Road Network Extraction Methods from Remote Sensing Images: A Review Paper

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Remote Sensing images are consists of photographs of Earth or other planets captured by means of satellites, helicopter, rocket, drone etc.. The quality of remote sensing images depends on sensor, camera used to capture images and number of bands. Due to repaid development of technologies made possible to access very high resolution remote sensing images through Quick Bird, Ikonos and many more sources. The applications of high resolution remote sensing images mainly in agriculture, geology, forestry, regional planning, geographic map updating and in the military. Extensive investigation has been proposed to detect road features from remote sensing images. Roads are the backbone and essential modes of transportation, providing many different supports for human civilization. The research of road extraction is of great significance for traffic management, city planning, road monitoring, GPS navigation and map updating. To identify and distinguish roads elements from remote sensing images which have similar spectral characteristics type background objects like buildings, rivers, and trees is a challenging task. This paper presents a summary of various road network detection methods from Remote Sensing (RS) images with respect to resolution of test and training images, accuracy, road features, advantages and limitation of method. It also gives information about recent approaches to extract road network from remote sensing images.

Keywords: Images classification, Image processing, Remote Sensing, Road Network Extraction, Satellite image.

1. INTRODUCTION

Remote sensing images are classified in aerial images and satellite images accordingly the images are taken by aircraft, spacecraft, drone or satellite with specific resolution. Remote sensing images are depends on type of sensor, weather conditions, light variations, spatial resolution, spectral resolution and ground characteristics. This cause the extraction of meaningful target information from Remote Sensing images is a big problem. Increasing research is therefore committed and focused on developing effective methods to extract meaningful features such as roads from digital remote sensing images. The road extraction from RS images provides fast services when any emergency (rescue) operation needs instant maps. Therefore extraction of road network from RS images is a demanding task of research. Various approaches of road network detection from high resolution satellite images have been presented in this paper.
First, paper starts with a brief overview of remote sensing images characteristics and technology enhancement cause to road extraction system from handcrafted features to learning features. After then various road features used to identify road networks. Then after covering different methods of road network extraction with different view point of data set, road features, test samples, methods and resolutions. Then the tabular and graphical results summarize the performance and limitation of the different methods of road detection system and finally paper ending with suggested method to detect road from RS images.

2. FROM HANDCRAFTED FEATURES TO LEARNING FEATURES FOR ROAD EXTRACTION SYSTEM

Preparation of the road network in earlier days is tedious and challenging task if it done manually. The persons go directly to the site in the conventional methods and measure the width of the road, level and plot on the map. This requires a great deal of human resources, time consuming and more money, though less accuracy due to human error and error in the instrument. Because of this problem map is out of date now. So remote sensing overcomes these difficulties and provides fast and cheap solution.

Remote sensing images are characterized by their spectral, spatial, radiometric, and temporal resolutions. Resolution depend on instrument is used to take satellite images and altitude of satellite orbit. High resolution RS images contain more ground details which become the main source for the automatic road network extraction system. However, remote sensing images usually have sophisticated heterogeneous regional features with considerable intra-class distinctions and small inter-class distinctions Xin et al. [2019]. So it is challenging when urban area, lots of trees and building and car on roads cause the shadow problem when remote sensing images are segmented. This problem also observed in high resolution satellite images. In earlier days road network extraction was based on road network knowledge, contour, with threshold function and edge detection algorithm with mathematical morphological operations. However these techniques are not efficient to detect road network automatically in the complex situations. In recent techniques this road network extraction from RS is avoided by two ways. In first method for road segmentation is used with handcrafted features of road images such as color, intensity, edges, surface, line and cornerLee et al. [2000]Vincent and Soille [1991]Wang [1997]Bakhtiari et al. [2017]Anil and Natarajan [2010]. This method is not required extensive training along with low processing time and simple algorithm. However it will work well only on specific condition, pre and post processing required and poor performance under complex environment. Second approached is learning features based in which algorithm learn from large training dataset contains different shapes of roads, types of road, and complex environment. This method improve accuracy for road network detection in extreme condition also but fail to multiple data set collected from different countries and types of road markings and high processing time Cheng et al. [2017] Liu et al. [2018] Shi et al. [2017] Farabet et al. [2012] Long et al. [2015].

