Road markings detection and measurement in aerial imagery

Kadiwala Adnan
School of Engineering & Applied Science
Computer Science & Engineering
Ahmedabad, India
adnan.k@ahduni.edu.in

Shah Vandit
School of Engineering & Applied Science
Computer Science & Engineering
Ahmedabad, India
vandit.s@ahduni.edu.in

Hingu Dhruv
School of Engineering & Applied Science
Computer Science & Engineering
Ahmedabad, India
dhruv.h@ahduni.edu.in

Patel Het
School of Engineering & Applied Science
Computer Science & Engineering
Ahmedabad, India
het.p5@ahduni.edu.in

***Abstract*—This report presents a method for road marking detection, more specifically using a segmentation approach. Our chosen method involves generating masks for the road markings. Utilizing the AU Drone Dataset, we obtained images depicting road lanes with markings, along with corresponding masks for each category or type of road marking. Presently, we are employing the UNet architecture to achieve image segmentation and train our model accordingly. Testing this model gave us good results for the segmentation.**

***Index Terms*—Road Marking Detection, Segmentation, Aerial Imaginary, Encoder-Decoder, U-Net.**

I. Introduction

Detecting road markings and measuring road features from aerial imagery plays an important role in various applications such as urban planning, transportation management, and infrastructure maintenance. Road markings serve as vital navigational cues for drivers and are essential for ensuring road safety. Moreover, accurate measurement of road dimensions is necessary for assessing road conditions, planning maintenance activities, and optimizing traffic flow, and also in upcoming technology of self-driving cars.

This report focuses on the exploration and evaluation of methods for detecting road markings and measuring road parameters from aerial imagery. By using computer vision, we aim to develop a robust and reliable system capable of accurately identifying various types of road markings and extracting essential road features from aerial images. Such a system has the potential to enhance the efficiency of transportation management, improve road safety, and contribute to the development of smarter cities.

II. Initial Approach

Our initial task involves segmenting the original images to isolate road sections, followed by annotating the road markings within these segments. This segmentation and annotation process aims to enhance the model's understanding of road features and improve its performance in accurately identifying and delineating road markings in real-world scenarios.

A. Detection vs Segmentation

Initially, we considered employing a detection method where the model would be trained by providing bounding boxes. However, acquiring a dataset suitable for this approach posed significant challenges. Upon further examination, we determined that segmentation offers several advantages over detection for road marking detection.

Firstly, segmentation provides finer-grained detail by precisely outlining the boundaries of road markings, resulting in more accurate localization. This level of detail is crucial for tasks such as lane departure warning systems, where precise positioning of markings is essential.

Secondly, segmentation inherently handles overlapping or occluded markings more effectively. Unlike detection, which may struggle with distinguishing individual markings in cluttered scenes, segmentation can segment each marking separately, enhancing overall performance in complex environments.

Furthermore, segmentation enables semantic understanding of road scenes by assigning each pixel a specific class label, facilitating downstream tasks such as road condition assessment or autonomous driving.

As segmentation offers good precision and robustness in handling complex scenarios and enhanced semantic understanding compared to detection methods.Also availability of data makes it a more suitable approach.

III. Dataset

The AU drone Dataset for road markings comprises 1971 high-resolution images depicting different roads and traffic scenarios. These images are categorized into three subsets: Train, Valid, and Test.

The training images exhibit a wide range of variations, posing a challenge for model fitting. Additionally, the dataset includes masked versions of the original images, aiding in model accuracy assessment.

The masks are divided into 5 classes:
* **White masks**: zebra crossing.
* **Brown masks**: lane-edge markings.
* **Blue masks**: lane markings.
* **Orange masks**: in-lane markings.
* **Black masks**: everything else.

Fig. 1. Original image

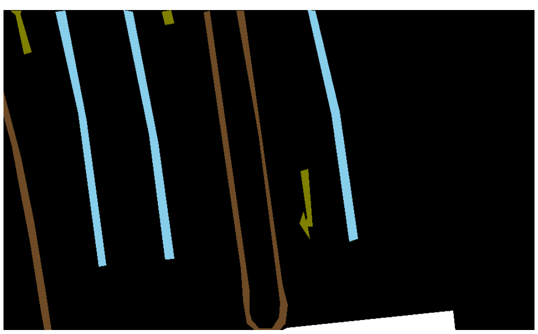

Fig. 2. Segmentation Masks

IV. Methodology

When we specifically want to detect/find something in the images, Convolutional Neural Networks (CNNs) are the most suitable tool. Among various methods for image segmentation, the **U-Net model** stands out as a prominent choice. Initially designed for segmentation tasks in medical imaging, U-Net has demonstrated effectiveness across various segmentation needs, including road marking detection.

