

# Brightness Transformation and CNN-MRF Model for Road Network Extraction using RSI

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**Abstract-** For effective urban planning and GIS database, it is necessary to extract effectively the network of road from remote sensing images. The very high spatial resolution images (VHR) taken by space and space probes are the main source of an accurate extraction of the route. Manual techniques disappear because they take time and are expensive. As a result, the much more automated route extraction method has become a research tool in the processing of remote sensing information. The extraction of road networks in remote urban areas of images plays an important role in many urban applications (eg. Road traffic, geometric correction of remote sensing images in cities, updating geographical information, etc.). Because of the complex geometry of buildings and the geometry of sensor detection, it is generally difficult to distinguish the road from its background. In this paper, a hybrid method is proposed for the extraction of paths from high resolution images based on the segmentation using sigmoid CNN-MRF model. The proposed method includes noise removal and enhancement using brightness transformation function then segmentation of road and non-road pixels using CNN and edges are joined using CNN model also. And lastly the markov random field is used connecting edges with similar end points. Simulation will be conducted on remote sensing images in urban, suburban and rural areas to demonstrate the proposed method and compare it with other similar approaches. The results show better performance of proposed road network extraction method as compared to existing technique.

**Keywords-** Remote Sensing Images, Road Extraction, Image Processing, Image Enhancement, CNN, MRF Model.

## I. INTRODUCTION

Remote images consist of photos of the Earth or other planets made of remote satellites, as shown in Figure 1.1. Remote images have many uses in agriculture, geology, forestry, biodiversity conservation, land use planning, education, reconnaissance and war. Images can be in visible colors and other spectra. Remote sensing applications (RS) mainly include: urban remote sensing, basic geographic mapping, environmental monitoring and evaluation, precision agriculture and public information services, etc. [1]. The purpose of the RS applications is to obtain information and identify the objectives involved in order to complete the understanding of the image.

Semantic segmentation of satellite images is a pixel-by-pixel classification activity for a satellite image. Satellite

imagery is becoming increasingly important for the community due to the compilation of maps, population analysis, efficient precision agriculture and the task of autonomous driving, since satellite imagery contains more structured and uniform data than conventional imagery [2]. Understanding satellite imagery, including how to extract roads, identify buildings and identify land cover types, is essential for sustainable development, agriculture, forestry, urban planning and climate change research.

Road extraction, building detection and land cover classification are based on semantic segmentation task. Image semantic segmentation has gained remarkable improvement with the development of fully convolutional neural networks. compared with the general semantic segmentation tasks, the challenges of high-resolution sub-meter satellite image semantic segmentation are to produce finer predictions for every pixel in the large-scale image [3].

Remote sensing data are important source to generate or update the GIS database in a variety of applications or needs discussed below:

- Several applications they were limited by relatively coarse spatial resolution of sources of available data.
- With development and employment of several applications that is based on remote sensing images or high-resolution remote data has been increased even more because the existing restrictions regard geometric and intrinsic precision.
- The geometric accuracy has been alleviated.
- Automatic classification of the remote control the collected data are an essential act in the process of generation or update the GIS databases.

## II. RELATED WORK

Road segmentation plays an important role in many applications, such as intelligent transportation system and urban planning. Currently, high-resolution visible remote sensing images are widely used due to the fast development of remote sensing technology. These high-resolution images present a new challenge for road segmentation methods, because high-resolution images have more details than conventional images and, thus, contain multiscale roads (containing both very wide and very narrow roads) and complex background. Many researchers applied object-based

feature extraction to obtain coarse road regions and then performed pixel-based road segmentation. However, it is difficult for this method to obtain consistent segmentations on road boundaries. Besides, machine learning methods have also been widely used for road recognition and segmentation. Some of them are discussed below:

Li et al. [1] investigate and exploit a deep convolution network, U-net, for road extraction from aerial images. We propose a model which is a union of a high precision network and a high recall network. Both the networks are based on deep U-net. Massachusetts road dataset is used in the experiments. The results demonstrate that our proposed model outperforms state-of-the-art frameworks in terms of accuracy, precision, recall, and F-score.