3. ROAD NETWORK EXTRACTION METHODS

Road extraction methods have been proposed by several authors from different characteristics of road features. It is divided into two main parts: semiautomatic road extraction methods and automatic road extraction methods Hormese and Saravanan [2016] Wang et al. [2016]. In semi-automatic methods there is a need for some human interface to detect road from RS images such as seed point for road starting. In a fully automatic method, additional information is required for road extract which creates a complex model for road detection. This semi-automatic and automatic method saves time and human resources to a great extent to update spatial road database. Recent surveys of the research papers shows various methods for road extraction system are listed as in Fig. 1

3.1 Knowledge Based Method:

Extracting road from RS image with texture feature and image spectrum is difficult. We need prior knowledge of roads, such as shape of road, gray level and road direction. Moreover, if it is asphalt road then it looks dark then cement road. Therefore gray level value of road pixel should be changed accordingly. So we have to consider average gray level value to distinguish between road and non-road element adjacent with edge of roads. It is also not enough information of grey level of the road but also shape information called elongatendess. Lee et al. [2000] proposed hierarchical multi-scale gradient watershed algorithm to segment 1m- resolution to avoid over and under segmentation problem of watershed algorithm Vincent and Soille [1991] Wang [1997] but

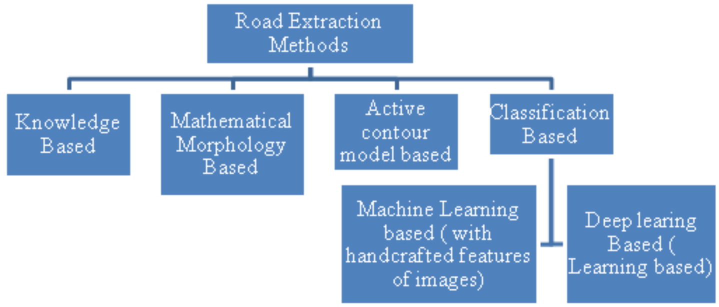

Figure 1. Various methods road network extraction system

this algorithm only works well for straight road only. Shen et al. [2008] used a semi-automatic signature angular texture algorithm to trace roads on a high-resolution Quick Bird images. The proposed algorithm tracks long ribbon roads so it did not fit well in complex scene with much shadow and occlusion.
Review: This method required prior knowledge of road features and it work well in straight road only. For extraction of road, Road seed point information given manually hence automatic road extraction system from remote sensing images is not possible.

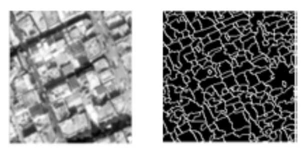

Figure 2. Road network extraction Jingshen algorithm Shen et al. [2008] (a) Original image (b) Road extraction result

Figure 3. Road detection by Gang Xu algorithm Xu et al. [2009] (a) Test image (b) detected road surface

3.2 Mathematical Morphological Based:

Most researchers have concentrated on mathematical morphology technique for the detection and monitoring of images. This method is always employed with any other image segmentation methods.
Bakhtiari et al. [2017] proposed semi -automatic road network detection system on various satellite images form Worldview, QuickBird and UltraCam airborne Images. In this method whole image was classified0020030with SVM (support Vector Machine) and various attributes of spatial, spectral and texture to form a road image. Then morphological operators used to remove non-road noises and pixels, fill gaps in the roads and increase classification accuracy .This method has good accuracy for especially when images of roads are straight, curve, spiral and intersection types. Whenever the road is complex, the accuracy of the method is reduced.
Xu et al. [2009] put method to detect road network of different grades of Google images. First of all, the dual threshold watershed algorithm is used to obtain a road network outline. Multi

weighted operation used to detect edges of the road. Then after, morphological operations used to remove noises and thin lines from images. At last shape index was used to detect the road area. Fig 3 shows result of Gang Xu algorithm for detection of road surface area.
Review: Mathematical morphology method for extraction of road network from RS images is widely used because of its ease-of-implementation benefits. It is used with various types of segmentation methods of image which rely on shape, size and intensity of road network. Due to uncertainly of the structure element, it is difficult to only use mathematical morphology method to obtain high accuracy and good extraction results.

