention-Based Models:

Chen et al. [22] proposed an attention mechanism that learns to softly weight multi-scale features at each pixel location. They adapt a powerful semantic segmentation model and jointly train it with multi-scale images and the attention model (Figure 1.4.9). The attention mechanism outperforms average and max pooling, and it enables the model to assess the importance of features at different positions and scales.

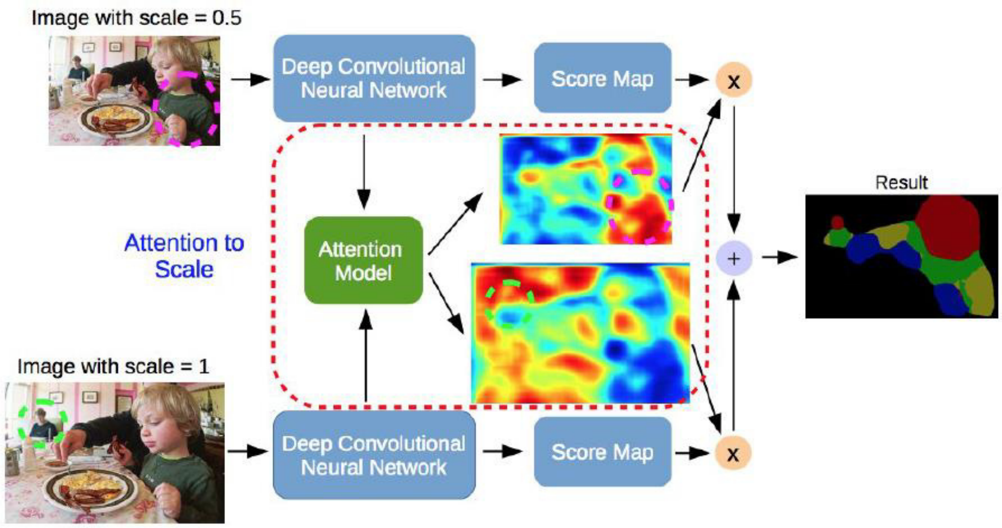


Figure 1.4.9: Attention-based semantic segmentation model

1.4.8 Generative Models and Adversarial Training:

Luc et al. [23] proposed an adversarial training approach for semantic segmentation. They trained a convolutional semantic segmentation network (Figure 1.4.10), along with an adversarial network that discriminates ground-truth segmentation maps from those generated by the segmentation network. They showed that the adversarial training approach leads to improved accuracy on the Stanford Background and PASCAL VOC 2012 datasets.

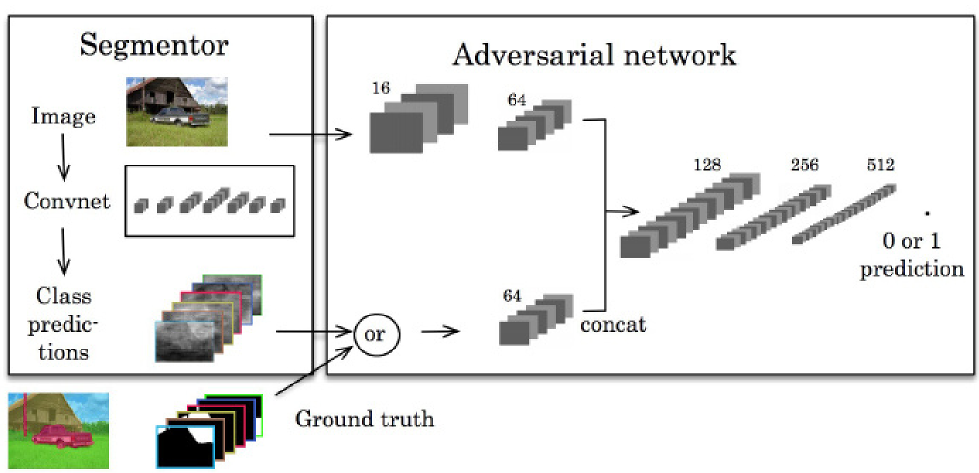


Figure 1.4.10: The adversarial model for semantic segmentation

The segmentation network (left) inputs an RGB image and produces per-pixel class predictions. The adversarial network (right) inputs the label map and produces class labels (1=ground truth or 0=synthetic).

