Satellite Based Detection of Informal Settlements in Desert Terrain using Deep Learning

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Abstract:
Remote sensing can collect information over wide areas and can be used for tracking new infrastructural development in challenging terrains like Rajasthan. With the availability of many Deep Learning (DL) model and VHRS data, study explained in the paper aims to leverage the potential of space-based remote sensing and deep learning techniques for automatic identification informal settlements in desert terrain. A better understanding about settlements location in desert area is very important to monitor any human activity and identify new infrastructural requirements. But mapping of informal settlements especially in these deserted areas is a challenging task because spectral signatures of settlements are often similar to the surrounding landscape, making them difficult to distinguish. In order to cope up with these challenges, there is a need for a Deep leaning based intelligent system for automatic detection of informal settlements, enabling better understanding and management of these areas. This paper will discuss about Dynamic Unet model with ResNet encoder developed for identification of informal settlements. The methodology is divided into three parts first will be data pre-processing which involves creation of diverse training data sets from VHRS with spatial resolution of 1m. Second part is development of U-Net model with skip connection for identification of individual objects. Third parts include training and validation of the model with tile-size 256 by 256, 60 epochs and batch size 16. Trained model is saved evaluated and further used on independent datasets for the detection of settlements in Rajasthan with classification accuracy of 85%.

Keywords: Deep Learning, Settlements, Unet, Resnet. Desert

Introduction

Remote sensing is advanced in the recent years in terms of availability of data and increased spatial and spectral resolution [1]. Remote sensing can collect information over wide areas with more frequency and can be used can be used for identification and tracking new infrastructural development in challenging terrains like outlying parts of Rajasthan or hilly terrain of Leh [2].

The object detection studies like building detection, trees detection in satellite data and drone data has rich background with lot of research and literature available [3,15]. But still object detection in Satellite data is always a difficult challenge, as it requires not only the identification of the category of an object of interest but also its exact location [9].

Traditionally, manual mapping methods were used for object identification and change detection in satellite data. But now with advancements in deep learning models, automatic systems for object detection in very high-resolution satellite (VHRS) data are becoming very popular [3]. Neural network forms the backbone of Deep Learning for detection, extraction, segmentation and classification in VHRS or Drone data. Most popularly used networks are Convolutional Neural Networks (CNN), U-shaped encoder-decoder network architecture (UNet), and Recurrent Neural Networks (RNN) [4,16].

Different architecture of CNN model has gained lot of popularity and is extensively used in various field of applications application like classifying objects on aerial imagery [11], Biomedical Image Segmentation [12], road segmentation in satellite imagery [13], war destruction detection for Syria [14] and many others like NATO challenge winner in 2018 explored the potential of RetinaNet for detection of cars in drone imagery with f1-scrore 0.91[10].

With the availability of many DL based model and VHRS data, study explained in the paper aims to leverage the potential of space-based remote sensing and deep learning techniques for automatic identification and mapping of informal settlements in hard terrain like Rajasthan.

A better understanding about settlements location in desert area are very important to monitor any human activity and identify new infrastructural requirements [7]. Additionally, remote places of desert areas are sometimes exploited for illegal settlements and smuggling [8]. But mapping of informal settlements especially in these deserted areas is always a challenging task because spectral signatures of settlements are often similar to the surrounding landscape, making them difficult to distinguish [5, 7].

To identify informal settlements with good accuracy it is required to understand their morphological characteristics. Contrast to planned one, informal settlements are small, clustered buildings and sometimes only vegetation boundary [18]. In order to cope up with these challenges, there is a need for a Deep leaning based intelligent system for automatic detection of informal settlements, enabling better understanding and management of these areas [4].

This paper will discuss about the system developed for identification of informal settlements for the Rajasthan and its neighbouring area as shown in Fig1. Paper is organized as Section1 “Introduction” where the problem statement and the current literature work are discussed; Section 2 talks about Methodology about U-net with ReSnet encoder along with implementation details is explained; the next section is the Results and Discussions wherein all the results are shown with figure followed by conclusion and finally the list of references.

Methodology

Our goal is to design Dynamic Unet model with ResNet encoder which can automate detection of settlement patterns in Rajasthan. The methodology is divided into three parts first will be data pre-processing and training data creation, second will be model building and third will model evaluation, testing and validation for the selected study area.