3.3 Active Contour Model:

Active contour model, also called snakes, is a framework in the field of computer vision and was first introduced by Michael Kass, Andrew Witkin and DemetriTerzopoulos (1988). The snake model is popular for the application such as object tracking, recognition, segmentation and edge detection. Conventional snake algorithm is based the minimization on energy.
Anil and Natarajan [2010]described three step method for road network extraction system from RS images. First the image is preprocessed using relaxed median filter to remove the noise by preserving the edges. Then initial seed points on the road were extracted. Finally active snake model used to detect road as shown in Fig. 4

Figure 4. Road Extraction by Anil P N algorithm Anil and Natarajan [2010] (a) Sample Image (b) Extracted Road

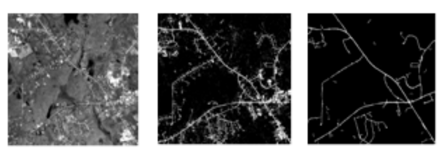

Figure 5. Song and Daniel Method Song and Civco [2004] (a) satellite image (b) after SVM(c) threshold operation on image (b).

Özkaya [2012] proposed Ribbon and Ziplock snake method to extract roads from the Gray level images from Google Map with 1m resolution which is based on traditional snake model. To detect road the author has defined two types of road scenario. First is salient road in which shadows or occlusion of building and trees do not effect. Second types of roads are non- salient roads that were found to have occlusion of buildings and trees. Ribbon snake model was used for salient road detection and non-salient road detection where Ziplock snake was used to detect non -salient road only. Ziplock snake method is developed by changing discrete representation of the conventional snake to decrease false detection range. Ziplock snake initialization step required to identify end points by output of the Ribbon snake method or users. Gaussian filter with different kernel sizes is applied together with ziplock method to smooth the RS images of roads.
Review: This is semi automatic road extraction technique in which initial position of road is given by user which gives preliminary approximation of the feature and hence feature extraction can be done more accurately. So it gives better results for any type of RS images. If the initial points are not given the Interpolation Routine can generate points out of track. The output of

road network extraction system is purely dependent on the Resolution of the images, Input road characteristics and variations.

3.4 Classification Based Method:

The majority of approaches to road detection in recent days Cheng et al. [2017] Liu et al. [2018]use the classification-based methods. Classification based approaches typically use a road's geometric characteristics, photometric characteristics, and texture features Shi et al. [2017]. Classification method-based accuracy for road detection depends on whether the unique algorithm classifies road and non-road pixels with the same spectral characteristics as river,, building block, tree and parking lots etc..
Classification based method for road network detection from RS images divided widely in two group based on handcrafted features and learning features. This method also further categorized by supervised classification and unsupervised classification methods based on training datasets. In Supervise classification methods training the model with labeled training data. Thus supervised method of classification has greater accuracy. Support vector machine, artificial neural network, k nearest neighbor etc. are typically supervised classification methods.

