Road Safety from Satellite Images

Arvind Ram
Department of Computer Science and Information Systems
Birla Institute of Technology and Science, Pilani, Pilani, India
f20201210@pilani.bits-pilani.ac.in
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***Abstract*—To analyze the safety standards and requirements of different highways from raw satellite images. In, this report, the research papers working on various road safety have been analysed and the methodology of collecting the dataset of raw satellite imagery and other necessary attributes necessary have been explained.**

I. Introduction

The key idea of this project is to analyze the potential works which could be partaken to analyze the safety standards of various highways across the globe from raw satellite imagery. We have discussed how the Google Earth Engine can be used to generate the necessary satellite images for our region of interest and avail other details, such as the elevation at a point, or the area covered within a given image.

II. Literature Review

Producing detailed safety maps of each highway is an important task in order to analyse the changes and repairs which need to made to ensure safety standards. The process currently is a lengthy and rigorous task which involves conducting fieldwork to obtain the details of the road networks. However, using satellite images along with Deep learning algorithms can help make this process cheaper, faster and more accurate as many minute details which would be missed by the human eye, can be picked up here. It can also be extended to make the process real-time making instant feedback possible. The following are a few papers which have worked on this particular problem.

A. Road Safety Map

This paper [1] proposes a model to avail a safety map of roadways from raw satellite images by combining the data available from satellite images along with open data which includes details like the accident reports in and around the area in question. So for this purpose, satellite images of New York and Denver were collected. Along with this a total of 647,868 traffic-accident reports from New York City. and 110,870 traffic-accident reports from Denver City. These reports had data mentioning the location of the accident, details of the vehicle involved in the accident and the severity of the accident.

The objective was to classify each location based on safety levels as high, neutral or low. Hence, after labelling each satellite image of New York City as one of the 3 levels, the satellite images along with the accident reports were used to train the AlexNet model which was first pre-trained on the Images205 and ImageNet dataset.

The model was then tested on raw satellite images of Denver city. Denver City and New York City are quite different from each other in terms of the level of development, area, population and traffic. The traffic reports of Denver were used to quantify the results.

Fig. 1: Ground Truth

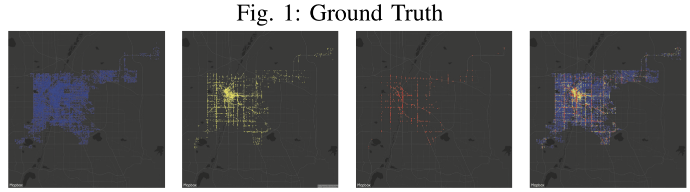
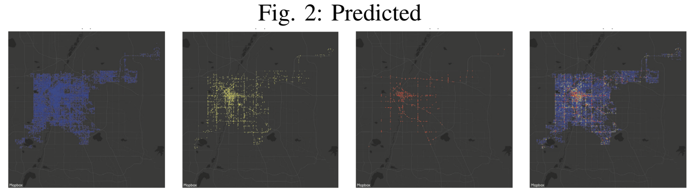


Fig. 2: Predicted



The given model achieved an accuracy of 73.1%. Hence, this model has shown that visual features contained in satellite imagery can be effectively used as a proxy indicator of road safety and that deep models learned from road safety data collected in a large city can be reused to predict road safety in smaller cities with fewer resources.

B. Infrastructure Safety Assessments

The paper [2] focuses on leveraging advanced satellite technology to analyze road conditions and identify potential safety hazards. The study involves the use of high-resolution satellite imagery to extract detailed information about road infrastructure, including road quality, signage, lane markings, and other relevant features. It aimed to check if the roadways were confined to International Road Assessment Programme (iRAP) guidelines. For this purpose object detection was performed to determine pedestrian crossings, whether the road was divided or undivided and to locate school areas. The open street map view and Satellite images of a region in Croatia called Split were used to vectorize the roadways, segment the satellite images and then perform object detection on them. A YoloV5 architecture was used for this purpose

The Model gave good results. However, it was observed that detection quality depended on the quality of road markings. There were many many false detections due to patterns similar to school zones and pedestrian crossings.

