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# Efficient Transportation System by Automated Road Extraction Model from High Resolution Satellite Images

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***Abstract: -*** A road extraction is a computer vision or machine learning technique created to recognize and classify routes or road sections within a given image or geographic information. Typical applications for these models include navigation, traffic monitoring, urban planning, map production, assisting businesses and governments in decision-making, transportation system optimization, and situational response. As a result, urban planning, transportation, and disaster response are all improved, but still need to improve the processing time and make autonomous process to use in real time. The proposed methodology uses the Mask RCNN Algorithm with improved Resnet backbone architecture to improve the result of road extraction. In this study, the mAP (Mean Average Precision Value) matrix is used to evaluate the accuracy of results. The proposed methodology results show good accuracy as compared to traditional algorithms or semiautomatic algorithms. This study uses the Massachusetts road dataset for result evaluation. The proposed methodology reduces the false detection rate and improves accuracy with processing time cost. The proposed methodology achieved mAP 0.90 for result accuracy, which is better than the traditional methods.

***Keywords:*** Road extraction, Precision, Detection, Segmentation, Image Processing, Traffic Management System

## I. Introduction

Road networks, which promote connectivity, trade, and transportation, are the lifeline of modern civilization in the world that is increasingly urbanizing today. For applications such as urban planning, disaster management, navigation systems, and many others, accurate and current information regarding road infrastructure is essential. In the field of computer vision and remote sensing, road extraction the automatic identification and delineation of road networks from aerial or satellite imagery has become a crucial task. Road extraction models use the capabilities of computer vision, machine learning, and artificial intelligence to identify and map road networks from massive geographic data sources. The time and labour-intensive physical work needed to map and maintain the road infrastructure is significantly reduced by the use of these models. When remote or inaccessible locations need to be rapidly, precisely, and affordably mapped, these models are particularly crucial. Due to the accessibility of high-resolution satellite images, strong computer resources, and cutting-edge algorithms, the development of road extraction models has made tremendous strides in recent years. These models are adaptable tools for a variety of applications because these models can distinguish between roads and other types of land cover, handle different road geometry and terrains, and adjust to different environmental circumstances. This study explores the field of road extraction models in this context, going in-depth into their methods, difficulties, and practical uses. We'll look at the guiding ideas, information sources, and evaluation criteria that went into creating these models, throwing light on how they can alter how we now plan and manage road infrastructure. Road extraction models have a lot of potential for enhancing the design of a more interconnected and sustainable future, whether for urban planning, disaster response, or bettering transportation networks.

The structure of this study is as follows: first section contains Introduction part; second section contain literature review that highlights key theories and findings in literature. Third section depicts the research design and methodologies. The fourth section gives the information about dataset used in this research and fifth section describe results. Finally, section six summarises this research paper and gives idea for future works as well.

Road extraction models can be grouped based on a number of criteria, including the kinds of data used, the methods, and the applications. Typical road extraction model categories are as follows:

### 1.1 Data Driven Models

A. **Satellite Images-Based Method:** These methods rely on satellite imagery as their principal data source are classified as data-based categories. Roads and road networks are frequently found in these photos using computer vision and machine learning techniques.

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B. **Aerial Photography-Based Method:** These methods, like those based on satellite imagery, make use of orthophotos or aerial photos acquired from planes. In general, aerial imagery has a higher spatial resolution and is particularly helpful for extracting urban roads.

C. **LiDAR Data Based Method:** These methods use 3D point clouds of the Earth's surface that are produced by Light Detection and Ranging (LiDAR) data. LiDAR-based models are useful for precise road extraction in difficult terrain because they can capture the vertical characteristics of roadways.

### 1.2 Technique-Based Categories

A. **Conventional Image Processing Models:** These models identify roads in photos by using traditional image processing methods like edge detection, line detection, and morphological operations. They are still used in specific situations even if they are less popular today.

B. **Deep Learning Methods:** Convolutional neural networks (CNNs) models are frequently used in road extraction. As a result of their ability to learn intricate characteristics and patterns from data, these methods are very useful in a variety of contexts.

C. **Segmentation Based Models:** A subset of machine learning models, semantic segmentation models divide each pixel in an image into various groups, such as "road" and "non-road." For fine-grained road extraction, this pixel-level accuracy is helpful.

### 1.3 Application Driven Methods

A. **Urban Road Extraction Methods:** These models concentrate on extracting roads in urban and densely inhabited areas, where road networks are complicated and call for great precision.

B. **Rural Road Extraction Methods:** The landscape in rural areas is frequently more difficult and there are less visible indicators. Models in this area are made to deal with such circumstances.