3.4.1 *Based on Handcrafted Features:.* Yager and Sowmya [2003] proposed supervised classification method for road network recognition system algorithm based on Support Vector Machine (SVM) is a classifier for distinguishing road from different surrounding object. Five layer classification–road edges, road edges pair, Linked Road edges pair, Intersection and finally Road network are used to detect low level object to high level object of road. The second level input was given level one output, and so on, and finally canny edge operator was used to detect road edges. The experiment were performed on images with 0.45m / pixel rural area resolution and the proposed method tests performance for level 1 and level 2 and has been given better performance than the result obtained in the clustering algorithm kNN and kMeans.
Song and Civco [2004] suggested a two-step approach to the identification of road network images for urban and rural areas from Ikons based on supervised learning method. First step was to identify road and non-road pixels with SVM and Gaussian Maximum Probability Classifier (GMLC) of the entire satellite image scene. The next step was masked the similar type of road class and region growing image segmentation technique have been used to detect roads regions from same spectral information. Fig 6 shows the visual result of road centerline detection after applied suggested method.
Soni et al. [2020] recommended semi-automatic supervised road network extraction method based on the Least Square Support Vector Machine (LS-SVM) which has better classification performance and easier to deal with complex remote sensing image scene. For obtain 1 pixel thick centerline of road network, the Euclidean distance knowledge property was used. The experimental results showed that the computational time and visual output were better than the methods recently developed. Also proposed approach was inappropriate for such as low resolution RSI, complex road junctions etc.
Various unsupervised learning algorithm such as Fuzzy, Hierarchical clustering are used to classify the image. Some of researcher proposed road network extraction system with Fuzzy inference system. Abraham and Sasikumar [2013] provided unsupervised learning approach for low resolution images by combined a wavelet based watershed segmentation method with fuzzy inference system. Author proposed 11 fuzzy rules to classify the satellite images as road and non-road pixel. The advantage of the method was better road detection performance when low resolution and noisy satellite images.
However, with the use of the post-processing algorithm it may be possible to increase the detection rate of road network to reduce noise in detected images. In the presence of speckle noise, the detection rate of road network extraction percentage is 84, which indicated remarkable accuracy and results shown in Fig. 6.
Review: A variety of supervised and unsupervised leaning algorithms were presented by researcher

to detect road network from remote sensing images. The majority of methods not perform well when remote sensing images have low resolutions further these methods require pre and post processing filter to increase detection rate. Among all methods ,SVM algorithm classify road network with high accuracy.

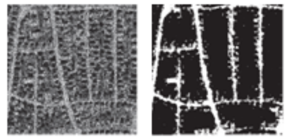

Figure 6. SPOT image (1m) urban area Abraham and Sasikumar [2013] (a) Test image (b) Extracted road network

3.4.2 *Based on deep learning:.* Due to of machine learning, computer vision and image processing is possible to extract road network and road centerline automatically with higher speed, however accuracy is less. This is solved by a deep learning system that is a subset of machine learning approach.

Alshehhi et al. [2017] proposed single patch-based Convolution Neural Network (CNN) architecture for extraction of roads and buildings from high-resolution remote sensing data. CNN consists of five convolution layers and replaces fully connected layers with global average pooling instead(GAP) of Global maximum pooling(GMP) since GAP does not require optimization parameter and over fitting is reduce. As a post processing step, shape feature of Simple Linear Iterative Clustering (SLIC) segmentation was applied to fill gap between segments of discontinuous roads. The proposed method was performed on Massachusetts urban roads data set with resolution of 1 m/pixel and Abu Dhabhi data set with resolution of 0.5 m/Pixel. Fig. 7 shows test images and extracted road network region. The correctness of proposed model obtained 91.7 percentage for Massachusetts Roads dataset and 80.9 for Abu Dhabhi data set. However it require more additional processing step to make more accurate model for road region detection.

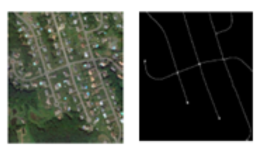

Figure 7. Rasha model for high resolution satellite images Alshehhi et al. [2017] (a) Input image (b) road network and centerline

Liu et al. [2019] suggested four step models for road centerline extraction from high resolution aerial images. Firstly CNN is applied for pixel wise classification of input aerial images. Secondly Edge preserving filter is used to optimize classification results. Then after shape filter, multidirectional morphological filtering and whole filling are used to increase reliability of road extraction system. At last Gabor filters and multiple directional Non-maximum suppression were used to extract road centerline. The disadvantage of this method is single pixel width centerline are not obtained in some complex scenario of road network

