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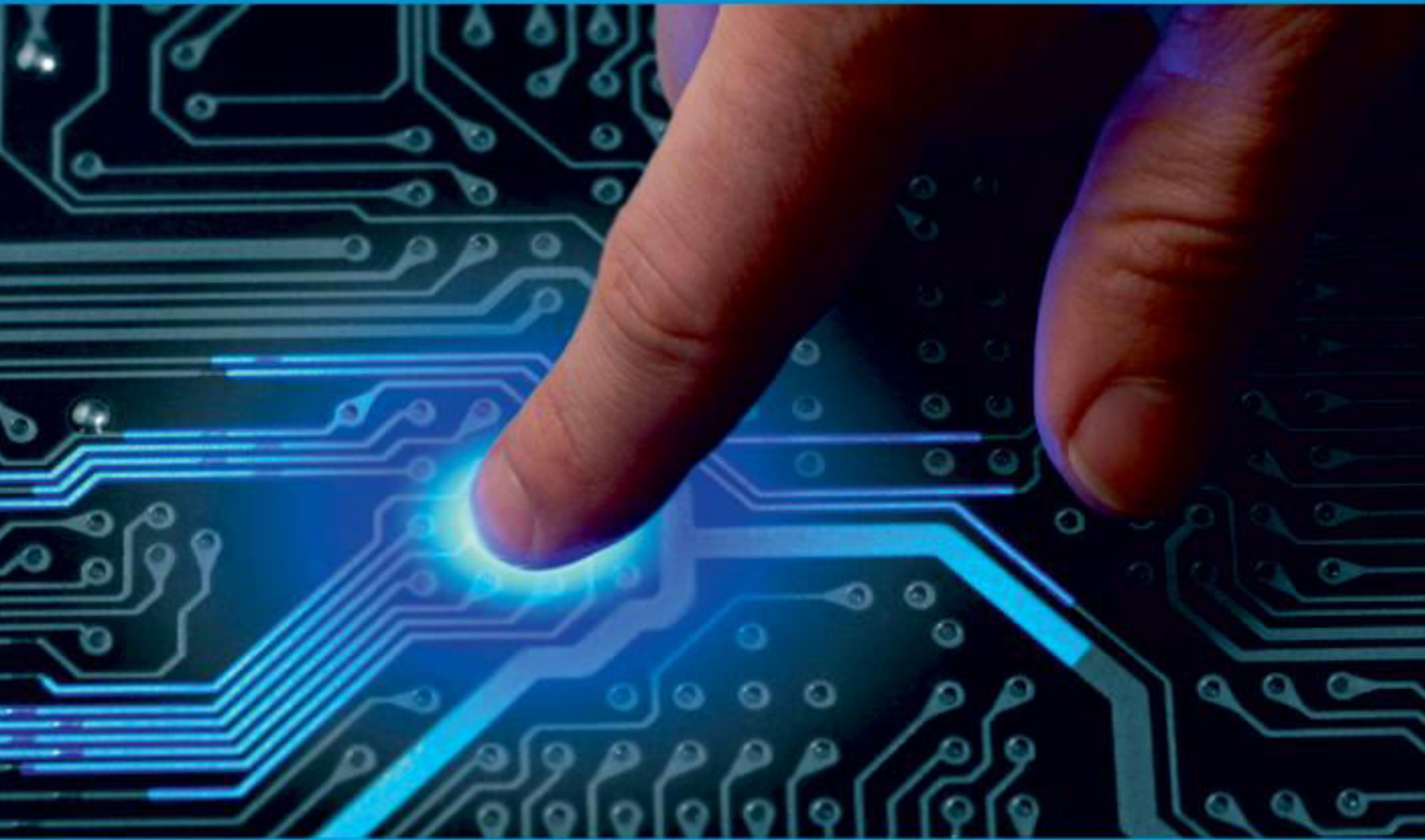

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Segmenting Roadways from Satellite Imagery

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ABSTRACT: As lack of knowledge about the road architecture can lead to delays in emergency services. With the rapid development of the economy, construction and alteration projects of roads are becoming increasingly frequent, so there is an urgent need for methods for rapid updating of road information. Interconnectivity in rural and semi-urban areas is required to understand progress of road construction. Poor road conditions halt the development of many expansion projects and industries.

The objective of our project is to extract roads from high-resolution satellite images. We plan on training and comparing the results of multiple image segmentation models to see which one is best suited for our task.

KEYWORDS: Semantic Segmentation, Road Extraction, U-Net

I. INTRODUCTION

Accurate and up-to-date information on the location of roads is an increasingly fundamental dataset for a wide range of planning, emergency response, conservation and research activities. However, the routine mapping of roads is often lacking, especially in more rural and forested regions where roads are often unpaved. Even small changes in rural road networks can have large impacts on human well-being like access to markets and availability of essential services. There is an urgent need to monitor the road development projects in these regions and update the corresponding road information and it is not fulfilled by the existing cartographic techniques.