Data pre-processing and Training dataset creation:

Creation of diverse training data sets is very important for the development of robust model. Thus, VHRS with spatial resolution of 1 m is taken from diverse terrain for the creation of the training data sets. The training dataset in geoJSON format is generated manual labelling buildings in satellite data using open source QGIS. Though this process is time consuming but it is equally important for the improving the model performance. After, creation of training datasets whole dataset is divided training (80%) and testing (20%) sets. Now convert the training datasets into the into tiles tile size of 256 by 256. Once the geometry is cropped into tiles it will be converted to mask of building dataset using Solaris python library [19]. These masks and validated with corresponding satellite data patches using fastai deep learning library [20]. This step creates the training datasets required for the training of the model.

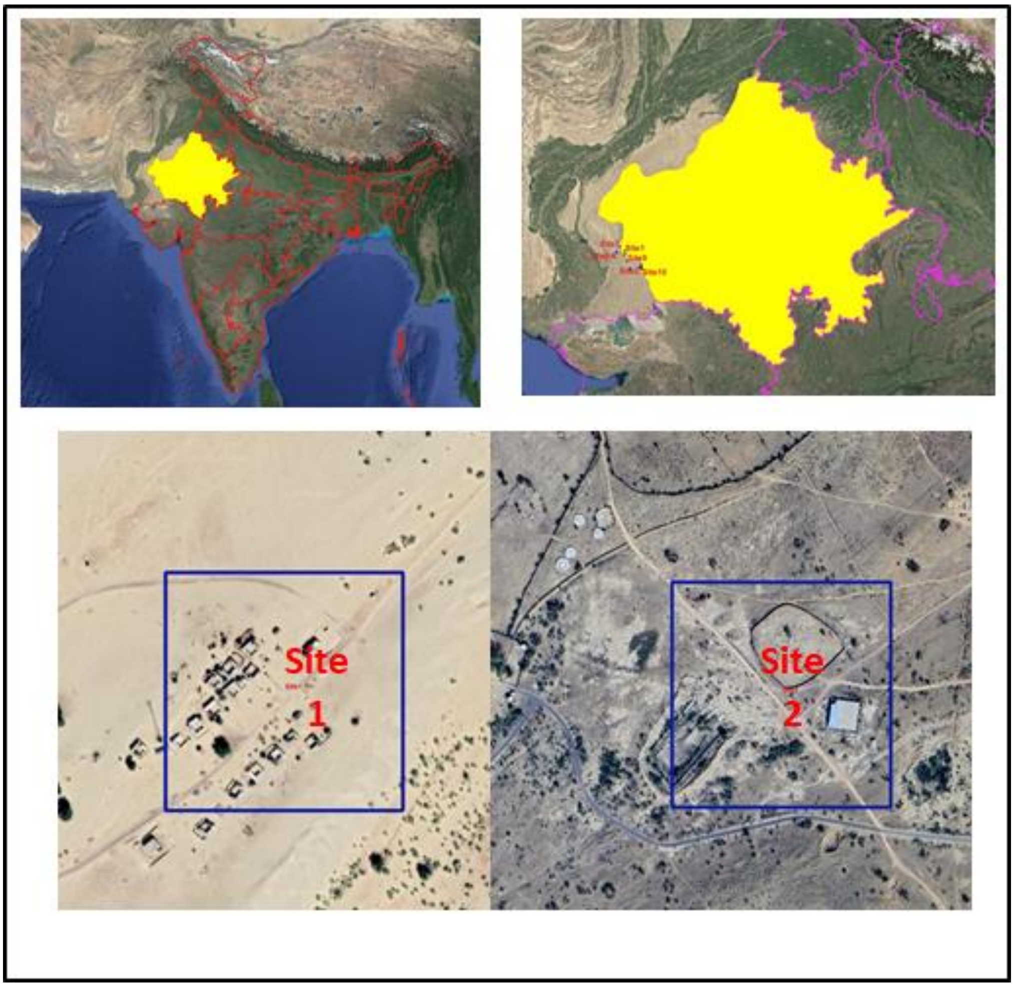

Fig. 1 Study Sites of Rajasthan.