Liu et al. [2018] recommended RoadNet architecture to examine road networks from high resolution RS images in complex urban scene. The RoadNet architecture consist of three end to end connected CNN with different task. First CNN detect road surface segmentation which was input to further CNN. Second CNN identify edges of road and parallel third CNN extracted centerline of road images. Proposed methods evaluated on stochastic gradient optimization utilizing a neural network training interface tool, tensorpack which is based on the TensorFlow and distributed machine learning system using a NVIDIA TITAN X GPU with batch size 1 for 200 epochs. The

reported method obtained of single pixel width centerline without any post-processing requirement and also solves occlusion and shadow problem along road regions.
Cheng et al. [2017] proposed a novel deep model, called CasNet, for simultaneous road and centerline extraction by cascaded end to end linked CNNs. Author also contribute urban road data set consists of 224 images from Google Earth. In First step of proposed method is to find consistent road area using CNN in presence of complex backgrounds and occlusions of cars and trees. Then road centerline extraction was done with two class classification problem through a convolution network. Finally thinning algorithm used to obtained smooth, complete and single pixel width centerline of road network. Proposed model is trained in MATLAB by used stochastic gradient descent with the fixed learning rate of 0.01, the dropout ratio was 0.5 and the Momentum was 0.95. Fig 8 and Fig 9 represent the result of proposed method. The benefit of this method was both quantitative and visual performance has been very good by means of results of road detection being smoother and consistent and 25 times faster than the literature reported. The system failed to detect road networks when there is a persistent and wide area of occlusion in test images.

Figure 8. Road are extraction using CasNet Cheng et al. [2017] (a) Sample Image (b) Road Area Extraction

Figure 9. Road Network Centerline Extraction Cheng et al. [2017] (a) Sample Image (b) resulted 1 pixel thick centerline

Xin et al. [2019] applied method for road network extraction from remote sensing images using a DenseUNet model with few parameters and robust characteristics. DenseUNet consist of dense connection units and skips connections, which enhance the fusion of different scales by connections at different network layers. The model accuracy was validated by two dataset namely , the Massachusetts dataset and Conghua datasets. The Conghua dataset's image resolution was 0.2 m and composed of three red, blue, and green bands (RGB). In this dataset were used total 47 images with each image consist of 3x6000x6000 pixels. From this 80%data were used for training and rest of 20% were used for model validation. The proposed model learning with hyper parameter such as batch size, learning rate and batch size was optimized with optimization algorithm with Adam rather than standard stochastic gradient.The proposed model measures road network extraction accuracy through precision, recall, F1 score, Intersection Over Union (IOU), and the Kappa coefficient The respective values were 78.25%, 70.41%, 74.07%, 74.47%, and 70.32% for the Massachusetts dataset and 85.55%, 78.51%, 76.25%, 80.89%, and 80.11% for the Conghua dataset. Suggested architecture effectively reduced the implementation cost of neural network and extract road network with high precision. However this method is failed to extract road edges and contour of road when non homogenous road segments were present.

Wei et al. [2020] proposed multistage framework for simultaneously extraction of road surface and centreline. The method consist of three steps: boosting segmentation, multiple starting points tracing, and fusion. Initially Fully convolutional network (FCN) was used for road surface segmentation then after lighter FCN was applied many times to boost the accuracy and connectivity of the initial segmentation. In the second step , CNN based a modified iterative search algorithm was introduced to detect centreline tracing that starts tracing from multiple intersection points , which were automatically derived from the road segmentation maps predicted from step 1. Finally, fusion method was applied to produce the final refined road surface and centrelines through fusing the segmentation and centreline maps from the preceding steps with OTSU algorithm and thinning algorithm. Suggested model performance was measures with various dataset as the Massachusetts data set, the Shaoxing data set and the Cities data set. The algorithm was implemented based on PyTorch and Adam optimizer was selected as the network optimizer. The suggested method worked well in complex scenario like narrow road affected by occlusion of trees.

Zhang et al. [2018] suggested technique to combines residual learning units to the U-Net for road area extraction. This combination bring advantages of ease training of the network and fewer parameters needed to design a neural network. Author proposed 7-level architecture of deep ResUnet which comprised with three parts encoding, bridge, and decoding. The proposed model was implemented using Keras and optimized by minimizing through the SGD algorithm and tested and training a model on Massachusetts roads datasets. The model was evaluated by breakeven point indicator which is defined as the point on the relaxed precision-recall curve, where its precision value equals its recall value. The method failed to detect roads in the parking lot.

