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Tahir Mujtaba
University of Kashmir

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Tahir Mujtaba
Department of Computer Science
University Of Kashmir
Email: mjtbatahir@gmail.com

M.Arif Wani
Department of Computer Science
University Of Kashmir
Email: awani@uok.edu.in

Abstract—The problem of Object detection insatellite/aerial imagery is a fundamental and challenging one receiving lot of attention in recent years and plays a vital role for different number of applications. After the huge success of Deep learning methods in computer vision field they are currently being studied in the context of satellite imagery for different purposes like object identification, object tracking, object classification, semantic segmentation of aerial/satellite images. Although various review studies related to object detection from satellite/aerial imagery have been carried out, a review study concerning object detection from satellite/aerial imagery using deep learning approaches is still missing. This study presents a review of the recent progress in the field of object detection from satellite imagery using deep learning. The focus is on detection of roads, buildings, solar panels and vehicles.

Keywords— satellite imagery; deep learning; object detection; convolutional neural networks.

I. INTRODUCTION

Big data associated with the problem of analyzing satellite imagery can be projected into sub-spaces or clusters so that the given problem can be divided into sub-problems. Each sub-problem can then be optimized with an appropriate model [43]. One of the approaches of dividing a given problem into sub-problems involves projecting the big data to various sub-space grids [44, 45, 46, 47], where each sub-space grid represents a sub-problem. A given problem can also be divided into sub-problems by projecting the associated data to various clusters [48-51] where each cluster represents a sub-problem. Each sub-problem can then be represented independently with various machine learning algorithms which can be combined by using a rule based system [52].

Machine learning approaches have been quite successful in solving problems of different domains, be it face recognition [33] gene sequencing [35], solar radiation forecasting [42], image segmentation [38-41], information retrieval [36], handwrittendigit classification [37]or fingerprint classification [34]. Here the problem of detection of objectsfrom satellite or aerial imagery is tofigure out whether a satellite or aerial image has one or moreobjects that belong to the class ofinterest and if present locate their positions in the image. Satellite or aerial images contain different types of objects like vehicles, buildings, solar panels, roads, ships etc. Object detection in satellite image analysis is a fundamental problem which plays a significant role for different types of applications, such as detection of geological hazard, urban planning, Land use and cover mapping, environmental monitoring, updation of geographic information system and agriculture.

With the remarkable advancement in the quality and quantity of satellite images and due to the object appearance variations caused by illumination, shadow, background clutter, occlusion, viewpoint variation etc. the problem of Object detection in satellite imagery is a challenging one. Keeping in mind such challenges the problem of object detection from satellite/aerial images has been extensively studied from the past decades. Earlier we were unable to detect separate man-made or natural objects because of low resolution satellite images. But with the availability of high resolution satellite and aerial images(HRSI) (having submeter resolution) we are able to recognize different range of objects and even can be separately identified than ever before which has opened new possibilities in the field of automatic detection of objects in satellite/aerial imagery. Considerable efforts have been made during the last decades to design and develop different algorithms and tools for object detection in satellite/aerial imagery like buildings, trees, roads, forests and vehicles. Different from previous studies this paper focus on the use of deep learning techniques for object detection from satellite imagery emphasizing on detection of roads, buildings, solar panels, vehicles. The deep learning models used in these studies have been presented in detail with their model architectures and results. This paper is organized as follows. Section II reviews the building and road detection from satellite/aerial imagery. Section III reviews the Solar panel detection from satellite/aerial imagery. Section IV reviews the detection of vehicles from satellite imagery. Section V presents future scope in the field of object identification from satellite or aerial images.

II. ROAD AND BUILDING DETECTION

The problem of automatic road and building detection has been studied quite a lot from past decades and finds various applications in urban planning, geographic information system (GIS), transportation and traffic practitioners, geodetic academic researchers, municipal management, which otherwise face complications in extracting useful information from the complicated and tousled data. Various studies [1-7], [18-22] have been carried out recently to automatically detect roads and buildings from satellite/aerial imagery. But only a few studies [1-3], [5] have been carried out using deep learning. Zhong et al [1] have applied the contemporary image segmentation model Fully Convolutional Network (FCN) for building and road extraction from HRSI.The datasets used are Massachusetts road and building dataset. To determine the prediction performance of the models precision, performance measures recall and intersection over union (IU) have been used. The prediction performance results on FCN-8s, enlarged FCN-4s, pruned FCN-2s are given in the table1.

