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ROAD EXTRACTION FROM SATELLITE IMAGERY USING DEEP LEARNING VOL - I

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Abstract - Road extraction involves the intricate process of generating road maps automatically through deep learning algorithms. This task, particularly from satellite imagery, presents significant challenges due to various factors like occlusions, shadows, noise, and fluctuating illumination conditions. As a result, achieving complete and accurate road extraction is daunting without relying on manual annotations or imperfect road maps for guidance. One potential strategy to enhance road extraction accuracy is by incorporating partial road maps as supplementary data. These partial maps, sourced from platforms like OpenStreetMap or Google Maps, may not offer complete or pristine representations of roads but can still provide valuable additional information. By integrating these partial maps with satellite images, we can exploit their complementary nature to mitigate uncertainty in the extraction process.

It's important to note that while road extraction may be relatively straightforward in some regions, such as rural areas, it becomes significantly more complex in urban or underdeveloped areas. These environments present unique challenges that require sophisticated algorithms and approaches to accurately extract roads from satellite imagery.

Key Words: Road Extraction, Satellite Imagery, Google Maps, Open Street Map, Auxiliary information, Disaster management, Occlusions, Illumination, Annotation, Shadow.

1. INTRODUCTION

Utilizing high-resolution satellite images for generating top-quality imagery from space introduces groundbreaking opportunities in automatic feature extraction. Mapping and extracting features from these images are fundamental operations for updating maps. While digital maps provide a foundation for inference, refining and optimizing road topology often rely on aerial photographs or high-resolution satellite imagery. In recent years, there has been significant interest in automatic inference through remote sensing data. Automatic feature extraction has emerged as a crucial objective to streamline data processing, saving valuable time. High-resolution satellite images play a vital role in extracting and processing road networks, facilitating the creation, improvement, and updating of urban road databases.

However, automatic extraction of such features encounters limitations, especially in urban environments, due to the complexity and noise present in the scenes. Polyline and edge detection algorithms face challenges in accurately extracting features in these settings.

2. OBJECTIVES

The focused objective for developing this system is:

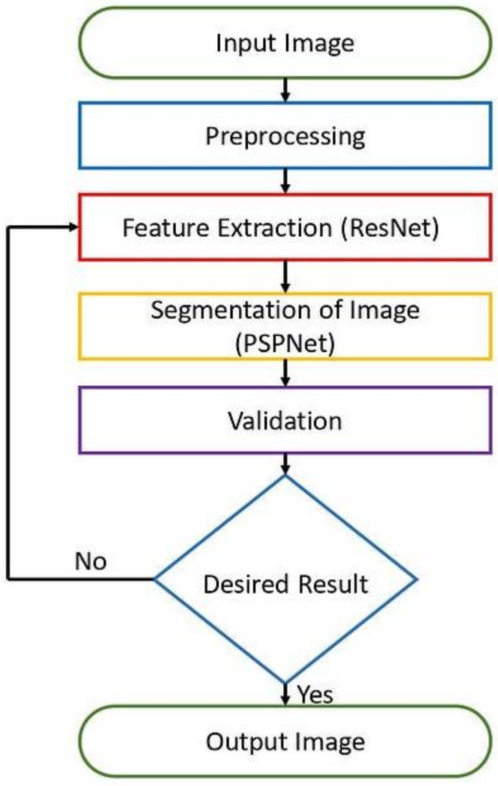
- ✓ To increase the correctness and efficiency of road extraction model by using advanced deep learning techniques.
- ✓ To train the model using large dataset of the study region.
- ✓ The functionality of model depends on its training dataset.
- ✓ To use segmentation for the dataset to grouping pixels in an image based on their color and shape characteristics.
- ✓ To generate an output based on a raster function input.
- ✓ The output raster format can be TIFF, GRID, ERDAS IMAGINE, MRF (Meta Raster Format) or CRF (Cloud Raster Format).