III. Proposed Solution

A. Satellite Image Collection

The first step is to obtain the raw RGB satellite images of the region of interest. We have used the Google Earth Engine API to accomplish the same. We obtained the satellite images for a stretch of the I-90 interstate highway in the United States for our problem. The following satellites' datasets have been used.

1) **Landsat**
The Landsat dataset contains atmospherically corrected surface reflectance and land surface temperature derived from the data produced by the Landsat 8 OLI/TIRS sensors. The RGB images have a resolution of 30 metres.

2) **Sentinel**
The Sentinel-2 dataset is a wide-swath, high-resolution, multi-spectral imaging mission supporting Copernicus Land Monitoring studies, including the monitoring of vegetation, soil and water cover, as well as observation of inland waterways and coastal areas. The maximum resolution of the RGB images is 10 metres.

3) **National Agriculture Imagery Program**
The National Agriculture Imagery Program (NAIP) [3] acquires aerial imagery during the agricultural growing seasons in the continental U.S.
NAIP projects are contracted each year based upon available funding and the imagery acquisition cycle. Beginning in 2003, NAIP was acquired on a 5-year cycle. 2008 was a transition year, and a three-year cycle began in 2009.
NAIP imagery is acquired at a one-meter ground sample distance (GSD) with a horizontal accuracy that matches within six meters of photo-identifiable ground control points, which are used during image inspection.

The NAIP dataset having the best resolution amongst the 3 satellites, gave the most usable satellite images which could be used for further training our model.

B. Elevation Calculation

The elevation data at any given point can give us valuable insights into the slope of the roads and help us analyze how dangerous the given terrain is.
The Google Earth Engine was used to avail the elevation for a given coordinate. The Shuttle Radar Topography Mission (SRTM) [4] digital elevation dataset has been used for this purpose. It was originally produced to provide consistent, high-quality elevation data at a near-global scope.

C. Scale Calculation from Satellite Images

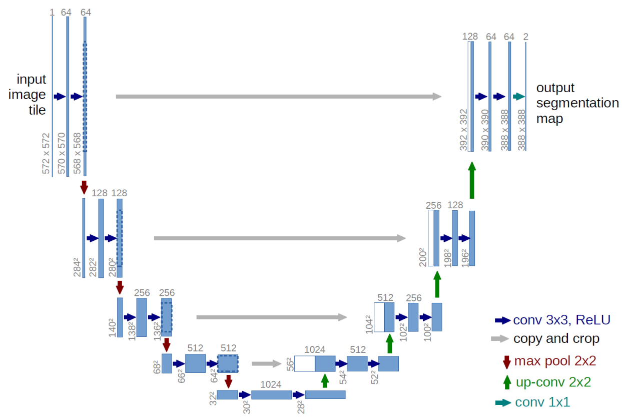
In order to extend the use of our code to any satellite, accurately finding the scale of the satellite images generated is essential. While Google Earth Engine lets you specify the scale of the image required to be generated, it is essential to have a formula for a robust system. For this purpose, we use Google Earth Engine's distance() function to get the distance between two coordinates by specifying the points' latitudes and longitudes.

```python
# Function to calculate distance between two points
def calculate_distance(lat1, lon1, lat2, lon2):
    # Create Earth Engine Point geometries
    point1 = ee.Geometry.Point(lon1, lat1)
    point2 = ee.Geometry.Point(lon2, lat2)

    # Calculate the distance (in meters)
    distance = point1.distance(point2)

    return distance.getInfo()
```

The pixel distance between two points on the image and the distance between these coordinates in metres can be divided to obtain the Scale for the image. This can be useful in further applications of finding the width of the road etc.