Objectives

- To facilitate faster ways of updating the existing databases and monitoring for changes with minimal or no human involvement.
- To organize the satellite data along with the tags for all the required regions.
- To test the designed network on a systematic basis to evaluate the performance and decide the fitness of the model for real-time deployment to generate the entire road way map of India.

Purpose:Our project helps in identifying the network of road architecture from satellite imagery. Road information plays an important role for the development of any area. The vast amount of satellite data available can be used to extract any updated road information.

Scope:The scope of the project is to extract road information from satellite images. We use deep learning techniques to achieve our task. Multiple variations of the CNN architecture like FCN, U-Net can be applied to extract the road information. We can achieve a binary segmentation map from the input satellite images denoting the roads and the non-road classes.

Motivation: The motivation of the project came mainly from the visible lack of road infrastructure knowledge in rural India. Due to lack of this information, people living in semi-urban areas face a lot of connectivity problems and they often miss out on essential services. We had a scope for reducing their plight by proposing a solution with the help of technology.

II. RELATED WORK

Drawbacks of Existing System

- Existing data collection methods are currently insufficient to properly capture either underserved regions or the dynamic changes inherent to road networks in rapidly changing environments.
- While satellites in theory provide an optimal method to rapidly obtain relevant updates, most existing computer vision research methods for extracting information from satellite imagery are neither fully automated nor able to extract routing information from imaging pixels.

Problem Statement:"To create a web application which semantically segment roads from high resolution satellite images and thus prevent manual updation of existing road databases."

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III. PROPOSED ALGORITHM

Our aim is to extract roads from high resolution satellite images. This can be achieved by performing a semantic segmentation of the given input image. Semantic segmentation generates a pixel-by-pixel classification of the input and can be achieved through deep learning algorithms. We propose the use of modified CNN algorithms like FCN and U-Net to achieve semantic segmentation of roads in the input satellite images.

System Design:

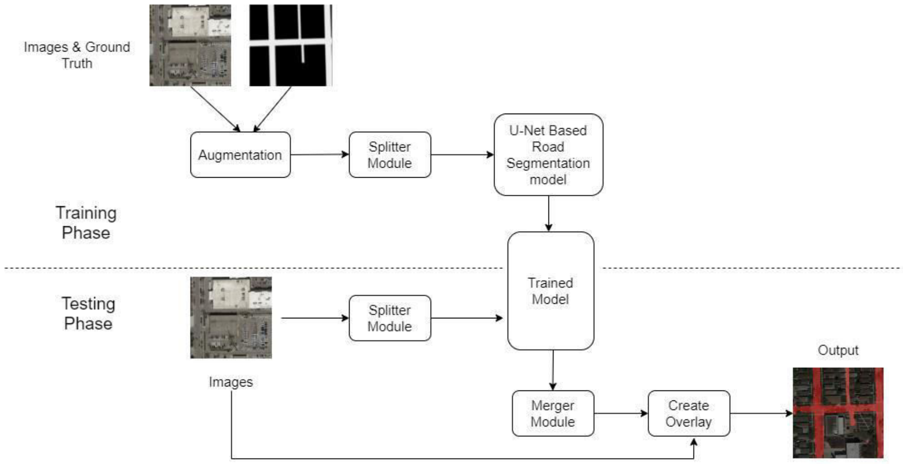

Figure 1: System Architecture

Here we take high resolution satellite images and their respective binary masks which will serve as ground truth data. Then images are given for augmentation. The image splitter module takes the high-resolution satellite image as input and splits it into 4 smaller images which are then passed through the semantic segmentation module to generate a segmentation map of roads in the image and then the four small segmented images are merged together by the merger module to get the output. The output of the merger module is then combined with the test input image to get a blended view of the mask over the roads identified in the test image as seen in the picture. The Overlay Creation Module is used to blend the output to generate a blended mask which lets us clearly visualize the roads in the input satellite image.

Component Design/Module Description

Image Splitter Module

It is the first module of our application and it is responsible for reducing the computational load on the semantic segmentation module.

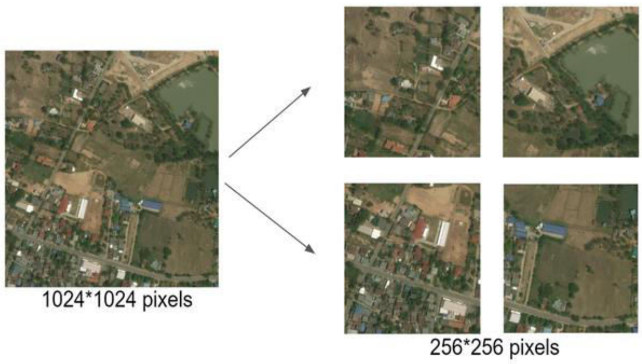

Figure 2: Image Splitter Module

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The image splitter module takes the high-resolution satellite image as input and splits it into 4 smaller images which are then passed through the semantic segmentation module to generate a segmentation map of roads in the image and then the four small segmented images are merged together by the merger module to get the final output.