Sun et al. [2] focused on the complex phenomenon of background and easily produced spurs around the true middle axes of the road. The method of using a convolutional neural network to extract road regions and smooth road segments into segments is proposed to overcome the above problems. Experience shows that the methodology of this work can overcome the influence of the complex background of high-resolution remote sensing images and can extract the road axis, which corresponds to the actual shape of the road and has great practical value.

Li et al. [3] proposed a framework based on a convolutional neural network (CNN) for the extraction of the road network in high resolution radar images with synthetic aperture (SAR). First, taking into account the richness of the structural information of the road areas in the high resolution SAR images, a CNN model is proposed to extract the characteristics of the road area and recognize the candidates of the road. The CNN model improves the accuracy of detecting street candidates at the entity level. An improved radon transformation and a random Markov field (MRF) are then used to complete the extraction of the global road network based on the identified candidate roads.

Zhong et al. [4] proposed an approach for road extraction in order to obtain a standard road area with high precision. Using road planning and construction specifications created by the transportation industry, road objects are divided into several classes. Subsequently, the corresponding activity is considered an image segmentation approach and a deep convolutional network is used to estimate the pixel level in order to predict the probability of ownership of different classes. A change management approach is also presented to take advantage of segmentation results and maintain a formal road network by linking missing or non-fluid road subsections. Experiments are conducted with remote sensing images that demonstrate the effectiveness of the method of acquiring different paths from complex situations.

Yapa et al. [5] proposed a linear search algorithm with vertical crossing and hybrid color segmentation to take into account variations in the appearance of the lane sign, due to different weather conditions, shadows and occlusions such as traffic on the road. The robustness of the application has been tested in different road conditions and the experimental results have provided an accuracy of 89% for the overall performance of the application.

Object detection algorithms localize objects and annotates them with an object class label. Both tasks face many difficulties. On one hand, the detection method must be

robust for different images or varying illumination conditions and it must account for changes in the object. On the other hand, these objects may appear of any size and at anywhere in an image [6,7]. Hence for practical systems, efficiency is very important factor.

### III. PROPOSED METHODOLOGY

The focus of this thesis is on one of our visual capabilities - finding objects of interest in geo-satellite images. There are two main facets of this problem - finding an unknown object and finding a specific known object. In this research work, the first problem is finding an unknown object of interest and the second one of detecting a known object of interest task-specific object detection or simply object detection. For the former, the proposed algorithm is developed to detect object from the remote images.

Figure 1 shows the proposed flow of algorithm. The proposed algorithm is designed for object detection from geo-satellite images.

The proposed algorithm is described in steps as follows:

Procedure: Object detection from RSI

Input:

Geo satellite images

Output:

Object detection in images

Step 1: Take input image.

Step 2: Afterward enhance the given image.

Step 3: After noise removal contrast of the image is enhanced.

Step 4: Compute the feature vector or maps using CNN model.

Step 5: In each feature maps find the road edge candidates using CNN model.

Step 6: Join all road candidates globally in all feature maps.

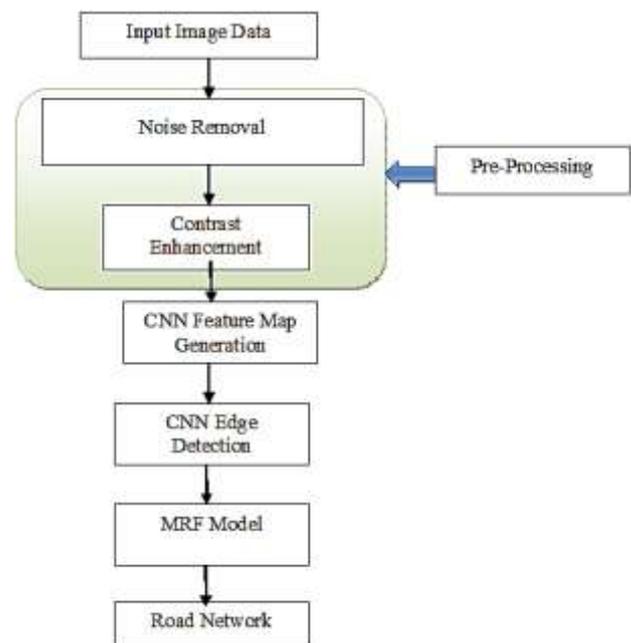


Figure 1: Proposed Methodology Flow Chart

#### A. Input Image Data

In this stage different input remote sensing images of different localities (urban, sub-urban and rural area images)

are taken and testing experiment are performed. The set of input images are of size 256 x 256.