D. Road Segmentation for Width Calculation

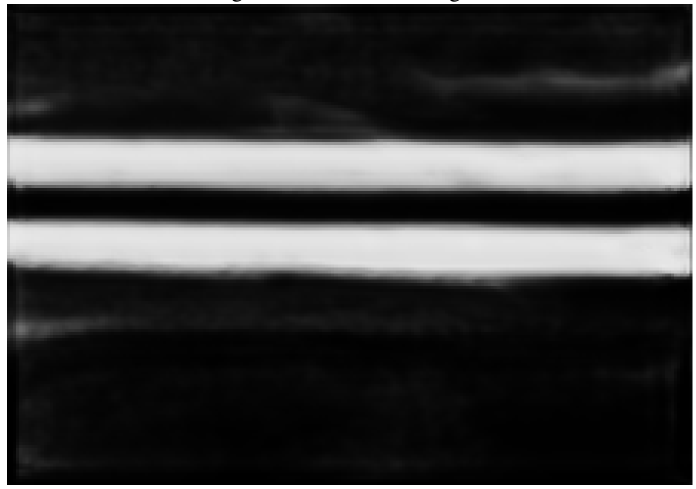
With the raw satellite images and the scale of the image available, we can use computer vision techniques to find the width of the road. This is crucial information for helping us with analyzing the safety standards of a certain roadway.
In order to calculate the width we must first segment the satellite images to create masks consisting of only the roadways. We have used a U-Net architecture to achieve this.



The U-net model was first pre-trained on the Massachusetts Road Dataset [5]. The Massachusetts Roads Dataset consists of 1171 aerial images of the state of Massachusetts. Each image is 1500×1500 pixels in size, covering an area of 2.25 square kilometres. The data is randomly split into a training set of 1108 images, a validation set of 14 images, and a test set of 49 images.
The model then had to be fine-tuned to be able to segment roads from the NAIP dataset. For this purpose, we annotated 150 pictures of the NAIP database manually using the Labelme software [6]. The masks created from these annotations were used to train the pre-trained model. The model was then run on a set of NAIP dataset images to obtain their masks.

Fig. 3: Satellite Image

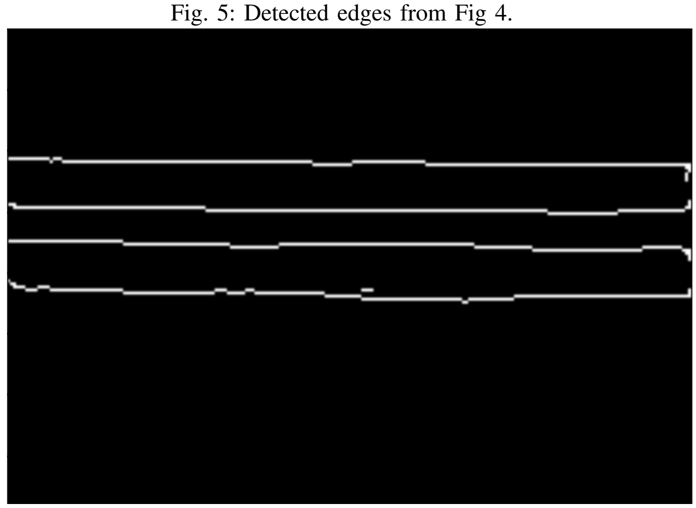
Fig. 4: Mask of the Image



E. Calculation of Width of the Road

We use the masks created from the previous section to calculate the width of the roads. We first detect the edges of the roads using OpenCV's Canny edge detection. We can then find the pixel width between two edges and by using the scaling factor which we found in Section C of the report, we can accurately determine the width of the roads.

Fig. 5: Detected edges from Fig 4.



IV. Future Work

The U-net model developed to create masks of the satellite image for road detection is still not robust enough generating a lot of noise along with it. This compromises our road detection algorithm to calculate the width of the roads as the road segmentation masks created are not accurate. Hence, the model can be further trained with more data from the NAIP dataset to create more reliable masks of the roadways.
Further attributes like the occurrence of bridges and flyovers along the highways can help us accumulate further data for analyzing the safety standards and potential danger spots along the way. Availing accident reports of the region of interest will be crucial to determining the safety levels of the highways.

With these attributes in hand, we can develop a model to analyse the safety levels of different areas and predict the safety levels using raw satellite images.
We can extend our model to work in other regions like India, using satellites like the Cartosat-3 dataset.

V. Conclusion

Obtaining Safety levels of roadways from raw satellite imagery is a useful tool which will help in reducing the huge amounts which would be spent on labour and capital otherwise to manually excavate and fix issues on the roadways. Predicting directly from Satellite imagery can help in anticipating potential issues and fixing them before a disaster could occur. The work done in this report could help in building such a robust and useful model.

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