2 Motivation

Deep Convolution neural network (DCNN) and its variants such as, U-Net, SegNet, DeepLab, PSPNet are mostly used in hypersectral image analysis. Such pretrained networks embrace hyperspectral image as a whole, extract and classify the deep features. Though these networks give high performance but consumes a huge amount of memory and millions number of parameters to set. For example, U-Net needs 357 MB Memory and 31 million parameters whereas SegNet requires 117 MB and 1.425 million parameters. It requires huge amount of computation time for producing the segmentation result. Another problem is over fitting, because there are very limited training samples available [24]. The deep clustering algorithm can be used to find the segments based on high similarity measure and DCNN will work on only a few segments instead of the whole image. This collaborative Deep Clustering and DCNN learning system can be used to boost the overall segmentation efficiency. Various pruning and quantization techniques can be used to minimize the network size and can thus be applied efficiently on low-restricted devices such as embedded systems, handheld devices etc.

3 Literature Survey

The literature survey is carried out by referring papers from reputed journal like IEEE Transaction, Springer, and Elsevier. The literature survey is summarized in table 2 as shown below

Table 2 Literature Review

Sr. No.	Title of the paper	Publication	Authors	Key Finding	Gap Finding
1.	Collaborative learning of lightweight convolutional neural network and deep clustering for hyperspectral image semisupervised classification with limited training samples	ISPRS Journal Of photogramme try and Remote Sensing 161 (2020) 164-178	Bei Fanga, Ying Lia, Haokui Zhanga, Jonathan Cheung	The proposed lightweight 3D-DPNet is based on depth wise and pointwise convolutions which have fewer parameters and higher classification accuracy than traditional 3D CNN on a small number of training samples. Due to the excellent clustering performance and low computational complexity of the AROC algorithm, the AROC-based pseudo-labeling method can generate high-quality pseudo labels for unlabeled samples.	The problem of limited labeled samples in the HSI datasets to develop a Unsupervised classification.
2.	Learning Deep Hierarchical Spatial–Spectral Features for Hyperspectral Image Classification Based on Residual 3D-2D CNN	Sensors 2019, 19, 5276; doi:10.3390/s19235276	Fan Feng , Shuangting Wang , Chunyang Wang and Jin Zhang	R-HybridSN (Residual-HybridSN) from the perspective of network optimization. With an organic combination of 3D-2D-CNN, residual learning, and depth-separable convolutions, R-HybridSN can better learn deep hierarchical spatial–spectral features with very few training data.	Fixed window size and principle component number may not be the best choice for different hyperspectral datasets with various spatial and spectral resolutions. Deformable convolutional networks can be used better exploit spatial correlations for different datasets. Subspace clustering can be used for high dimensional data.
3.	Research on Semantic Segmentation of High resolution Remote Sensing Image Based on Full Convolutional Neural Network	IEEE,2018	Xiaomeng Fu, HuimingQu	FCN network is based on VGG16, is applied to the semantic segmentation of high-resolution remote sensing data, and the matrix expansion technique is combined to optimize the convolution operation and improve the computational efficiency.	FCN network can extract feature features better, and can more accurately mine the spatial distribution law of high-resolution remote sensing image data from massive remote sensing data, and improve Segmentation .

4.	Towards resource-frugal deep convolutional neural networks for hyperspectral image segmentation	Elsevier, 2020	Jakub Nalepa, Marek Antoniak	Proposed resource-frugal quantized spectral convolution neural networks greatly reduce their size without adversely affecting the classification and segmentation capability. In this paper, quantization process was applied during the training. Resource-frugal CNNs are much easier to deploy in hardware-constrained execution environments e.g., on board an imaging satellite in real-life Earth observation scenarios	Quantize networks after training obtain better results as compared with those that quantize during training.
5.	Algorithms for semantic segmentation of multispectral remote sensing imagery using deep learning	Elsevier, 2018	Ronald Kemker, Carl Salvaggio, Christopher Kanan	Model uses synthetic multispectral imagery to initialize a DCNN for semantic segmentation of RIT-18 MSI dataset.	The DCNN models we explored still produce classification maps with some salt-and-pepper label noise. This could be remedied in future work by newer end-to-end DCNN segmentation frameworks, GEOBIA methods, or CRF-based algorithms
6.	Pixel-Wise Classification Method for High Resolution Remote Sensing Imagery Using Deep Neural Networks	ISPRS Int. J. Geo-Inf. 2018	RuiGuo, Jianbo Liu	Training Phase: 1)pre-segment training images and their labels into small patches using graph-based segmentation and the Selective search method. 2) FCN with atrous convolution is used to perform pixel-wise classification. Testing Phase: post-processing with fully connected conditional random fields (CRFs) is used to refine results. FCN is based on a VGG16 architecture	• VGG16 Architecture contains numerous parameters and requires time-consuming inference. • It is unusable for mobile or battery-powered real-time applications that require processing images at rates higher than 10 fps. • It needs a large number of high-quality ground truth labels for model training that relies on professional and experienced interpreters and a large amount of manual processing. • a significant amount of GPU memory is required due to atrous convolution
7.	Segmenting Hyperspectral Images Using Spectral-Spatial Convolutional Neural Networks	IEEE Geoscience and Remote Sensing	JakubNalepa, Lukasz Tulczyjew	spectral-spatial CNN combines both spectral and spatial hyperspectral pixel features extracted by its initial 3D convolutional layers.	Although data augmentation has been shown very effective in allowing large-capacity