### B. Image Preprocessing

Satellite images often contain noise. Therefore, these images are preprocessed and enhanced before extracting objects. Image enhancement modifies digital images and improves their visual interpretability. The resulting images are therefore more suitable for analysis. Contrast enhancement is one of the image enhancement techniques. It improves the appearance of the object and the brightness between the object and its background.

Low-light images can be generally divided into two categories: global low-light images and local low-light images. Typical global low-light images are mainly generated by low illumination, whereas local low-light images such as backlight images are due to nonuniform illumination.

Equation 4.1 describes the relationship between image irradiance  $E$  and pixel values  $P$  such that,

$$P = f(E) \quad (i)$$

Where,

$f$  = nonlinear function

$E$  = irradiance

$P$  = Pixel Value

When the exposure change, the irradiance,  $E$ , reaching the camera sensor will change linearly. However, in many real time scenarios, the image intensity  $P$  may not change linearly. Therefore, the mapping function between different exposure images may also be a nonlinear function.

With the definitions of above, following equation is evaluated:

$$g(f(E), k) = f(kE) \quad (ii)$$

Where,

$g$  = Brightness transformation function

$k$  = Exposure ratio

According to equation 4.2, the scatter of brightness transformation function is obtained with specific exposure ratio  $k$  using the equation 4.3:

$$g(I, k) = f(kf^{-1}(I)) \quad (iii)$$

Then the enhanced image  $I_{enc}$  can be calculated using spline interpolation methods.

Two-parameter model Sigmoid model calculates  $f(E)$  as in equation 4.4:

$$f(E) = (1 + a) \frac{E^b}{E^a + a} \quad (iv)$$

Where,  $a$  and  $b$  are the parameters for the model

Then according to Equation 4.2, the Brightness transformation function,  $g$ , of Sigmoid is calculated as in equation 4.5:

$$g(I, k) = (1 + a) \frac{k^b I (1 + a)}{(k^a - 1)I + 1 + a} \quad (v)$$

### C. CNN Feature Map Generation and Edge Detection

To combat the issues of fully connected neural network, convolutional neural networks (CNNs) were created and will be used as the foundation of this dissertation. These are a type of neural network which is designed specifically to be used with images, and differ slightly from traditional neural network structure. Another key property of CNNs is that they are not fully connected, where every node in a layer is

connected to every node in the previous layer. There are four main elements to a CNN:

- Convolutional layer
- Rectified Linear Unit
- Pooling layer
- Fully connected layer

#### 1) Road Region Detection

Convolutional neural network is a type of feed-forward artificial neural network, which can extract features for visual recognition tasks automatically. The use of CNN to extract features and detect road candidates is performed in this step. Let  $I(i, j)$  be the enhanced image.

If  $p(i, j) \in R_{area}$

then  $R(i, j) = 1$

else  $R(i, j) = 0$

Where,  $p(i, j)$  = pixel

$R(i, j)$  = Road candidates

$R_{area}$  = Road area

#### 2) Road Edge Detection

Edge detection is the task of identifying object boundaries within a still image. As a fundamental technique, it has been widely used in image processing and computer vision areas. Accurate, simple and fast edge detection algorithms can certainly increase both performance and efficiency of the whole image processing system. Conventional edge detection algorithms rely heavily on gradient computing.

Conventional edge detection algorithms rely heavily on gradient computing [1]. Pixels with large gradient magnitude are labeled as edges. Other techniques, such as non-maximum suppression [6], are usually combined to yield a better result. These methods are all based on the assumption that color or intensity changes sharply on the boundary between different objects while it remains unchanged within one object [9,10]. Unfortunately, this is not always true. Large color gradient can appear on texture within one object while small color gradient can also appear on object boundaries. Having realized the limitation of local gradient cues, this works start to introduce learning techniques when designing edge detection algorithms.