3. PREVIOUS WORK

- The recommended Road-RCF model of road data derivation gives lots of profit from the recent success of the RCF network model.
- The architecture of the RCF network model is based on the moderation of the VGG16 (CNN model that supports 16 Layers) network.
- The Road-RCF network model rejects the fully connected layer, and uses the deconvolutional layer for up-sampling to reimpose the real image size. This technique enables input images to be flexible in size, and finally maintains the corresponding size of the classification image.
- Automatic threshold segmentation can convert grays cale images into binary images based on the distribution of gray values.

- Predicted from the network based on the road map (g rey map) dataset full of "shadows".
- The reason for the shadows is the increase in the performance of the integration and communication receivers and the decrease in the resolution of the slow-looking image.

4. SYSTEM ARCHITECTURE



The system architecture consists of:

Modules

- Input Raster (preferred .tiff)
- Preprocessing (model training)
- Segmentation
- Validation
- Output Raster Generation

Module Description

❖ Input Raster:

Input raster in is a term that refers to a raster dataset that can be used as an input for various raster analysis tasks. A raster is a type of data that represents continuous or discrete values in a grid of cells, such as elevation, temperature, land cover, or imagery. Raster data can be stored in different formats, such as GeoTIFF, JPEG2000, or NetCDF.

❖ Preprocessing:

Model training is a process of creating and using deep learning models to perform various tasks such as object detection, pixel classification and objects classification. Deep learning models are computer models that are trained using training samples and deep learning neural networks. Training a deep learning model can be very critical, as it requires large quantity of data, computing resources, and knowledge of deep learning and its libraries.

❖ Segmentation:

Segmentation is a process of grouping pixels in an image based on their color and shape characteristics. It is a key component of the object-based classification workflow, which allows you to extract features from imagery that have certain attributes. Segmentation can be used to create segments, which are super-pixels that represent objects of interest. Segments can then be further classified into classes that correspond to real-world features on the ground.

❖ Validation:

You need to validate your model if all processes in the model have been run and you want to run them again. Validation rules specify permissible attribute configurations and general relationships of a feature. Validation means checking that all tool and parameters are correct and providing benificial messages if they are not. Validation is a very vital step in the full process

❖ Output Raster Generation:

Output raster generation is the process of creating a raster dataset from an input raster function or function chain. You can use the Generate Raster From Raster Function tool to perform this task. This tool is designed for raster processing using multiple threads to help speed up the processing. The output raster format can be TIFF, GRID, ERDAS IMAGINE, MRF (Meta Raster Format) or CRF (Cloud Raster Format)

5. DATA FLOW DIAGRAM

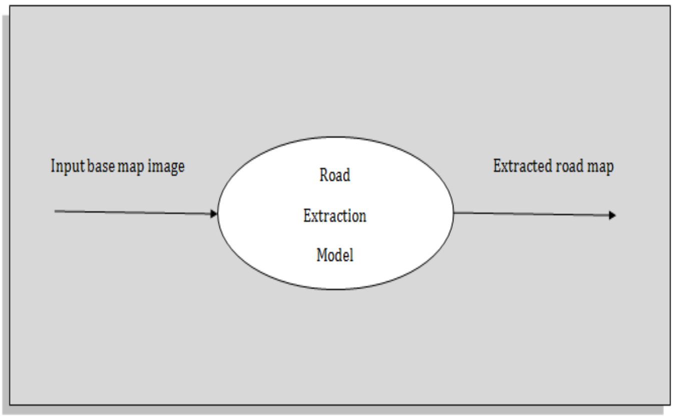


Fig: DFD level 0

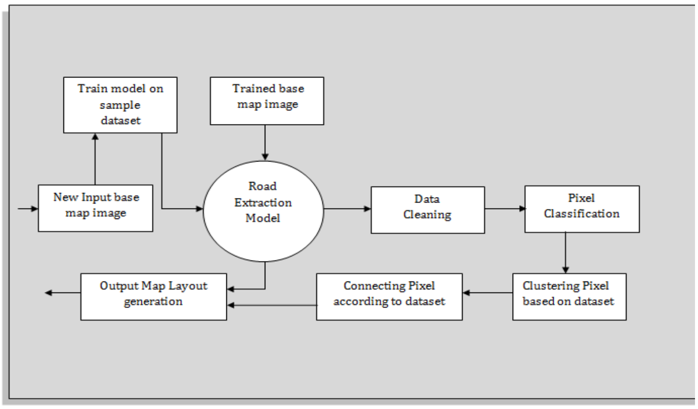


Fig: DFD level 1

6. PROBLEM STATEMENT

To implement model using Deep Learning for Extracting Road using Satellite Imagery as a raster. As its not that easy to extract roads because the quality of datasets are affected by noise and shadow. These factors can make it hard to distinguish roads from other objects or backgrounds in the image.