Semantic Segmentation Module

This is the heart of our application and it is responsible for generating the segmentation map of the roads in the given input image.

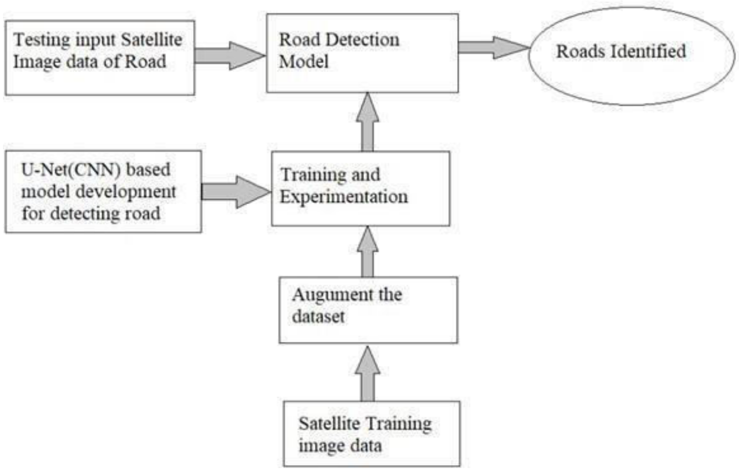

Figure 3: Semantic Segmentation Module

Image Merger Module

This module in our system architecture is responsible for generating the final masked output.It merges the output of the semantic segmentation module to generate the segmentation map of the single large input satellite image (1024*1024 pixels). This module will also be implemented using the standard image processing libraries in python.

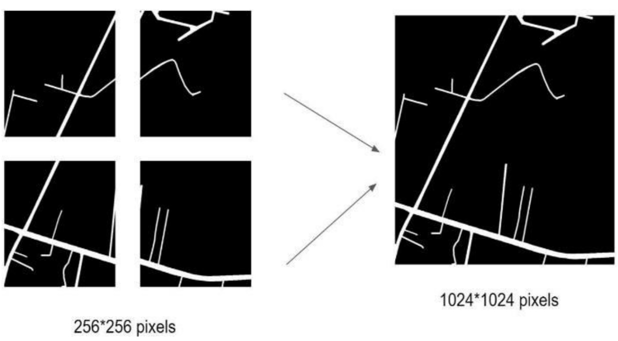

Figure 4: Image Merger Module

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Algorithm Design

U-Net

The contracting or down sampling path consists of 4 blocks where each block applies two 3x3 convolution followed by 2x2 max-pooling.The horizontal bottleneck consists of two 3x3 convolution followed by 2x2 up-convolution.
The expanding or up sampling path, complimentary to the contracting path, also consists of 4 blocks, where each block consists of two 3x3 conv followed by 2x2 up sampling (transpose convolution). The number of features maps here are halved after every block.
The architecture contains two paths. First path is the contraction path (also called as the encoder) which is used to capture the context in the image. The encoder is just a stack of convolutional and max pooling layers.
The second path is the symmetric expanding path (also called as the decoder) which is used to enable precise localization using transposed convolutions. At each convolution it takes a feature and localizes it and finally after all the features have been localized it uses the final up sampled feature map for our output. Thus, it is an end-to-end fully convolutional network (FCN), i.e.it only contains Convolutional layers and does not contain any Dense layer because of which it can accept image of any size.

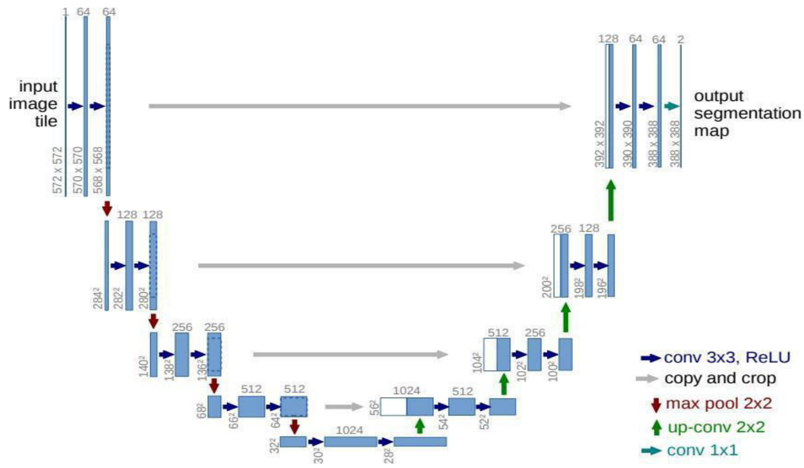

Figure 5: Convolutional U-NET

IV. PSEUDO CODE

Load the training data set
Initialise the unet model
Set model to use IOU LOSS function and Adam's optimiser for gradient calculation.
For every epochs:
    # For every image in training data set:
    # Transforming image dimensions as per the requirements of the Model
    # Propagate forward through initial model
        # Apply Sigmoid activation function to get the model outputs
        # squeeze abundant dimensions
        # Compute loss using IOU Loss function
        # Backpropagate the error
        # Update network parameters based on current gradient
        # compute average loss and F1 score for current iteration
Calculate total average Loss and F1 Score