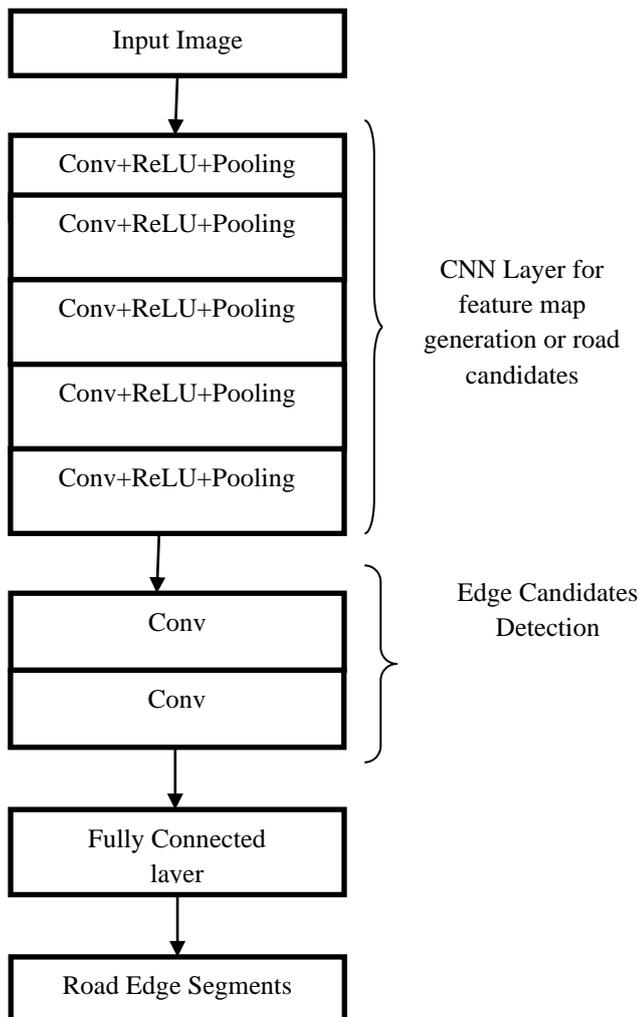


Figure 2: Proposed CNN Architecture for Road Candidate and Edge Detection

Figure 2 provides an overview of proposed road candidate and edge detection system. First the convolution Relu and pooling layers extracts the road region pixels. Then a convolutional neural network scans over the all feature maps generated and making edge prediction for every pixel based on the feature maps. Further, morphological operation is adopted to serve as a post-processing step, rendering a thinner edge map in the final output. Table I shows the CNN model configuration.

TABLE I  
PROPOSED CNN MODEL CONFIGURATION

Layer	Filters	Kernel Size	Stride	Output size
Conv	96	11*11	4	11*11*96
Pooling	N/A	3*3	2	N/A
Conv	256	5*5	1	5*5*256
Pooling	N/A	3*3	2	N/A
Conv	384	3*3	1	3*3*384
Pooling	N/A	3*3	2	N/A
Conv	384	3*3	1	3*3*384
Pooling	N/A	3*3	2	N/A

Conv	256	3*3	1	3*3*256
Pooling	N/A	3*3	2	N/A
Conv	N/A	3*3	1	256
Conv	N/A	3*3	1	3*3*256
Fully connected	N/A	N/A	N/A	3*3*256

D. Markov Random Field (MRF) Edges Joining

After finding the edge candidate regions, MRF model is used to connect the edges into global connection of road. Let S be the set of all possible detected edge segments such that:

$$S = M_i M_j \ S \in A_i^j \tag{vi}$$

Where,

i and j denotes the end points of line segment M.

$A_i^j$  = The possible connection between two segments i and j

Then the graph G is defined such that Each segment,  $S_i$  and  $S_j$ , are linked if they share a common endpoint. The real network is the subset of S. Thus, we can extract network by labeling the graph.