	With Training-Time Data Augmentation	Letters, 2019		an end-to-end approach which combines 3D convolutional autoencoders with a clustering layer	learners train from small training samples, it has not been intensively applied in HSI analysis, especially in the case of spectral-spatial deep networks.
8.	CRF learning with CNN features for hyperspectral image segmentation	IEEE Geoscience and Remote Sensing Symposium (IGARSS),2016	F. I. Alam, J. Zhou, A., X. Jia	It uses both spectral and spatial information to segment remote sensing hyperspectral images. It is a 2 step process Step 1:It produces superpixels using Simple Linear Iterative Clustering (SLIC) algorithm Step 2:CNN+CRF combination performs superpixel level labeling and CRF refines weak and coarse segmentation outputs as a post-processing step.	Gabor features can be included in different wavelengths to form a more robust feature vector for the pixels in the hyperspectral dataset.
9.	Semantic segmentation of small objects and modeling of uncertainty in urban remote sensing images using deep convolutional neural networks	IEEE conference on computer vision and pattern recognition workshops,2016	Kampffmeyer, M., Salberg, A. B., Jenssen, R	It combines patch-based Deep CNN with pixel-to-pixel approach FCN to improve the classification performance. Incorporate median frequency balancing to reduce class imbalance problem of satellite images.	The results showed that class imbalance may lead to reduced performance if not accounted for properly. This was evident when using the FCN approach, where the car class 7 was only classified with an accuracy of 27.4%
10.	Deep Learning For Hyperspectral Image Classification: An Overview	IEEE Transaction S On Geoscience And Remote Sensing, Vol. 57, No. 9, September 2019	Yushi Chen, Pedram Ghamisi, Jón Atli Benediktsson	The classification accuracies obtained by different methods demonstrate that deep learning-based methods overall outperform the non deeplearning-based methods and the DFFN, which combines the RL and feature fusion,achieves the best classification performance. Deep features and network weights were visualized, which is useful for analyzing the network performance and further designing the deep architecture.	The classification maps Obtained by the SVM and JSR methods are not very satisfactory since some noisy estimations are still visible. The main drawback of DFFN is that the optimal feature fusion mechanism depends on a handcrafted setting with abundant experiments.
11.	A Semi Supervised based Hyper Spectral Image (HSI) Classification Using Machine Learning	International Journal of Recent Technology and	C. Rajinika nth, S. Abraha m Lincoln	A novel dictionary learning method called MbIE and Statistical based clustering for HSI classification has been proposed. The SS	The feature extraction is difficult for hyperspectral images in remote sensing. Given the complex hyperspectral dataset has

	Approach	Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-5S2, January 2019		representation show the outstanding ability to give better description of the HIS classification, especially exploiting MbIE and Statistical based semi supervised classifier. The experiments conducted for Salinas A datasets prove the better performance of the proposed method compared with multi-labelling image extraction methods of different HSI classification procedure.	limited labeled samples. The inadequate labelbased classification of HS remote sensing is still facing great tasks
12.	A hyperspectral image classification algorithm based on atrous convolution	Zhang et al. EURASIP Journal on Wireless Communications and Networking (2019)	Xiaoqing Zhang, Yongguo Zheng, Weike Liu, Zhiyong Wang	A 15-layer DCNN model with NG-APC module to classify single-pixel of HSI. First,the single-pixel classification of HSI learns the whole spectral information of each pixel, which not only solves the problem of large computational complexity of high dimensional data, but also solves the problem of insufficient samples in DCNN training. Second, aiming at the reasonable combination of 1D atrous convolution, we propose NG-APC module, which solves the gridding problem and enlarges the receptive field from 7 to 45	If directly input DCNN model, the kernels of each layer should have several times the number of dimensions of the original. Small spatial size of hyperspectral dataset is not suitable for DCNN model. The number of parameters has to be kept as small as possible to achieve fast computational speed
13.	Unsupervised Segmentation of Hyperspectral Images Using 3D Convolutional Autoencoders	IEEE,2019	Jakub Nalepa, Michal Myller, Yasuteru Imai	(i) Enable practitioners to generate groundtruth HSI data in affordable time. ii)Anomaly detection within a captured region by analyzing unexpected heterogeneous parts of the segmentation map (iii) See beyond the current ground-truth HIS	The problem of limited ground-truth hyperspectral sets Method is computationally expensive.