The road network structure can vary depending on the type of road (asphalt, gravel, sand), the terrain (flat, hilly), and the season (snowy, rainy). These variations can affect the shape and width of roads in different images. The appearance of roads depends on the spatial resolution of the satellite images. Higher resolution images can provide more details and accuracy, but they also require more computational resources and storage space.

The images of different resolutions or different levels of image features (low-level features, high-level features). The purpose of feature fusion is to explore how to effectively utilize these multi-scale images to obtain more accurate road feature information . The model of multi-scale feature modules often implements an inspiration from parallel or serial multi-branch network structure, such as feature pyramid networks (FPNs) , Inception, and HRNet.

This part provides an abstract of the multi-scale feature fusion modules and methods employed in road image segmentation tasks. Researchers have utilized supervised learning by combining edge information with image features to enhance road image segmentation networks. Various module designs have been proposed to address issues related to extracting road shapes and enhancing connectivity, such as the multi-scale context augmentation module, spatial context module, and feature review module .

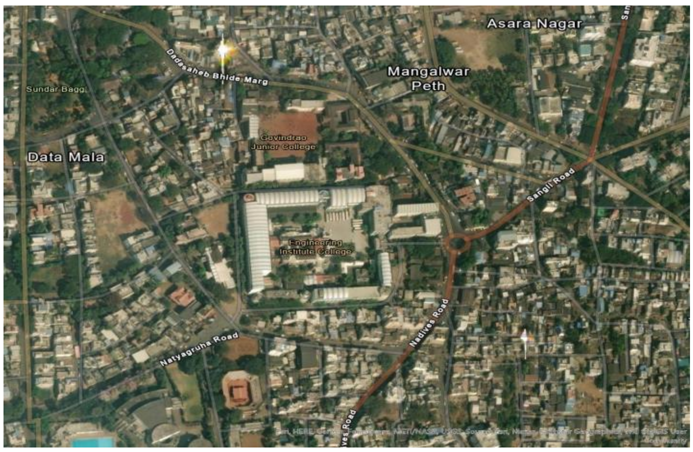


Fig:- Sample Input Image

Fig:- Sample Output Image

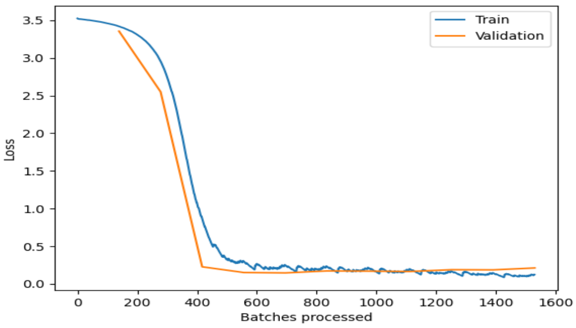


Fig:- Loss Graph of model

7. CONCLUSIONS

High-resolution satellite imagery serves as a critical input for extracting road networks in the creation, refinement, and updating of urban road databases. However, the complexity of urban environments and the lack of clarity in datasets pose significant challenges to automated feature extraction using traditional line and edge detection algorithms.

To address these challenges, we are actively developing a model based on deep learning techniques for road extraction. This approach holds promise as it can effectively overcome the limitations of traditional methods by leveraging the power of deep learning algorithms to extract roads from satellite imagery accurately.

Moreover, the development of such a model is particularly advantageous for applications in India. Given the unique characteristics and challenges of Indian datasets, having a deep learning-based road extraction model tailored to these specific conditions can significantly enhance its performance and utility. Therefore, not only does this model offer a solution to the challenges of urban road extraction, but it also promises to provide valuable insights and applications for Indian datasets, further contributing to various purposes such as urban planning, transportation management, and infrastructure development.

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