IV. RESULT ANALYSIS

In this research work a database is created using collection of different images from remote sensing images of size 256\*256 pixels to show the performance of proposed algorithm. To evaluate the performance of the proposed system following parameters such as Accuracy, Detection Rate, False Alarm Rate, Precision and Fmeasure are used.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \tag{vii}$$

$$\text{False Alarm Rate} = FP/(TN+FP) \tag{viii}$$

$$\text{Recall / Detection Rate} = TP/(TP+FN) \tag{ix}$$

$$\text{Precision} = TP/(TP+FP) \tag{x}$$

$$\text{Fmeasure} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{xi}$$

Where,

True Positive (TP) = Correctly detected object in image

True Positive (TN) = No object region correctly detected in image

False Positive (FP) = Object incorrectly identified in images

False Negatives (FN) = Object that are failed to be detected in image

The results of proposed methodology are evaluated on different input images the result analysis of some of images is illustrated in Table II.

TABLE II  
EXAMPLES OF PROPOSED METHOD OF EXTRACTED ROAD NETWORK





The results of proposed methodology are evaluated on different input images the result analysis of these images is illustrated in Table II. To evaluate the performance of the extraction on the parameters such as Precision, Detection Rate, Accuracy, Fmeasure and False Alarm Rate are evaluated.

A. Comparative Analysis

In [1] author proposed a hybrid convolutional network using preexisting U-net, for road extraction from aerial images. They propose a model which is a union of a high precision network and a high recall network. Both the networks are based on deep U-net. Massachusetts road dataset is used in the experiments. The results demonstrate that our proposed model outperforms state-of-the-art frameworks in terms of accuracy, precision, recall, and F-score. This network is quite complex in architecture as well as it also generates more processing complexity.

Table III Shows the comparative analysis of different contributions or works that have been presented in road network extraction from RSI. Four different parameters are used to compare the result analysis with proposed algorithm.

TABLE III  
COMPARATIVE RESULT ANALYSIS FOR ROAD NETWORK EXTRACTION

Techniques	Accuracy	Recall	Precision	F_measure
Proposed	99.8	99.17	99.26	99.21
2-step CNN [1]	98.1	87.9	89.3	88.6
U-net [1]	97.6	86.7	88.2	87.4

LR-Unet [1]	97.8	87.1	87.9	87.5
ELU-Unet [1]	97.1	84.5	89	86.7

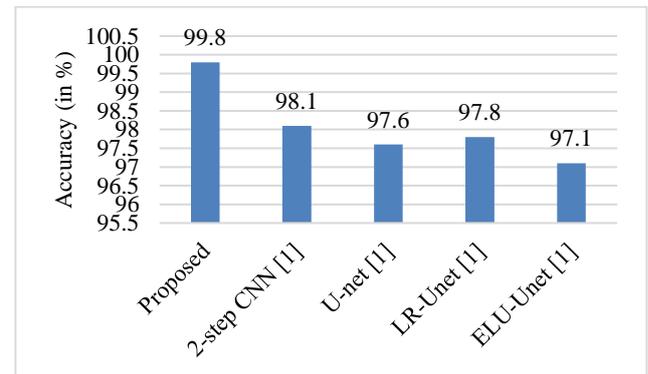


Figure 3: Comparative Analysis of Accuracy

Figure 3 shows the comparative analysis of accuracy of existing work and proposed work. The proposed work shows approx. 1% improvement over existing work.

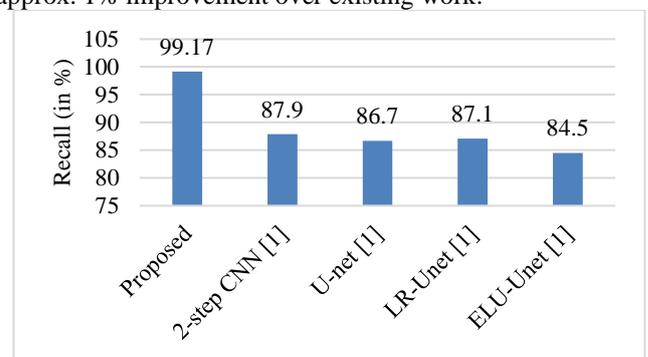


Figure 4: Comparative Analysis of Precision

Figure 4 shows the comparative analysis of recall of existing work and proposed work. The proposed work shows approx. 11% improvement over existing work.