C. **Methods for Disaster Response and Monitoring:** These models are tailored for removing roadways in the wake of natural disasters or during activities for emergency response. In urgent situations, they put speed and accuracy above all else. Road extraction is crucial for navigational systems and driverless vehicles.

D. **Navigation and driverless Driving Methods:** Models in this category might need high precision and real-time processing capability.

### 1.4 Data Source Categories and Availability

A. **Web Based Methods:** These models are available to a wide range of users since they rely on freely obtainable satellite or aerial imagery.

B. **Customized Data Methods:** Some applications could need specific data sources, such as pictures taken by drones or specialized sensors. Models in this category are frequently customized for particular tasks.

C. **Multi-Modal Methods:** For increased accuracy and resilience, several route extraction models incorporate numerous data sources or approaches. For instance, a model might fuse data from optical and radar sources or combine satellite imaging with LiDAR data.

### 1.5 Scalable Categories

A. **Real-Time Methods:** These models are suited for applications like autonomous vehicles, where low latency is essential, and are tailored for real-time processing.

B. **Batch Computing Methods:** Batch processing models are made for offline or non-real-time applications where thoroughness and accuracy take precedence over speed.

### 1.6 Generalization Type Methods

A. **Geographic region Based Methods:** These methods are explicitly trained for a given geographic region, taking into consideration the unique difficulties and characteristics of that region.

B. **Extended Methods:** These methods are trained on a variety of datasets to handle a larger range of situations and aim for broader applicability.

These classifications show the variety of road extraction models, each adapted to handle particular difficulties and demands in diverse locations and applications. The available data, the desired level of accuracy, and the intended use case are just a few examples of the variables that influence model selection.

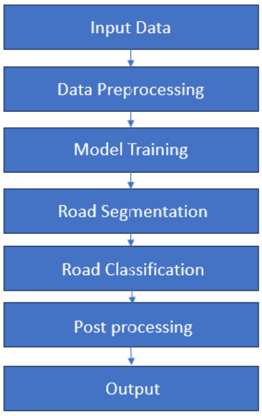



**Fig. 1.** Road Extraction Method Framework

## II. Literature Review

Two criteria road area extraction and road line extraction are used to classify the various road elicitation techniques. Whereas autonomous road extraction strategies concentrate on whole road area elicitation from pictures semi-automatic approaches are employed for lane edge extraction procedures. The "data-based technique," often referred to as classification methods, are an addition to the pre-existing methods for road region retrieval. It is helpful to extract roads from real-time, based on information techniques. Instantaneous updates for applications based on geospatial information systems (GIS) are highly sought-after these days. For real-time updates, data-based techniques outperform manually operated and automatic techniques in terms of quality and accuracy. Cheng et al. [1] suggested a three-stage method for extracting the centre line of a road. First, the homogeneous road area segmentation approach was adopted in this research. It was used both during the precise and efficient road baseline extraction process as well as at intersections of roads. Different vertex cut strategies and cooperative joint visualizations were used for feature extraction. The morphological operator, scalar voting, and optimal inhibition strategies were used to fill in potholes in the roads. The third phase explained the fitting-based centre line algorithm for identifying junctions on roads. The graphical performances are excellent. Additionally, this technique performed better in a dynamic data context.

The Otsu's approach was put out by Jayaseelia et al. [2] to figure out the minimum threshold, and the support vector computation is then employed for categorizing the items to be classified. This strategy utilizes multiple cutoff metrics for division compared to just one criteria value. As utilizing a single criterion cannot produce an appropriate result for categorization, certain studies articles concentrate on the multi-level cutoff value strategy. Making assumptions about the correct the limit of the attribute or figuring out the maximum value are two difficulties in finding multi-level limits. The research employed GPS data for categorization and segmentation strategies and utilized multiple algorithms to determine various attribute limit values. Sghaier et al. [3] based on characteristics road scene extraction techniques included numerous phases. To extract road features, this research encompassed texture assessment, geometrical operators, and broad beam-let shift. Geographical data from texture assessment was effectively obtained to identify motorways with proportional pavements.