14.	Semi Supervised Hyperspectral Image Classification via Spatial Regulated Self Training	MDPI	Yue Wu ,Guifeng Mu ,Can Qin ,Qiguang Miao ,Wenping Ma and Xiangrong Zhang	This paper proposes a novel semi-supervised hyperspectral image classification framework which utilizes self-training to gradually assign highly confident pseudo labels to unlabeled samples by clustering and employs spatial constraints to regulate self-training process.	The shortcoming of self-training algorithm is that the mislabeled samples in the previous iteration will affect the later iterative process and will increase its impact. At present, there is no way to completely solve this problem.The problem of boundaries between different scenes, adjacent samples have different classes. Adjacent samples have a large overlap of image patches, so the features extracted by CNN may be similar.
15.	Learning Hyperspectral Feature Extraction and Classification with ResNeXt Network	arXiv:2020	Divinah Nyasaka, Jing Wang, Haron Tinega	MixedSN model that extends the HybridSN and SSRN methods for hyperspectral image classification. Application of HSI deep learning models on low-resolution multi-spectral satellite image classification.	This experiment still suffers from the limited number of training samples available among the experimented datasets hence causes Overfitting
16.	Fully Convolutional Networks for Semantic Segmentation	IEEE conference on computer vision and pattern recognition, 2015	Jonathan Long, Evan Shelhamer	They have used AlexNet, VGGNet and GoogleNet pre-trained models on ILSVRC ILSVRC data, as base model. They transferred these models from classifier to dense FCN by substituting fully connected layers with 1 × 1 convolutional layers and append a 1 × 1 convolution with channel dimension 21 to predict scores for each of the PASCAL VOC 2015.	AlexNet, VGGNet and GoogleNet requires huge number of parameters hence require large amount of time
17.	Research on Semantic Segmentation of High resolution Remote Sensing Image Based on Full Convolutional Neural Network	IEEE,2018	Xiaomeng Fu, HuimingQu	Full convolutionalneural network (FCN)based on VGG16 modelis applied to the semanticsegmentation of high-resolution remote sensing data, and thematrix expansion technique is combined to optimize theconvolution operation and improve the computationalefficiency.	Extract feature features better, and can more accurately mine the spatial distribution law of high-resolution remote sensing image data from massive remote sensing data, and improvesegmentation accuracy and efficiency.

18.	Semantic Segmentation of Remote Sensing Images Using Multiscale Decoding Network	IEEE geoscience and remote sensing letters,2019	Xiaoqin Zhang, Zhiheng Xiao, Dongyang Li	FCN and transfer the feature of VGG16 net. The decoding part of our architecture is an inception module that combines three decoding paths.This is based on encode –decoder structure. Encoder structure extracts the raw semantic features of images and an asymmetric decoding path that enables precise localization Decoder structure combines unpooling, transposed convolution,and dilated convolution .	
19.	Hyperspectral Classification Based on Lightweight 3-D-CNN With Transfer Learning	IEEE,2019	Haokui Zhang ,Ying Li, Yenan Jiang, Peng Wang, Qiang Shen , and Chunhua Shen	Proposed 3-D-LWNet for spectral–spatial classification of HSIs. Compared to conventional 3-D-CNN that is used for HSI classification, the depth of 3-D-LWNet is much deeper, whereas the number of parameters involved is much less and the classification accuracy of 3-D-LWNet is higher.	The design of CNN architectures has been mainly based on experience and empirical experiments. It would, therefore, be very interesting to investigate to optimize the structure of a CNN via intelligent algorithms.
20.	Satellite Image Super-Resolution via Multi-Scale Residual Deep Neural Network	Remote Sens. 2019, 11, 1588; doi:10.3390/ rs11131588	Tao Lu , JiamingWang , Yanduo Zhang , Zhongyuan Wang and Junjun Jiang	Multi-scale residual neural network (MRNN) adopts the multi-scale nature of satellite images to reconstruct high-frequency information accurately for super-resolution (SR) satellite imagery. MRNN fuses the complementary high-frequency information from differently scaled networks to reconstruct the desired high-resolution satellite object image	MRNN is mainly designed for true color satellite images SR. Hyperspectral images have higher spectral resolution but lower spatial resolution. fusion of the Hyperspectral images and the true color images can be used improve the visualized quality of the Hyperspectral images.