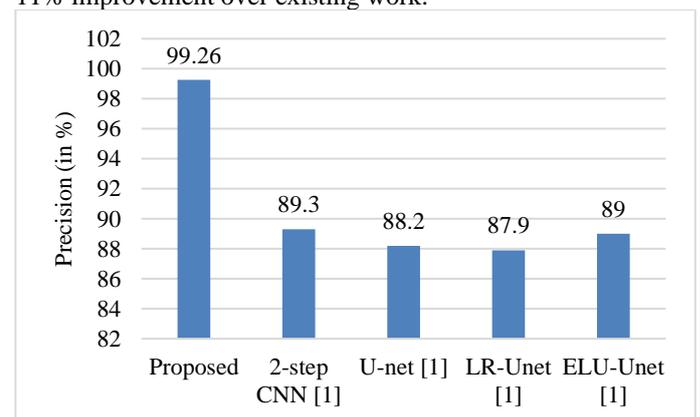


Figure 5: Comparative Analysis of Precision

Figure 5 shows the comparative analysis of precision of existing work and proposed work. The proposed work shows approx. 10% improvement over existing work.

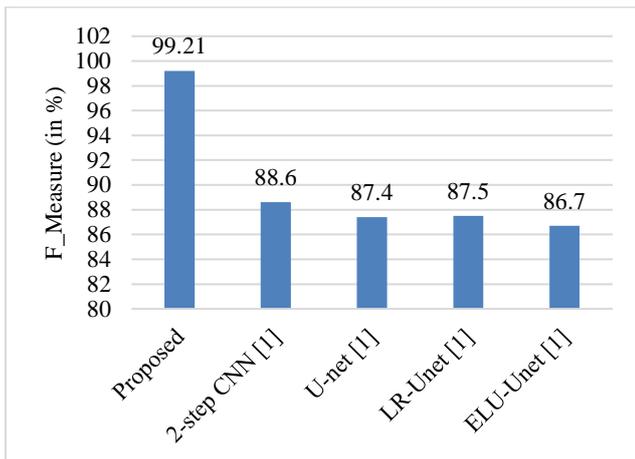


Figure 6: Comparative Analysis of F<sub>measure</sub>

Figure 6 shows the comparative analysis of F<sub>measure</sub> of existing work and proposed work. The proposed work shows approx. 11% improvement over existing work.

## V. CONCLUSION

Road segmentation plays an important role in many cases applications such as intelligent transport systems and town planning. Currently visible in high resolution Remote sensing images are widely used due to rapid development of remote sensing technology. This in high resolution Images represent a new challenge for road segmentation methods because high resolution images have more detail than contain multiscale roads and complex background.

In this research the image segmentation techniques used for image remote sensing are discussed and evaluated. It has been found that there is no perfect method for image segmentation because the result of image segmentation depends on many factors, i.e. Pixel color, consistency, intensity, image similarity, image content and problem area. The main objective of this research is the extraction of road space from the RSI.

The extraction of road networks in remote urban areas of images plays an important role in many urban applications (eg road traffic, geometric correction of remote sensing images in cities, updating geographical information, etc.). Because of the complex geometry of buildings and the geometry of sensor detection, it is generally difficult to distinguish the road from its background.

In this work, a hybrid method is proposed for the extraction of paths from high resolution images based on the segmentation using sigmoid CNN-MRF model. The proposed method includes noise removal and enhancement using brightness transformation function then segmentation of road and non-road pixels using CNN and edges are joined using CNN model also. And lastly the markov random field is used connecting edges with similar end points.

Experiments will be conducted on remote sensing images in urban, suburban and rural areas to demonstrate the proposed method and compare it with other similar approaches. From the result analysis, accuracy is improved by 1% and recall, precision and f<sub>measure</sub> is improved by approx. 11%, 10% and 11% respectively.

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