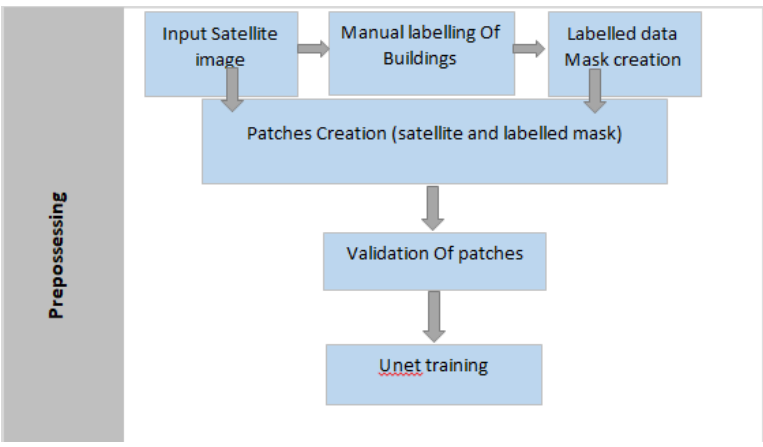

Fig. 2 Methodology.

Model Training:

This step involves the training of the UNet model using training dataset of images and mask prepared in the above steps. Unet model is a segmentation model which was initially designed for medical image segmentation [21]. The UNet architecture is like U shape with an encoder and decoder with skip connections. The encoder is generally for down-sampling and decoder is up-sampling.

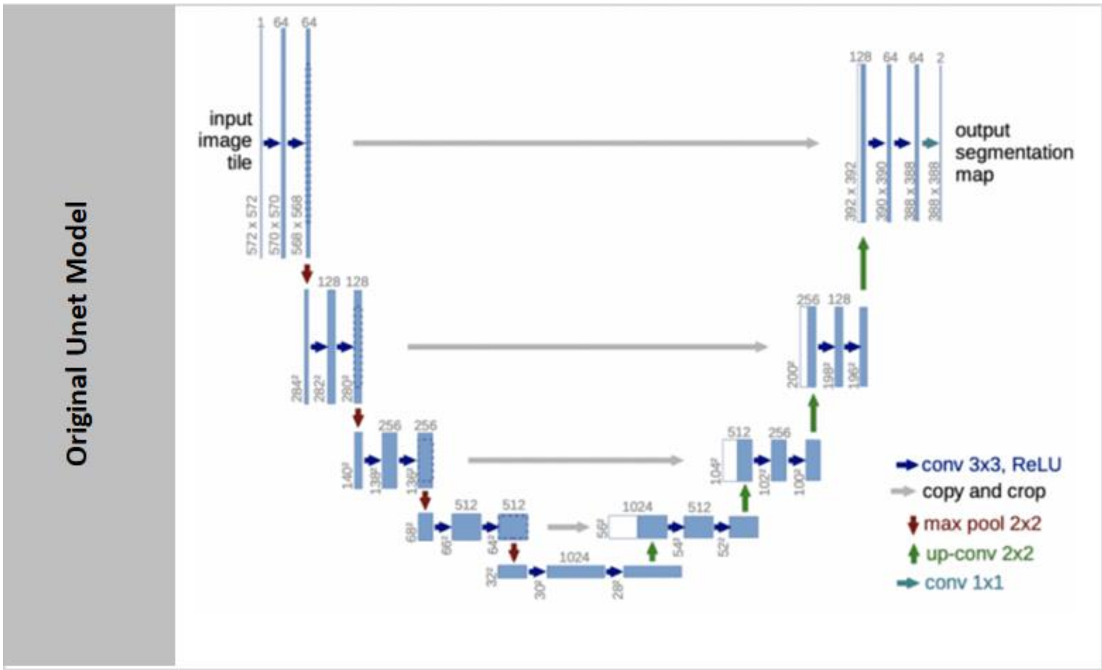

Fig. 3 Original Unet Model.

Identifying and distinguishing individual elements becomes difficult due low contrast between features and the background. Basic Unet model will not be able to detect features in such areas as it tends to lack the finer details. In Order to address such issue, we have combined the UNet along with pretrained Resnet34, it is found to be more effective and used less memory [22].