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V. SIMULATION RESULTS

We use U-Net to build a road segmentation model with considerable F1-score, after using proper loss function, data augmentation, post morphological processing, regularization and tuning parameters. Finally our U-Net model achieves a 0.892 F1 score.

Unit Testing: It is a testing method by which individual units of source code are tested to determine if they are ready to use. It helps to reduce the cost of bug fixes since the bugs are identified during the early phases of the development lifecycle. It is kind ofWhite Box Testing.

Test	Test Data(input)	Expected Result	Actual Result	Pass/Fail
1	Relevant .png image with roads is selected	Roads should be segmented from the image	Roads appear segmented from the image	Pass
2	.png image with roads and other linear objects uploaded	Roads appear segmented from the image	Objects other than roads also appear in the segmented image	Fail
3	Irrelevant .png images without roads is uploaded	Shows a warning to upload relevant images.	The model identifies random linear objects as roads.	Fail

Table 1: Unit Testing

Integrated Testing: The idea behind Integration Testing is to combine modules in the application and test as a group to see that they are working fine.It a is kind of Black Box Testing

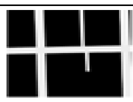
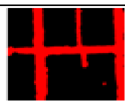
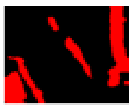
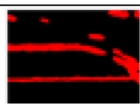
Serial No.	Input	Expected Result	Actual Result	Pass/Fail
1				Pass
2				Fail
3				Fail

Table 2: Integrated Testing

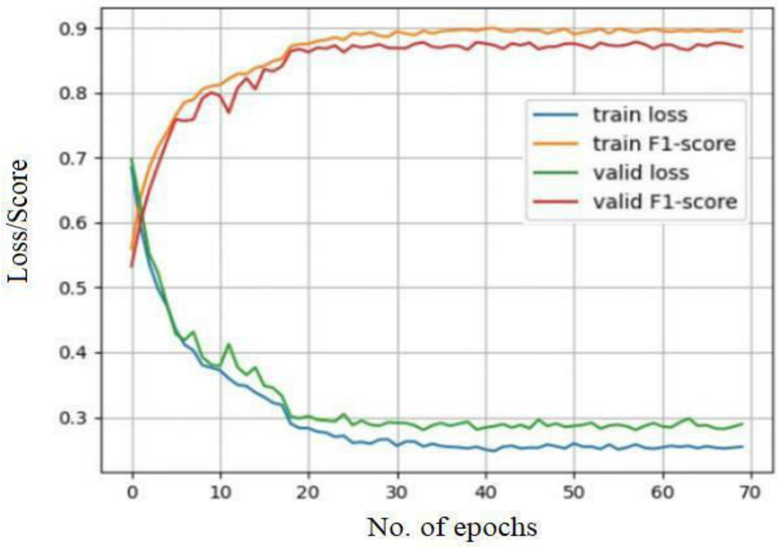


Figure 6: Loss and F1-score on train and validation set

We have collected the loss parameters and f1 scores while training after each epoch and plotted this accuracy graph. Training data set is used while training to adjust the weights but at the same time we also want to check the performance of the dataset with respect to unknown data. That's where the validation dataset is used.

VI. Conclusion and Future Work

Conclusion: This investigation demonstrates that a road segmentation task can be tackled by patch-wisely distinguishing between road and background in a set of satellite images. To this end, we show convolutional neural networks, specifically U-nets, can produce satisfying results after data augmentation, dealing with imbalanced data, post-processing and tuning hyperparameters. Finally, our U-net model achieves a 0.892 F1-score.

Limitations of the system

- The model sometimes cannot detect very narrow roads and it cannot detect diagonal roads very well even though the data is augmented by rotation.
- The baseline did not use data augmentation for the purpose of saving training time and get intuition about the performance on small dataset.

Future Scope of the Project

- If computational power permits, one can further enlarge the dataset using various transformations such as shear transformation and shifting, or one can find more data to improve the model.
- The post morphological opening block still can eliminate some real road classes by fault, because the model can predict some narrow road discontinuously as small pieces.
- The hyper-parameters can be better tuned with proper cross validation.

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