Zhang et al. [2019] develop a four step method to extract road network using Sentinel-1 SAR. This four step method divide in pre-processing and sample preparation, model training and, training optimization, extraction based on the pre-trained model, and model validation and comparison. Optimization of proposed method was done with four optimization algortihm namely, stochastic gradient descent (SGD), Momentum, root mean square propagation (RMSProp), and adaptive moment estimation (Adam). Wang et al. [2020] reported three step method coord-dense-global (CDG) model for road network extraction from Gaofen-2 satellite images and aerial data set images. Lan et al. [2020] Proposed a novel global context based dilated convolution neural network (GC-DCNN) is similar to UNet type encoder decoder architecture

Review: Recently due to high processing hardware easily available deep learning based algorithms are used to detect road network from remote sensing images. . With the emergence of deep learning the Convolution Neural Networks (CNN) improves the interpretation of by learning more discriminative features Ghasemloo et al. [2013] such as structural features of images.

4. COMPARISON OF ROAD NETWORK EXTRACTION METHOD:

Table 1 and Table 2 displays summaries of different road extraction methods using RS images which was discussed detailed in section 2 . Performance of various algorithms is measured with correctness, completeness or overall accuracy. Some of the published work used to measure efficiency of road network extraction system by recall and precision rather than completeness and correctness. Here we converted all summarized method in table 1 with respect to correctness, completeness or overall accuracy. Correctness (precision) is ratio of truly classified number of road pixel (TP) to actual no of total road pixel (TP+FP). Completeness (Recall) is ratio of truly classified road pixel (TP) to the no of pixel which is predicated as road (TP + FN).

We can infer from table 1 that each algorithm has its own advantages and limitations. Fig 10 is the plot and its results of different methods of road network extraction. From the graph we can conclude that it is difficult to obtain remarkable accuracy without using properly trained datasets and different features of the road. It also shows that using classification method we can accurately classify road and non-road pixels as opposed to Active Contour, knowledge-based method, and morphological operator method. Data set with presence of cars on roads, trees and building occlusion, junction of roads and sharp turned road is difficult to train. Using the classification method, we can better train the data set that will give better accuracy for road network extraction system.

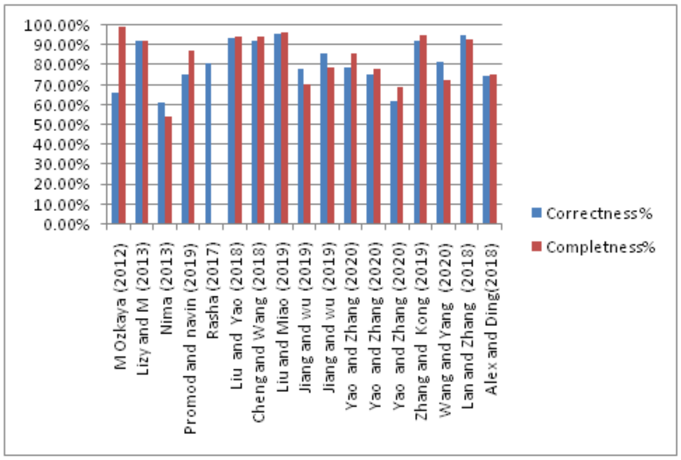

Figure 10. Various road extraction methods performance Comparisons

5. PROPOSED METHOD

Road features such as geometric, photometric and texture features of road are used to set the weight of filter which is used by neural network for classification of road and non road data. For this purpose modified CNN based on UNet architecture would be used to detect road network from RS images. There are lots of various deep learning based architecture are used to train the model for semantic segmentation. The U-Net perform very well in semantic segmentation tasks Ronneberger et al. [2015]. It was originally proposed for biomedical image segmentation. This network is extensively used in image segmentation for two reasons: it is trained from end-to-end and performs well on a tiny dataset. Therefore here proposed novel approach to detect road network based on modified UNet. In the modified UNet ,the encoder section of UNet and Decoder section of UNet was modified respectively. According to previous research, when the number of convolutional layers is increased, the network may extract higher-level image characteristics. Image features extracted are simple when the number of convolutional layers is limited. Here in proposed method binary classification was used extract road features from the background. So it is not required deeper neural network for segmentation. So in the modified UNet number of convolutional layers at encoder and decoder sides should be reduced. The Satellite imagery semantic segmentation applied to road surface detection by Modified UNet. This model will be trained by Massachusetts Roads data set and higher resolution RS images. The model hyper parameter will be optimized by Adam optimizer with cross entropy loss. However the detected road surface network will be given input to the edge detection filter and centerline detection filter to detect edges and centerline of road's respectively. Sometimes to increase model accuracy post processing filters are used to fill the gap between detected edges and centerline of road network. The accuracy of road network extraction model will be measured through Completeness, Correctness. This will be found from confusion matrix by correctly detected road and non road pixels. The proposed method's flow chart of automatic road network extraction and Centerline detection using modified UNet is given in Fig 11.