Model	Object	Prec.	Rec.	IU	Iter.
FCN-8s	Road	0.43	0.49	0.30	10000
	Building	0.54	0.67	0.43	20000
Enlarged FCN-4s	Road	**0.71**	**0.66**	**0.52**	4000
	Building	0.73	0.60	0.50	12000
Pruned FCN-2s	Road	0.58	0.61	0.42	39000
	Building	**0.78**	**0.61**	**0.52**	15000

(*Prec.: precision accuracy; Rec.: recall accuracy; IU: intersection of unit; Iter.: optimum iteration*)

TABLE I. Results of different FCNs from [1]

The study [2] has proposed a DL framework for automatic detection of buildings from high resolution remote sensing (HRRS) databased on Imagenet. The proposed model has integrated certain spectral information by using multispectral band combinations into the training procedure. An SVM(support vector machine) based binary classification procedure has been used for the building detection.To refine the classification results MRF problem issolved using linear programing. The experimental results of the developed approach are quite promising. The proposed DL network contains 8 learned layers with 5 conv layers and three fully connected layers with sixty million parameters fifty thousand neurons. The dropout regularization method has been used in the fully connected (FC) layers to reduce overfitting. The quantitative results are shown in table II. The building detection results on a test image are shown in figure 1.

Images	method	TP	FN	FP	Compl.	Corr.	Qual.
Case #1	class	381	102	61	79%	77%	70%
	mrf	388	83	34	**82%**	86%	**76%**
Case #2	class	682	220	108	76%	86%	68%
	mrf	633	179	59	78%	91%	73%
Case #3	class	278	77	60	78%	82%	67%
	mrf	297	80	27	79%	**92%**	74%
All Cases (mrf)		**1318**	**342**	**120**	**80%**	**90%**	**74%**

TABLE II. Results from [2]

Figure 1 Detection results on an image from [2]

The study [3] proposes a single patch-based Convolutional Neural Network (CNN) architecture for extracting roads and buildings from high-resolution remote sensing data. To improve the performance low-level features of roads and buildings of adjacent regions are integrated with CNN features during the post-processing stage. Same approach has been followed in [30-32]. To minimize the number of parameters use of fully connected layers has been avoided. In [30] [31] during training average pooling is used to prevent overfitting. In [32] global maximum pooling has been utilized to localize a point lying on object boundaries, rather than the complete extent of the objects. Proposed architecture is given in figure 2. Datasets used in [3] are Massachusetts dataset and Abu Dhabi dataset. Evaluation metrics used are Correctness and completeness. Results of the study are given in table 3 and 4.

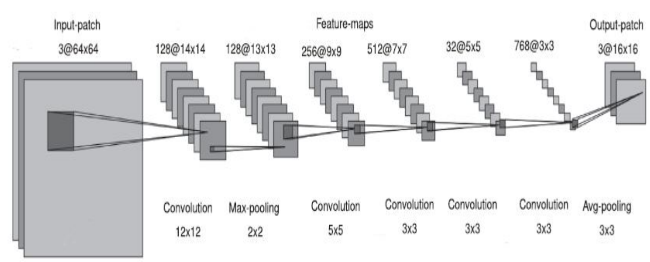

Figure 2: The architecture of proposed CNN in [3]

Correctness (%) at breakeven of multi-class prediction in Massachusetts data.

Dataset	Methods	Roads	Buildings
Massachusetts	Proposed method with GAP	91.9 ± 2.1	94.8 ± 1.9
	Proposed method with GMP	88.7 ± 2.1	92.3 ± 2.0
	Proposed method with FCLs	90.7 ± 1.9	94.5 ± 2.2
	Proposed method with GAP + Multi-scale	92.3 ± 2.0	95.1 ± 2.1
	Proposed method with GAP + CRF	92.1 ± 2.1	95.0±2.5
	Proposed method with GAP + segmentation	93.1 ± 2.1	95.5 ± 2.0

TABLE III Results for Massachusetts data from [3]

Correctness (%) at breakeven of multi-class prediction in Abu Dhabi data.