The three methods utilized by Hui et al. [4] in their SRH Li-DAR procedure were organizational merging and efficiency, rotational area, and deviation levelling. The evaluation of accurateness and quality was done using three criteria. The road image extraction technique was simplified down to several stages by Alshehhi et al. [5]. Initially characteristics were extracted using structural processing. The graphic clarity was improved using the technique known as the Gabor approach. The final phase involved breaking down images using image characteristics and cleaning them up with a further processing method. Using a single hidden layer and a back dissemination network, Mokhtarzade et al. [6] applied their method. The dynamic technique was employed in this study to reduce the erroneous learning rate. For envision improvement, Reddy et al. [7] used the Bot-Hat inversion and an equation-based morphological function. To predict the seed point and duration of the excursion, Etten et al. [8] applied an adaptive learning technique using off-nadir images from satellites as data. This work used the Res-Net 34 encoder and U-net decoder framework to generate a deep learning model using a multiple interfaces activation mask. Pre-trained data sets respond well to this technique. Multi-resolution delineation and the use of the fuzzy rule classification technique were employed by Yadav et al. [9]. In this work, the accuracy of the approach was assessed using a dataset of pan-sharpening photographs.

Wagh et al. [10] proposed the geographical texture element was incorporated into the finding of urban roads using an approach based on information that was developed and suggested. The regional Moran's equation first obtained the geographic texture characteristic, and the resultant image was next applied to the image's band spectrum for segmenting the image. The prediction and verification model were then created using parameters including intensity, median deviation, rectangularity, dimension ratio, and size that rely on road information. Last but not least, roads are retrieved using the verification and the prediction model. Pan et al. proposed [11], extract roads from remote sensing photos, this article suggested a new context-augmentation and self-attention encapsulated comprise pyramid structure (CS-CapsFPN). The proposed CS-CapsFPN can extract and fuse various levels and scales of high-order capsule aspects to produce an excellent resolution and semantic robust graphical representation of features for forecasting the road area images. This was done by constructing an enclosed feature pyramid network framework. The suggested approach CS-CapsFPN utilized numerous scales spatial qualities at a high-resolution image's viewpoint and stress channel-wise descriptive characteristics to additional increase the characteristic representation strength by incorporating the context-augmentation and self-attention modules to function.

Maboudi et al. [12] proposed an object-driven image processing (OBIA) method, where road features were analysed. The ant colony optimization (ACO) approach was introduced for tackling the road structure finding challenge incorporated object-driven data as intuitive knowledge. For the purpose, to reduce street empty spaces, an updated neighbourhood specification in the area of objects was implemented. The resulting definition altered the phase change rule. Additionally, a creative desirability procedure for ACO was created to successfully identifying the road substances. The results of the study shown that the suggested technique for extracting roads from VHR photos was effective. Park et al. [13] proposed a template matching based algorithm to detect road from an image. This study used manual input to provide seed point for each road segment then orientation of road was calculated by burns line extraction algorithm. Gruen et al. [14] integrated a dynamic programming-based model linear character extraction technique with the use of wavelet decomposition for road smoothing. Semi-automatic refers to the process of extracting a road automatically following the human being has manually defined some seed points by clicking a mouse using an easy-to-use dynamic image-graphics the user experience. By choosing a certain wavelet, a wavelet transform can be applied in order to improve intriguing visual structures and produce a multiresolution description. Mathew et al. [15] highlights the transition from conventional manufacturing methods to concepts of the smart industry and sets the foundation for understanding the crucial role that AI plays in supporting these principles. Kumari et al. [16]By integrating flexible, intelligent robotics into logistical and manufacturing processes, it seeks to support Industry 4.0's objectives for smart automation and digital transformation.

**Table 1:** Comparative Analysis of Different Road Extraction Methods

| Reference No. | Algorithm | Strength | Limitation |
|---|---|---|---|
| [1] | FMCR, Graph Cut and NMS Method | Smooth Road network extraction | Ineffective for occlusion condition |
| [2] | Otsu's technique based on numerous cutoff criteria | Appropriate outcomes for segmentation are obtained by the use of numerous threshold amounts. | Calculating the attribute's highest possible value or assuming the appropriate value for the threshold |
| [3] | Used texture analysis and beam let transform. | Small spaces can be efficiently filled in | Prolonged execution time |
| [4] | The SRH Li-DAR approach is built upon three algorithms: the hierarchy-based fusion and optimizer algorithm, the rotating nearby individuals' strategy, and the skewness adjusting algorithm | Accuracy, comprehensiveness, and excellence | Low centre-line accuracy as a result of big holes brought on by vehicles and gloomy trees |
| [5] | Based on a hierarchical graph, segmentation method | Effectively reduces image noise and performs | Work on multispectral and infrared imaging is required |