4. Research Problem

The research aims towards enhancement of segmentation techniques for hyperspectral images. Multilabel classification will help to overcome the drawback of consideration of single semantics within a remotely sensed image patch. Multi-scalable analysis is proposed for improving the current similarity measurement techniques which will be based on color, texture and edge features considered on multiple scale. For better segmentation accuracy, Overall efficiency in terms of precision, recall and similarity measurement values of the existing systems can be increased by incorporating the above Per Pixel Accuracy (PPA), Mean Class Accuracy (MCA), Mean Interview Over Union (MIOU) and Cohen's kappa techniques .The purpose of research is to evaluate and enhance the deep learning technique to segment the hyperspectral satellite images.

5. Research Objectives

1) To study different segmentation algorithms for remote sensing applications
2) To implement existing segmentation techniques and to find optimum solution
3) To design segmentation algorithms for improving overall efficiency
4) To build a CNN with optimized hyper parameters.
5) To implement existing RNN/LSTM based models for generating captions.

6. Research Design

The proposed system has three modules Preprocessing, Classification and Caption Generation and shown in Figure 6.1.

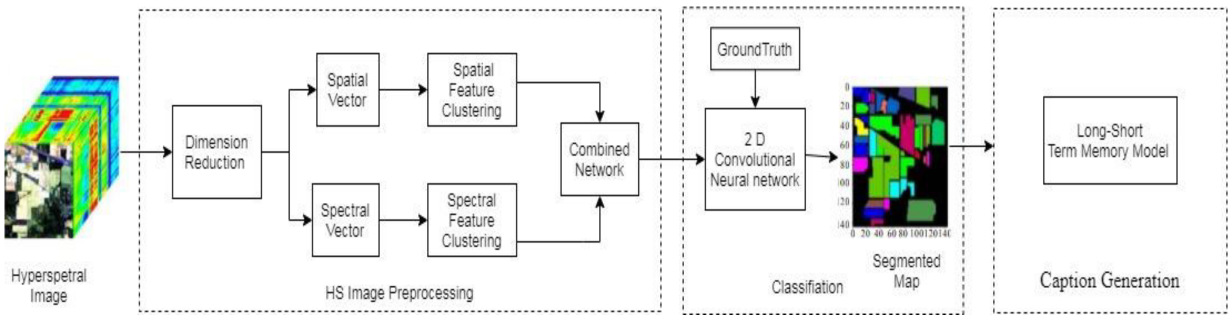
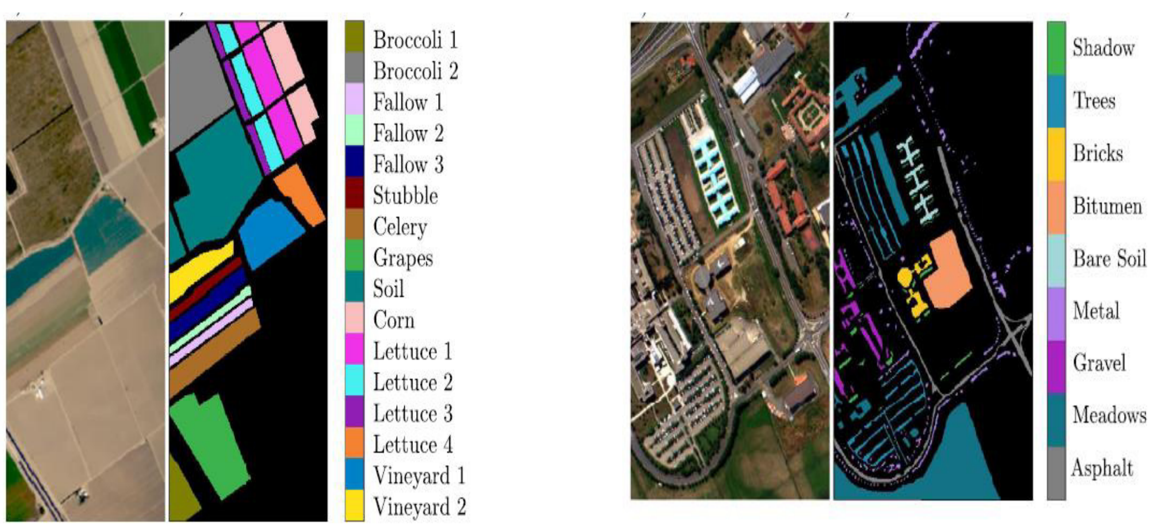


Figure 6.1. Proposed Architecture of Hyperspectral Image Segmentation using deep neural networks

The various unites used in proposed approach are explained below.