Dataset	Methods	Roads	Buildings
Abu Dhabi	Proposed method with GAP	81.1 ± 2.0	78.8 ± 1.9
	Proposed method with GMP	78.2 ± 2.1	77.0 ± 2.2
	Proposed method with FCLs	79.8 ± 2.1	76.7 ± 2.1
	Proposed method with GAP + Multi-scale	81.5 ± 1.7	79.0 ± 1.8
	Proposed method with GAP + CRF	81.8 ± 1.9	80.2 ± 1.6
	Proposed method with GAP + segmentation	82.9 ± 1.7	81.6 ± 1.8

TABLE IV Results for Abu Dhabi data from [3]

A unique CNN architecture has been proposed in [5] that integrates activations from multiple preceding stages for in the last stage for pixel-wise prediction. For output representation a signed distance function of boundary buildings has been used which has an enhanced representation power. The proposed CNN has seven ConvNet stages and for pixel level classificationthere is a last stage. At the first stage fifty filters of size 5x5x3 are applied to a 500x500x3 input image anda max-pooling operation is doneover a 2 x 2 unit region. For the next three stages a similar structure is followed containingconv (convolutional) layer and a max-pooling layer. The Conv layers have 70 filters of size 5x5x50, 100 filters of size 3x3x70, and 150 filters of size 3x3x100, respectively. In each of the next three stages the conv layers has hundred filters of size of 3x3x150, seventy filters of size of 3x3x100, and 70 filters of size of 3x3x70, respectively which filters the output from its previous stage and produces feature maps.However no max-pooling is used in these stages. For nonlinearity Rectified Linear Unit (ReLU) is used in all conv layers. The structure of the network is given in figure 3 and results on one of the test image are given in figure 4.

Apart from the above studies various other studies for extraction of roads and buildings in remote sensing imagery are present in the literature. The work in [18] has proposed a patch based CNN for road extraction. The input to this CNN is extracted from Principal Component Analysis (PCA) features The work in [19] illustrated the main differences between the performance of the CNN architecture and image segmentation on the same dataset. In [20], [21] a single CNN architecture has been used for extracting roads and buildings. The dataset used

Figure 3 Architecture of proposed model from [5]

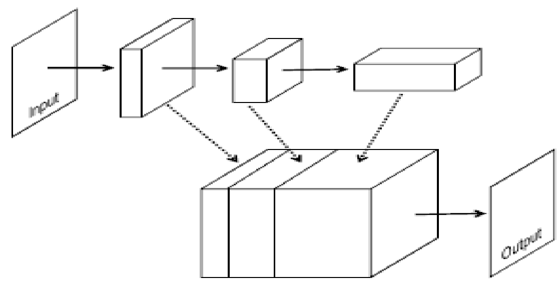

Figure 4 Results on test image from [5]

is Mnih imagery dataset [18] with all images having RGB channels. The proposed CNN simultaneously predicts a multi-class probability output of background, roads and buildings. To suppress the effect of the background channel-wise Inhibited Softmax (CIS) function has been applied. A similar architecture as in [19] has been suggested by [22] to detect buildings but a pixel based approach has been used by applying deconvolution operators. These operators use upsampling to produce dense pixel-based classification. A dual-stream deep network model based on Alex-Net [24] and VGG-Net [24] has been proposed in [23] to extract roads and buildings separately. Alex-Net having larger filter size considers information from large areas around the object of interest. While as VGG-Net network having smaller filter size focuses on local and object level information. A final subnet is created by combining both networks which composes of three Fully Connected (FC) layers.

III. SOLAR PANEL DETECTION

As solar photovoltaics (PV) become a major sector of the energy market, there is a growing necessity for granular data regarding distributed rooftop solar PV. Solar power providers and customers, urban planners, grid system operators, and energy policy makers would vastly benefit from an imagery-based solar panel detection algorithm that can be used to form granular datasets of installations and their power capacities.