| | | | |
|---|---|---|---|
| | | admirably for shadow effects | |
| [7] | MRF | Improve the time and cost outcomes of road digitalization | Experience occlusion-related problems |
| [9] | OBIA | Both the picture segmentation outcomes and the speed of computation are great | Work needed for the intricate road framework |
| [10] | Uses spectral and geometry data derived from principal component evaluation; the suggested method is a knowledge-driven strategy | Eliminate interference from images with efficiency | Showing a short section of shattered road |
| [11] | The segmentation algorithm employed is referred to as k-means grouping. Images are divided into multiple groups according to level of intensity | Road structure trajectory-efficient method for clustering | K-value hypothesis for Scaling |
| [12] | Swarm intelligence-based methods | Due to the concurrent processing of attributes, produces superior outcomes. | Obstruction problem failure |
| [13] | According to template alignment, the proposed method used a certain geometry frame for comparing | leads to more accurate highway surveillance | Reliant on dimension, orientation and sensitive to changes in geometry and orientation |
| [14] | Emphasizes the usage of an adaptive programming-based approach using a maximal measurements merit factor | Find the most effective outcomes | Identifying a subproblem's response iteratively could result in a long phase of processing. |

## III. Proposed Methodology

A deep learning framework that combines recognition of objects with instance segmentation is designated as Mask R-CNN. It is an advancement of the framework known as Faster R-CNN. Mask R-CNN is a novel system since it can separate instances pixel-by-pixel in addition to detecting objects. To do this, an additional "mask head" stream is introduced, which creates accurate segmentation masks for every object that is recognized. This makes it possible for precise and thorough instance segmentation with coarse-grained pixel-level limits. The integration of ROI Align and Feature Pyramid Network

(FPN) into Mask R-CNN constitutes two important advances. By utilizing bilinear interpolation throughout the pooling process, ROI Align overcomes the drawbacks of the conventional ROI pooling technique. Enhancing the precision of segmentation is possible by reducing incompatibility problems and guaranteeing precise spatial information extraction from the input attribute map.

This Study uses Mask RCNN algorithm for extracting road. The more sophisticated Mask R-CNN detection algorithm has been created on top of convolutional neural networks as a base. Mask R-CNN was the main algorithm employed for this study. Convolutional layers, the underlying structure of which provides the starting point of the CNN algorithm, are at the basis of convolutional neural networks. The aforementioned convolutional layers carry out the convolutional procedure. During this procedure, an image is divided into pixel matrices with predefined dimensions. Following completion of this step, a weight is constructed to identify an attribute of an object that has to be recognized. Then, to get a single value, the weight and pixel matrix's sum of products are added. The remaining pixel matrices, including overlapping ones, are subsequently subjected to the filter. A pooling layer is then applied to the feature map once the feature map has been retrieved.

Since feature maps consider where an identified feature is located, the algorithm will link the recognized feature to its location, which will result in erroneous object identification. This is avoided by the pooling layer, which examines the feature map and reports if an element is present at a certain point on the map. The pooling layers function similarly to the filters mentioned above, working across a limited area of a feature map to find the key features that are present. This is done to drastically reduce the size of the feature map, which will then enable the algorithm to run more quickly. In order to considerably reduce the size of the image, the average pooling layers determine the average values of the convolutional layer outputs that are present in a certain region. The original feature map is also reduced in size as a result of the highest aligned pooling layer's recognition of the convolutional layer's maximum output values and reporting them on an updated map. The convolutional and pooling layers in CNN repeatedly exchange information, which is condensed and converted into a single matrix by the fully connected layer. The final output vector is further processed by a fully connected layer, which builds a prediction of the object in the image. Mask R-CNN's core components comprise the Region of Interest Align layer, which predicts segmentation masks for the chosen ROI and uses Feature Pyramid Networks (FPN) to do so. The addition of the ROI-Align layer to the recognition process and the segmentation masks outlined above distinguished Mask R-CNN from CNN.

For tasks like object detection, instance segmentation, and others, feature pyramid network (FPN) is a common network design. It facilitates the management of items at various scales and enhances the spatial resolution of feature maps. The proposed study uses FPN 101 as a backbone architecture. Many object identification models, including Faster R-CNN, YOLOv2+, and others, depend heavily on a Region Proposal Network (RPN). Its main goal is to produce potential object bounding boxes or regions of interest (RoIs) from an input image that might include objects. For additional processing, such as object classification and precise location, these suggested regions are subsequently forwarded to successive layers. In order to extract feature maps of different scales, the input image is fed through a convolutional neural network (CNN), often a deep architecture ResNet 101. An array of predetermined anchor boxes—also known as anchor regions or anchor windows—are used by the RPN. The sizes and aspect ratios of these anchor boxes vary. These anchor boxes are densely scattered across the feature map in various spatial locations and serve as prospective object candidates. In order to eliminate anchor boxes that are heavily overlapping, the RPN uses non-maximum suppression. This action lessens redundancy in the suggested regions. The last anchor boxes with high abjectness scores after NMS are taken into consideration for region suggestions, or RoIs.