Paper	Algorithm	Data set name	Resolution (m/pixel)	Road Feature	Road parameter detected	Limitations	Precision (correctness) %	Recall (completeness) %
Lee et al. [2000]	Knowledge based	IKONS satellite image	1	Intensity, Shape	Extract road region	Only work for simple road Method is Susceptible to occlusion and shadows Roads are missing and falsely detected	Visual performance	Visual performance
Özkaya [2012]	Active contour	Google Map	1	Geometric , Intensity	Road edges, road crossing	User interface require	66.13%	98.96%
Bakhtiari et al. [2017]	Mathematical Morphology	Worldview, QuickBird and UltraCam airborne Images	3 cm/pixel, 12.5 cm/pixel	Intensity, texture, color, gradient	Various road types detected such as straight, curve ,spiral and intersection, semi -automatic	When road is more complex accuracy of road detection is reduced	Overall accuracy: 81.8%	Kappa coefficient 78.13%
Abraham and Sasikumar [2013]	Fuzzy	SPOT	1 m 60 cm/pixel	Gradient, mean, deviation, Intensity	Road network extraction	Less detection rate	92%	92%
Ghasemloo et al. [2013]	ANN	SPOT	10	Histogram, Gradient, Texture, Intensity	Junction of road detection	Less accuracy Not detected edges and centerline of road	60.77%	54.31%
Senthilnath et al. [2012]	Hierarchical	Landsat 7 and QuickBird	30 2.4	Gradient, Mean shift, Intensity	Classify images into 6 class	Not detect road surfaces alone	Classification efficiency: 84.7	-
Soni et al. [2020]	SVM	Quick Bird, Tu¨retken	1 1.5	Intensity, mean, edge, shape, geometric	Centerline of road, road surface	Centerline extraction is discontinuous at junction of roads and presence of occlusion	74.9%	87.39%
Alshehhi et al. [2017]	patch-based CNN	Massachusetts And Abu Dhabhi Roads data set	1 0.5	Geometric Photometric Road		It requires additional processing stage to outline boundaries more accurately.	80.9%	

Table I: Comparison of road network extraction method part 1

6. CONCLUSION AND FUTURE WORK

- In the presence of complex environments such as occlusion or shadows of trees and high elevation building, sharp turn, junctions of road etc., it is difficult to obtain accurate and fast road surfaceand edges and from RS images with single algorithm.
- Centerlines are seen to be discontinuous after surveying lots of method to identify centerline when road turns, or intersection takes place. Sometimes, spurs were produced in the centerline of road in the presence of shadows of trees, cars on roads or sharp turn. So it will need a well-trained model to detect single pixel width centerlines.
- Comparing different algorithms, it concludes that using only one type of road feature cannot accurately detect road network. Thus, we should use more than one route feature to detect accurate road network extraction system from RS images.
- Model accuracy to detect road network and centerline extraction also depends on resolution of satellite or aerial images that are used to test and train the road detection model. High resolution road images give us more precise road detection than low resolution.
- Road network extraction system performance depends on collection of training datasets. Classification based approach trained the datasets with complex road structure.
- Multitask and multimodal method of extracting road surface, edges and centerline from RS