Increased attention to the global warming crisis has led to the rapid adoption of distributed rooftop solar photovoltaics (PV) across the world. With the recent proliferation of solar panels across the world, remote object detection has become an increasingly attractive tool to help track solar installations nationwide. Updated installed solar photovoltaic panel maps play a vital role for financial and policy management of solar distributed generation. The other reason for solar panel detection being that solar panel installers usually don't share the information about solar panel installations.That's why a prominent solar panel detection mechanism/algorithm is highly desired. Although the detection of other objects like roads and buildings have been extensively studied, very less work has been done for detection of solar panels from aerial or satellite images. Some approaches used for detection of solar panels are presented in [8-12]. However only in [8] the solar panel detection task has been carried out using deep learning algorithms. A deep CNN has been used. CNNs when trained with large amount of data proved to be very powerful to extract features in images and the ability of generalization of test data [25]. Due to these capabilities CNNs have achieved a great success in image classification [26] and are actively studied for object localization and image segmentation [27], [28].The work in [8] introduces a deep CNN based approach for solar panel mapping from aerial images. The proposed approach has been able to map solar panels from aerial images for about 200 sqkms using only training images (manually labeled) of only 12 sqkms. The study has utilized the CNN based approach proposed in [29]. The proposed CNN architecture consists of seven ConvNet stages, each stage consisting of conv layer and a max-pooling layer. The number and size of filters used in Conv layers of the 7 stages are 50 withdimensions 5 x 5 x 3, 70 with dimensions 5 x 5 x 50, 100 with dimensions 3 x 3 x 70, 150 with dimensions 3 x 3 x 100, 100with dimensions of 3 x 3 x 150, 70 with dimensions of 3 x 3 x 100, and 70 with dimensions of 3 x 3 x 70, respectively. For the first four stages a max-pooling over a 2 x 2 unit region has been used.The architecture is as presented in figure 5:

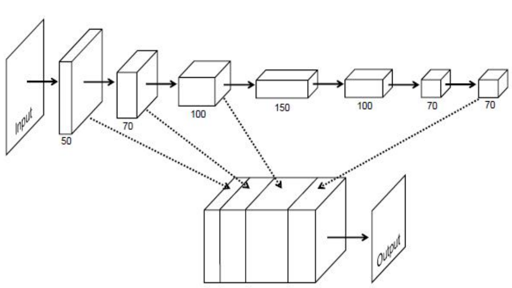

Figure 5 Proposed architecture in [8]

As can be seen from the figure 5 an integration phase has been employed which upsamples features maps from first, second, third and seventh stages generating a stack of features. Such network architecture outputs pixel-level predictions, which enables it to detect small objects like solar panels and captures information at different semantic levels. From early stages extracted features capture low-level information such as corners and edges useful for precise localization, while from later stages features extracted capture high-level/coarse information such as a roof or a road. Last stage uses128 filters of size 1 x 1 x 290 to the feature stack, which results in a prediction vector for each pixel normalized by the softmax function. The dataset used contain RGB band images with resolution of 0.3 covering five major cities. Training is performed with SGD (stochastic gradient descent) with 5 images as mini batch and weight updation adopted from [26]. Performance measures used are completeness and correctness. Extraction results on the test imagesare given in figure 6 and results in table V.

Figure 6 Extraction result on test image from [8]

Image	Completeness	Correctness
San Francisco	0.873	0.855
Boston	0.840	0.812

Table V. Detection results from [8]

IV. VEHICLE DETECTION

Among other things the problem of vehicle detection from satellite images is an important one and finds its use in military applications, homeland surveillance systems, transportation planning, and intelligent traffic systems.Various approaches used for vehicle detection from satellite imagery are presented in [13-17]. The work in [14] presents a hybrid Deep CNN which extracts variable scale features by dividing the feature maps of the last conv layer and the max-pooling layer of deep neural network into multiple blocks, each having different receptive field or max-pooling field sizes.The dataset for the model consisted of 63 images (1368 × 972) of San Francisco. From which training set composed of 31 images, 3901 vehicles. The remaining 32 images and 2870 vehicles were kept part of test set. The architecture is given in figure 7. The hybrid CNN was trained by back-propagation algorithm on a GPU and needed 5–6 days. While as testing a single image on the same GPU needed 7–8 s. The result of hybrid CNN on false alarm rate on the vehicle dataset using different structures is given in table VI.