In order to evaluate the performance of the algorithm by comparing the projected outcome to the expected outcome, a loss function is essential to neural networks. Losses resulting from classification and localization and mask, are all taken into consideration by the loss function used by Mask R-CNN. In equation (1) L shows the loss and $L_{Classification}$ represent the classification loss during identification of object, $L_{Localization}$ loss shows bounding box location around the object. $L_{Mask}$ is related to the masking or segmentation where IOU value should be grater then the redecided threshold value, which is in our experiment in greater or equal to 0.5.

$$L_{Total\ Loss} = L_{Classification} + L_{Localization} + L_{Mask} \quad (1)$$

Mask RCNN model is trained on google colab pro+, where batch size is 16, warm up learning rate is set to 0.001, training iteration is 32000, anchor aspect ratio is 0.25, 0.5 and 1.0.

Threshold value for this experiment is 0.5. if intersection over union value is greater than threshold value then object will consider otherwise its discarded. The recall and precision matrices are used to evaluate the model quality for that application. For calculating recall and precision value equation 2 and 3 are used respectively.

$$R\ (Recall) = \frac{TP}{TP+FN} \quad (2)$$

$$P\ (Precision) = \frac{TP}{TP+FP} \quad (3)$$

True Positives (TP) are occurrences of road that have been correctly recognized as such in the two equations above. False Positives, or FPs, on the other hand, are situations in which the algorithm incorrectly recognizes a result. Basically, recall measures the algorithm's ability to detect road regularly and properly in the image, while precision measures how precisely the model can identify road.

## IV. Dataset

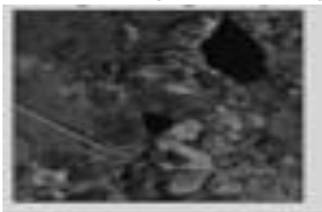
Each image in the Massachusetts Roads dataset has a resolution of 1,500 pixels, making it possible to create train, validation, and test sets with 1,108, 14, and 49 images. this study resizes each image to 512 by 512 pixels after filling each one to 1,536 by 1,536 pixels. The Massachusetts Roads dataset has partially obscured a portion of the image to enhance the model's capacity for generalization. To remove the portion of the photos in train sets that is obscured by the cropped image since it is fully covered. Following a sequence of operations, 21782, 126, and

443 images corresponding to the train set, validation set, and test sets with a pixel size of 512 by 512 are eventually present in the processed dataset of Massachusetts Roads.

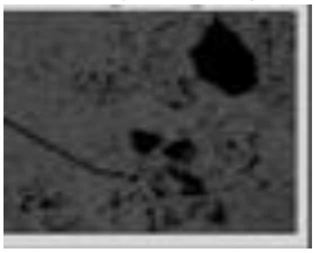
## V. Results

The algorithm typically worked well to locate instances of road stress. The proposed method achieved mAP (Mean average precision value) value 0.90, Val accuracy is 0.50. In the proposed method for experiment used number of epochs is 50 and batch size for image dataset is 16

(a) Original Ariel Image



(b) Grey Scale Image



(c) Edge Image

(d) Road Segment Image

**Fig. 2.** Shows the: (a) original image (b) gray scale image(c) egde of the image (d) road segment Image

Figure 2 shows the results, where fig. 2(a) depicts the original image, fig. 2(b) shows the converted grey scale image, Fig. 2(c) shows the edge of the image, which represent the reduce noise in resultant image and 2(d) shows the road segment image.

## VI. Conclusions

The researchers want to take steps in the future to enhance the current model and offer higher-resolution photos of road for the algorithm's training in order to produce more accurate findings. This might be done by utilizing satellite imaging for detecting road. Furthermore, given the rapid advancement of computer vision algorithms, it's feasible that the present Mask R-CNN strategy will be replaced by a quicker and more effective approach to object detection. The development of a real-time detection system to identify road in real-time may be considered by researchers looking to improve this model. With its pixel-level segmentation capacity, Mask R-CNN can extract roads with great accuracy. Even in complex situations with a variety of road kinds, lighting conditions, and obstructions, it can generate precise outlines of road sections. Road extraction tasks can be honed using pre-trained models on sizable datasets like COCO or ImageNet, which eliminates the requirement for enormous, annotated road datasets and reduces training time. Map generation, traffic analysis, autonomous vehicles, and other applications can all use road extraction models based on Mask R-CNN. The proposed study reduces the noise to extract road network but still need improvement for complex road network and processing time cost.

## VII. Acknowledgment

There is no conflict of interest in this paper.

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