Hyperspectral Image:

The Salinas Valley dataset has been acquired using the NASA Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor, whereas Pavia University has been acquired using the Reflective Optics System Imaging Spectrometer (ROSIS) sensor.



a) Salinas Valley image is 217 ×512 pixels with a spatial resolution of 3.7 m and Spectral Bands 224

b) Pavia University image is 340×610 pixels with a spatial resolution of 1.3 m and Spectral Bands 115

Figure 6.2. Hyperspectral Image

Module I- Preprocessing:

Hyperspectral Images size is particularly large, if you directly train the neural network, the computer's memory can't bear it, Dimension reduction Algorithm cut images randomly to obtain small-sized high-resolution HS images, removes the noise, compress the HS image and extracts spectral and spatial features. The deep clustering algorithm accepts spectral and spatial features separately and based on similarity bases segments are firmed. Then a combined NN represents both features in vector format and given to 2 D Quantized CNN classifier which classifies the final result.

Module II-Classification:

A lightweight 2D CNN model is proposed for spectral-spatial classification. It is based on multi-scale and multilabel spectral-spatial feature extraction approach. The proposed lightweight 2D CNN is based on depthwise and pointwise convolutions which have fewer parameters and higher classification accuracy than traditional CNN on a small number of training samples.

Module III-Caption Generation:

A Multi-Level Attentions based Long-Short Term Memory (LSTM) Model is proposed for generating captions for final classified image. The model is based on three attention structures, which represent the attention to different areas of the image, the attention to different words, and the attention to vision and semantics.

7. Evaluation Method

The quality of a Hyperspectral Image segmentation can be evaluated with the help of evaluation Metrics and it depends on the type of input and quantization and pruning technique. Following are the various measures which are widely used for testing machine and deep learning approaches.

The evaluation metrics for the accuracy of segmentation results are per pixel accuracy (PPA), mean class accuracy (MCA), mean intersection over union (MIoU).
Assuming that there are n_c feature types in the image data to be processed, n_{ij} is the number of pixels of class i predicted to belongs to class j, and the $t_i = \sum_j n_{ij}$ is the total number of pixels of class i. Then there are:

a) Average accuracy per pixel (PPA):

$$\frac{\sum_i n_{ii}}{\sum_i t_i}$$

b) Average Class Accuracy (MCA):

$$\frac{1}{n_c}\sum_i \frac{n_{ii}}{t_i}$$

c) Average IOU (MIU):

$$\frac{1}{n_c}\sum_i \frac{n_{ii}}{t_i + \sum_j n_{ji} - n_{ii}}$$

d) Precision is the ratio of correctly predicted instances divided by the total of predicted instances.

$$Precision = \frac{TP}{TP + FP}$$

e) Recall or true positive rate indicates what percent- age of correctly predicted instances for the positive class has been correctly identified.

$$Recall = \frac{TP}{TP + FN}$$

f) Accuracy is the proportion of true positive and true negative in all evaluated cases.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

g) F_measure represents the weighted average of the precision and recall.

$$F\_measure = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Table 2. System evaluating parameters

Symbol	Meaning
TP	Events with positive event type classified correctly
FP	Events with negative event type classified as positive
TN	Events with negative event type classified correctly
FN	Events with positive event type classified wrongly

8. Expected Outcomes

This work proposes comparison of segmentation techniques for hyperspectral images. Comparison can be carried out using various transforms. As hyperspectral images amount to huge data, information is collected in the spatial and the spectral domain where each pixel is represented by more than 100's of bands of data. Moreover the images does not belong to a single scene but to a mixed environment for example image representing water, soil, wet land, dry land and vegetation together in one scene. Due to which getting a pure pixel becomes difficult. Storing such huge data requires efficient compression techniques and so does the segmentation techniques needs to be effective.

Work will be targeted towards solving problems of pure-signature classes at a macroscopic level and mixed pixels. Deep Clustering Learning combined with DCNN model can be implemented for remotely sensed images which may be able to solve complex image segmentation problem. Multi-labeling can solve problems of mixed pixel whereas current technology considers that, each image patch belongs to single semantic, which is not true in the sense of remotely sensed image data hence, multiple semantics needs to be considered for the same. Multi-scalable analysis can be used for similarity measurement to improve segmentation techniques.

A Multi-Level Attentions based Long-Short Term Memory (LSTM) can be used to improve the image captioning performance.