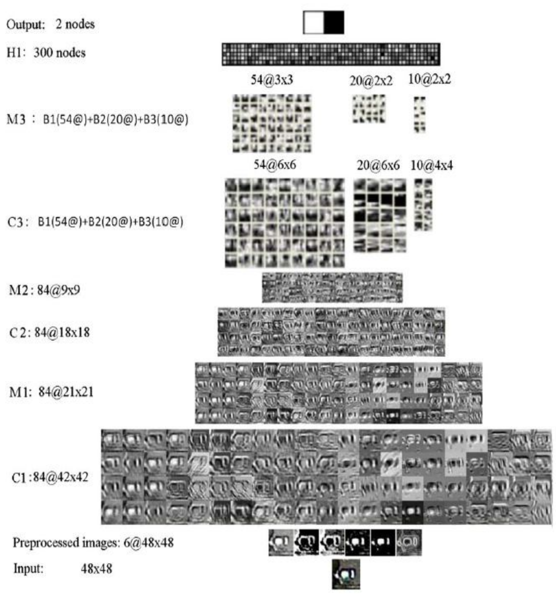

Figure 7 Proposed architecture in [14]

$n_1 - n_2 - n_3$	Given Recall Rate					
	95%	90%	85%	80%	75%	70%
84-00-00	20.2	9.57	5.49	3.57	2.31	1.65
54-20-10	15.0	6.51	3.69	2.34	1.56	1.11
44-20-20	12.8	5.73	3.12	2.01	1.35	0.93
34-30-20	13.8	6.57	3.78	2.49	1.74	1.29
28-28-28	15.5	7.02	4.11	2.61	1.80	1.23
20-44-20	16.3	7.98	4.74	3.00	2.01	1.47
34-10-40	18.3	8.67	4.89	3.12	2.07	1.44

Table 6: False rate alarms Results from [14]

The study in [15] addresses the vehicle detection and recognition problems using Deep Neural Networks (DNNs) approach. It first detects the moving vehicle based on framedifference and thenextracts the frontal part of the vehicle based on symmetrical filter, the frontal part of the vehicle is fed into the deep architecture for recognition. The Top 1 accuracy of proposed algorithm is 96.31%. The proposed MMR system involves the following three main steps: (1) Moving vehicle detection from a video, (2) extraction of frontal view of vehicles and (3) vehicle make and model recognition (MMR).Network architecture is based on GoogleNet architecture. The proposed framework has been evaluated on a vehicle database, which contain 291602 images from 766 image categorizations. These images were taken from real street CCTV. The results of the approach are summarized in table VII:

Methods	Top1 Accuracy	Top 5 Accuracy
Proposed	96.31	99.47
AlexNet	92.54	98.02

TABLE VII Results from [15]

The study in [16] presented a DL based method called segment-before-detect method for segmentation, detection and classification of vehicles in HRRS images. The proposed approach is shown in figure 8.

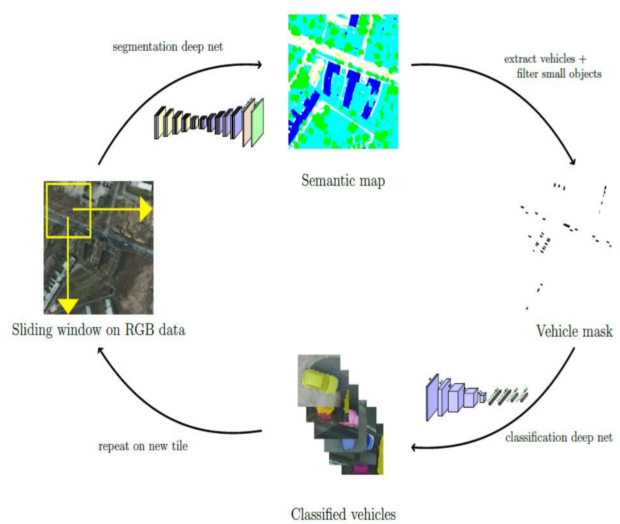

Figure 8 Illustration of proposed approach in [16]

V. FUTURE SCOPE

The problem of object identification from satellite images can be reduced to problem of image segmentation and different deep learning segmentations models like FCN and UNet, and

Segnet can be used to detect/extract different objects from such images.

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