The U-Net architecture follows a distinctive **encoder-decoder design**. In the encoding phase, the model learns features from input images and consolidates common features to generate masks. This process involves reducing spatial dimensions while retaining essential information. Subsequently, the decoder component expands the learned features, ensuring that the masks are accurately positioned spatially, akin to the original image. Through this process, U-Net effectively captures intricate details of road markings, enabling precise segmentation in complex scenes.

As the architecture of the U-Net is in *'U'* shape it is called 'U'Net, the architecture is shown below:

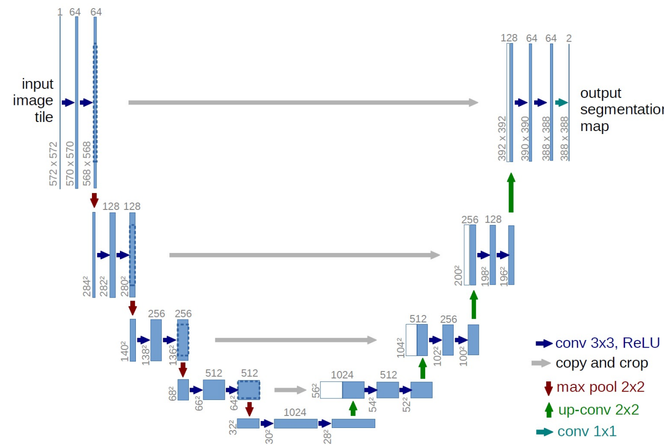

Fig. 3. U-Net Architecture

Here we also faced some challenges when classifying the markings, as they were in multiclass, so currently we employed a binary classification of the markings and we have got some results for the same.

V. Results and Inferences

Here are the results which we have got when we applied the U-Net on our dataset.

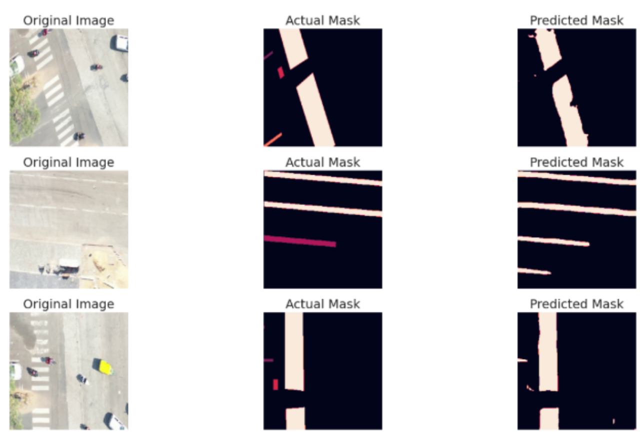

Fig. 4. Results

The following results were taken by considering the stopping criteria as **Intersection over Union** (IOU).

Also, it can be inferred from the prediction masks that the learning is not that accurate as the model is not yet robust to the noise.

VI. Future Work

We have previously focused on binary-level classification, and our next objective is to extend our model to achieve **multi-class classification** for the same task. Following this, our goal is to explore methods for **pixel-to-'cm'** mapping of road markings. To accomplish this, we will need to determine the Ground Sampling Distance (GSD).

VII. References

[1] Ronneberger, O., Fischer, P., Brox, T. (2015, May 18). U-NET: Convolutional Networks for Biomedical Image Segmentation. arXiv.org. https://arxiv.org/abs/1505.04597

[2] S. M. Azimi, P. Fischer, M. Körner and P. Reinartz, "Aerial LaneNet: Lane-Marking Semantic Segmentation in Aerial Imagery Using Wavelet-Enhanced Cost-Sensitive Symmetric Fully Convolutional Neural Networks," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 5, pp. 2920-2938, May 2019, doi: 10.1109/TGRS.2018.2878510.