9. Conclusion

The proposed work will mainly focus on the collaborative approach of DCNN with Deep Clustering for remotely sensed Hyperspectral Images. The proposed system subdivides the original Hyperspectral Image into segments/regions that ideally represent real-world objects of interest, extract the complex spatial as well as spectral features, and then generate captions conditioned on the visual features and the words predicted before using RNN or LSTMs. But it requires huge amount of time to get the outcomes, making retrieval of huge, sensitive and target specific data in a mixed environment a challenging task.

The need to find the visual information with textual information of Hyperspectral Image are widely used in many applications like land-use mapping, weather forecasting, environmental study, natural hazards study, resource exploration, prevention of natural disasters, population growth etc.

Presented paper: Mr.Namdeo Badhe, Dr. Vinayak Bharadi , presented paper on
“Real Time Multiple object detection on low con-strained devices using Lightweight Deep Neural Networks”, at the Intelligent Computing and Networking, 978-981-15-7420-7, 488116_1_En (12)

References

[1] Maggiori, E., Tarabalka, Y., Charpiat, G., and Alliez, “Convolutional neural networks for large-scale remote-sensing image classification” IEEE Transactions on Geoscience and Remote Sensing 2017

[2] Zhu, X. X., Tuia, D., Mou, L., Xia, G.-S., Zhang, L., Xu, F., and Fraundorfer, F “Deep learning in remote sensing: a comprehensive review and list of resources”. IEEE 2017 Geoscience and Remote Sensing Magazine, 5(4):8–36.

[3] Everingham, M., Eslami, S. M. A., Van Gool, L., Williams, C. K. I., Winn, J., “The pascal visual object classes’ challenge: A retrospective”. International Journal of Computer Vision, 2015 111(1):98–136.

[4] Cramer, M.”The dgpf-test on digital airborne camera evaluation–overview and test design. Photogrammetrie-Fernerkundung-Geoinformation”,2010(2):73–82

[5] Marmanis, D., Schindler, K., Wegner, J. D., Galliani, S., Datcu, M., and Stilla, U.”Classification with an edge: Improving semantic image segmentation with boundary detection”. ISPRS Journal of Photogrammetry and Remote Sensing, 2018 135:158–172.

[6] Pal, Nikhil R., and Sankar K. Pal. "A review on image segmentation techniques." Pattern recognition 26, no.9 (1993): 1277-1294.

[7] Khan, Muhammad Waseem. "A survey: Image segmentation techniques." International Journal of Future Computer and Communication 3, no. 2 (2014):89.

[8] Kaur, Dilpreet, and Yadwinder Kaur. "Various image segmentation techniques: a review." International Journal of Computer Science and Mobile Computing 3, no. 5 (2014): 809-814.

[9] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3431–3440.

[10] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, “Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks,”. Springer, 2017, pp. 178–190

[11] Y. Li, H. Qi, J. Dai, X. Ji, and Y. Wei, “Fully convolutional instance aware semantic segmentation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 2359–2367.

[12] Y. Yuan, M. Chao, and Y.-C. Lo, “Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance,” IEEE transactions on medical imaging, vol. 36, no. 9, pp. 1876–1886, 2017.

[13] Yue Wu ,Guifeng Mu ,Can Qin ,Qiguang Miao ,Wenping Ma and Xiangrong Zhang ,”Semi Supervised Hyperspectral Image Classification via Spatial Regulated Self Training”, MDPI

[14] N. Liu, H. Li, M. Zhang, J. Liu, Z. Sun, and T. Tan, “Accurate iris segmentation in non-cooperative environments using fully convolutional networks,” in 2016 International Conference on Biometrics (ICB). IEEE, 2016, pp. 1–8

[15] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, “Semantic image segmentation with deep convolutional nets and fully connected crfs,” arXiv preprint arXiv:1412.7062, 2014

[16] H. Noh, S. Hong, and B. Han, “Learning deconvolution network for semantic segmentation,” in Proceedings of the IEEE international conference on computer vision, 2015, pp. 1520–1528

[17] V. Badrinarayanan, A. Kendall, and R. Cipolla, “Segnet: A deep convolutional encoder-decoder architecture for image segmentation,” IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 12, pp. 2481–2495, 2017.

[18] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, “Pyramid scene parsing network,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 2881–2890

[19] K. He, G. Gkioxari, P. Dollar, and R. Girshick, “Mask r-cnn,” in ´ Proceedings of the IEEE international conference on computer vision, 2017, pp. 2961–2969

[20] F. Visin, M. Ciccone, A. Romero, K. Kastner, K. Cho, Y. Bengio,M. Matteucci, and A. Courville, “Reseg: A recurrent neural network-based model for semantic segmentation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2016, pp. 41–48

[21] F. Visin, K. Kastner, K. Cho, M. Matteucci, A. Courville, and Y. Bengio, “Renet: A recurrent neural network based alternative to convolutional networks,” arXiv preprint arXiv:1505.00393, 2015

[22] L.-C. Chen, Y. Yang, J. Wang, W. Xu, and A. L. Yuille, “Attention to scale: Scale-aware semantic image segmentation,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 3640–3649.