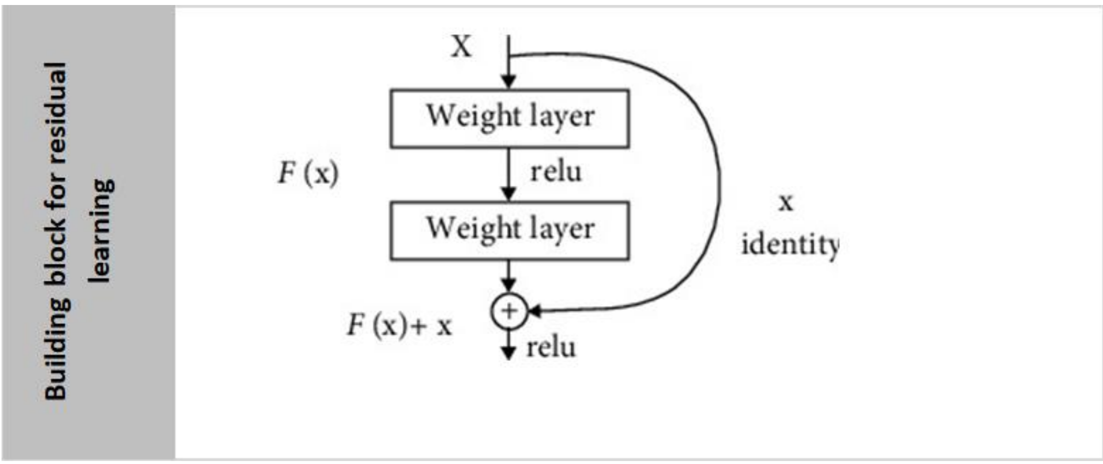

Fig. 4 Building block for residual learning.

Model training for this study is done using open source 16 GB GPU available through google collab with batch size 16 and 60 learning cycle with training sample size of 256 by

256. Loss and accuracy metrics is checked after very epochs and best fit model is saved in the user defined location.

Model evaluation, testing and Validation:

The model performance is evaluated using precision (P), recall (R), crossroads over union (IoU, Jaccard Index), and F1 score (Dice coefficient). Mathematical equations used for assessment of deep learning metrics are sown as below [23].

Precision = (True Positives) / (True Positives + False Positives) (24)

Accuracy = (Number of correctly classified samples) / (Total number of samples) (25)

Recall = (True Positives) / (True Positives + False Negatives) (26)

F1 Score = 2 * (Precision * Recall) / (Precision + Recall) (27)

IoU = (Intersection Area) / (Union Area) (28)

This step is crucial for checking the overall performance of the model. The best saved model is loaded from the drive using fast ai python library and tested on new imagery.

Results

The present study has implemented Dynamic Unet model with an ImageNet-pretrained resnet34 encoder for identifying the settlements in desert area like Rajasthan. The model has achieved the accuracies of about 85% in very low contrast and up to 95% in high contrast areas. The proposed model can be implemented for automatic identification of informal settlements of different patterns with can reduce the manual effort significantly as shown in Fig. 5 and Fig. 6.

Fig. 5 Settlement pattern #1.

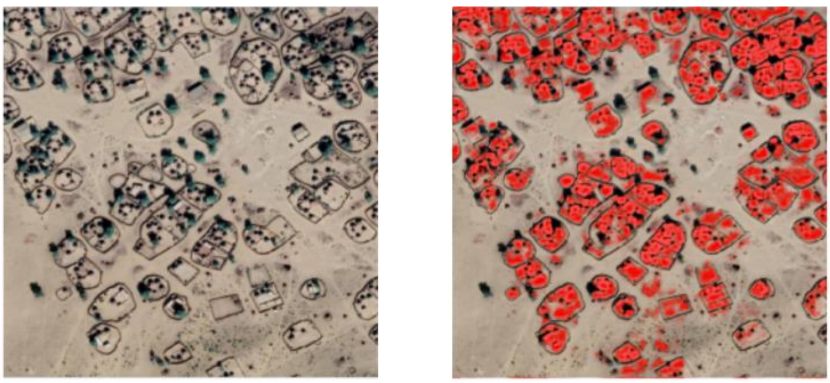

Fig. 6 Settlement pattern #2.

Conclusion and future work

The work has shown that deep learning approaches are excellent for identifying settlements in desert areas. The designed model with Unet and pre-trained ResNet 34 models can recognise settlements with different patterns within the study region. The designed model is providing the satisfactory results in terms of reducing the manual effort and reducing time for detection. Although the model results are satisfactory but further more research and testing are required to increase the model generalizability for different geographical locations.

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