Paper	Algorithm	Data set name	Resolution (m/pixel)	Road Feature	Road parameter detected	Limitations	Precision (correctness) %	Recall (completeness) %
Liu et al. [2018]	CNN-RoadNet	Own data set	0.21	Intensity, Semantics segmentation, low level feature, topological, Geometric	Road surface, Road edges, Road Centerline, semi-automatic	User interaction required, Many predicted centerlines are broken	93.6%	94.2%
Mangala and Bhirud [2011]	CNN-CasNet	224 VHR urban data set	1.2	Intensity, Semantics segmentation, Loss	Road surface ,Road centerline, fully automatic	Sensitive to large continuous area of occlusion present in test image	92.14%	94.18%
Liu et al. [2019]	CNN	Massachusetts Roads data set, resolution	1	Intensity, Semantics segmentation, shape, Edge	Road surface, road centerline	Some centerline is not single pixel width	95.70%	96.23%
Xin et al. [2019]	CNN-DenseUnet	Massachusetts dataset Conghua Dataset	1 0.2	Road edges semantics segmentation	Road surface Road edges	method is failed to extract road edges and contour of road when non homogenous road segments were present	78.25% 85.55%	70.41% 78.51%
Wei et al. [2020]	Boosting segmentation[32]	Massachusetts data set Shaoxing data set the Cities data set	1 0.6 60 cm/pixel	topological information semantic segmentation	Road surface Road Centerline Road Width		78.47% 75.19% 61.73%	85.86% 77.75% 69.07%
He et al. [2019]	FCN-CNN	Sentinel-1 SAR images	geometric resolution 20 m × 22 m	Road edges	Regional Road network	Faster but not work well in complex situations	92.13%	95.17%
Yang et al. [2019]	Dense CNN	Gaofen-2 satellite dataset Massachusetts road dataset	1 1	High level features	Coordinate of road edges	When the road is blocked by many trees the proposed method was not work well	81.63%	72.07%
Zhou et al. [2018]	DCNN	CasNet Roadtracer dataset (RTDS)	1.2 1.2	Spatial information Semantic segmentation	Road surface	Average road detection speed	94.86%	92.88%

Table II: Comparison of road network extraction method part 2

images should be constructed to address above problem.
- However an automatic and fast extraction of road network and centerline extraction from RS images is still challenging task.

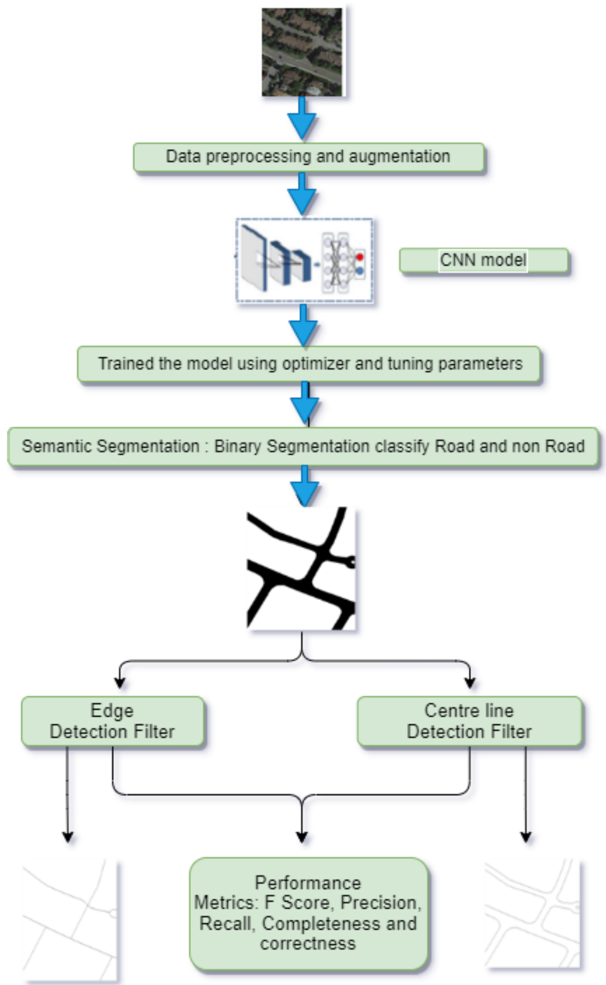

Figure 11. Proposed method for automatic Road network and Centerline detection using Modified UNet based on CNN

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