[23] P.Luc, C. Couprie, S. Chintala, and J. Verbeek, “Semantic segmentation using adversarial networks,” arXiv preprint arXiv:1611.08408, 2016

[24] Bei Fanga,Ying Lia,Haokui Zhanga,Jonathan Cheung,”Collaborative learning of lightweight convolutional neural network and deep clustering for hyperspectral image semisupervised classification with limited training samples” ISPRS Journal of photogramme try and Remote Sensing 161 (2020) 164-178

[25] Fan Feng , Shuangting Wang , Chunyang Wang and Jin Zhang,” Learning Deep Hierarchical Spatial–Spectral Features for Hyperspectral Image Classification Based on Residual 3D-2D CNN” MDPI,2019

[26] Xiaomeng Fu, Huiming Qu ,“Research on Semantic Segmentation of High-resolution Remote Sensing Image Based on Full Convolutional Neural Network” IEEE,2018

[27] JakubNalepa,MarekAntoniak “Towards resource-frugal deep convolutional neural networks for hyperspectral image segmentation” Elsevier, 2020

[28] Ronald Kemker, Carl Salvaggio, Christopher Kanan “Algorithms for semantic segmentation of multispectral remote sensing imagery using deep learning”, ISPRS Elsevier,2018)

[29] RuiGuo, Jianbo Liu,” Pixel-Wise Classification Method for High Resolution Remote Sensing Imagery Using Deep Neural Networks” ISPRS 2018

[30] JakubNalepa, Lukasz Tulczyjew,” Segmenting Hyperspectral Images Using Spectral-Spatial Convolutional Neural Networks With Training-Time Data Augmentation”, IEEE,2019

[31] F. I. Alam, J. Zhou, A., X. Jia," CRF learning with CNN features for hyperspectral image segmentation", IEEE ,2016

[32] Kampffmeyer, M., Salberg, A. B., Jenssen, R," Semantic segmentation of small objects and modeling of uncertainty in urban remote sensing images using deep convolutional neural networks", IEEE conference on computer vision and pattern recognition workshops,2016

[33] Yushi Chen, Pedram Ghamisi, Jón Atli Benedikt sson ,"Deep Learning For Hyperspectral Image Classification:An Overview", IEEE Transaction S On Geoscience And Remote Sensing, Vol. 57, No. 9, September 2019

[34] C. Rajinika nth, S. Abraha m Lincoln," A Semi Supervised based Hyper Spectral Image (HSI) Classification Using Machine Learning Approach" (IJRTE) ISSN:2277-3878,Volume-7Issue-5S2,January 2019

[35] Xiaoqing Zhang, Yongguo Zheng, Weike Liu, Zhiyong Wang," A hyperspectral image classification algorithm based on atrous convolution" Zhang et al.EURASIP Journal on Wireless Communications and Networking 2019

[36] Jakub Nalepa, Michal Myller, Yasuteru Imai," Unsupervised Segmentation of Hyperspectral Images Using 3D Convolutional Autoencoders", IEEE,2019

[37] Yue Wu ,Guifeng Mu ,Can Qin ,Qiguang Miao ,Wenping Ma and Xiangrong Zhang," Semi Supervised Hyperspectral Image Classification via Spatial Regulated Self Training", MDPI,2018

[38] Divinah Nyasaka, Jing Wang, Haron Tinega," Learning Hyperspectral Feature Extraction and Classification with ResNeXt Network", arXiv:2020

[39] Jonathan Long,Evan Shelhamer," Fully Convolutional Networks for Semantic Segmentation", IEEE conference on computer vision and pattern recognition,2015

[40] Xiaoqin Zhang, Zhiheng Xiao, Dongyang Li," Semantic Segmentation of Remote Sensing Images Using Multiscale Decoding Network", IEEE geoscience and remote sensing letters,2019

[41] Haokui Zhang ,Ying Li, and Chunhua Shen,"Hyperspectral Classification Based on Lightweight 3-D-CNN With Transfer Learning" IEEE,2019

[42] Tao Lu, Jiaming Wang , Yanduo Zhang , Zhongyuan Wang and Junjun Jiang "Satellite Image Super-Resolution via Multi-Scale Residual Deep Neural Network" Remote Sens. 2019