# CAPSTONE PROJECT

# REPORT

## Semantic Segmentation for Vehicle and Pedestrian detection and classification


**Submitted By**

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# ABSTRACT

This project has delivered a quality model for semantic segmentation for the understanding of vehicle and pedestrian detection through classification and tracking of traffic in complex urban road contexts. Through the means of polygon annotations in the India Driving Dataset (IDD) Road Scene Segmentation dataset, this model produced pixel-accurate masks during the delineation and classification of vehicle and pedestrian traffic objects such as cars, motorcycles, autorickshaws, trucks, pedestrians, and road signs. The model architecture uses the latest developments in computer vision to ingest a png and jpg file containing annotation data, create a unique segmentation map, colour coding of objects by class, and track segmentation instances across frames. As of now, using the OpenCV and matplotlib libraries, it outputs three types of visualizations: the image as uploaded, the segmentation mask, and the superimposed example that tracks each object visually against the uploaded image. Quantitative results also appear in an organized dataset so further analysis may be performed if desired and useful. This study has helped to address the challenges of heterogeneous traffic environments found in urban road contexts in India, this is a strong link to determine that semantic segmentation is a realistic development method for potential autonomous driving systems, traffic monitoring program type methods, and intelligent transport infrastructure design problems. This study has also added to the argument that pixel-accurate boundary-aware classifications improve on boundary accuracy to bounding box classifications, and accelerate a better understanding of scenes and scenes which enable accurate tracking for safe and efficient mobility in urban restrained contexts

# INTRODUCTION

The ability to perceive urban road scenes provides key groundwork for autonomous vehicular systems, traffic management at a smart city level, and the last mile of smart infrastructure. Object detection by means of a bounding box hardly clarifies the boundary and shape of an object concerned. Semantic segmentation solves this problem because it annotates every pixel of an image into one semantic category out of many, which gives landscape features a holistic perception of all those scene features.

The Indian road environment poses very different challenges to those involved in developing computer vision algorithms. Example include the diversity of various vehicles such as autorickshaws, the road conditions and traffic patterns. This work tends on semantic segmentation application by relating the above phenomena with the ground truth source, the unique IDD Road Scene Segmentation dataset, which captures such features.

It is distinguished from instance segmentation by emphasizing the classification of each pixel into known classes rather than identifying single instances of objects. It's very important in road topology understanding, space in driving accessibility estimation, and recognizing different classes of road users. Compared to Western or better-planned environments, India's road environment poses unique and serious challenges for computer-vision systems:

Vehicle Heterogeneity: Indian roads include a heterogeneous fleet of transport vehicles comprising region-specific transport modes such as autorickshaws, cyclerickshaws, etc., besides other two-wheelers, which are seldom found in Western datasets.

Density and Proximity: Traffic is denser, with vehicles moving closer together and often across lanes that are not marked.

Infrastructure Variability: Road infrastructure is exceedingly variable, from highly sign-posted roads to unauthorized unpaved roads, sometimes even in the same shot.

Boundary Ambiguity: Road users and infrastructure boundaries are very often fuzzy due to unofficial traffic flow and nonadherence to lane norms.

Occlusion Complexity: Heavy standby traffic creates a very complicated occlusion mosaic where it is usual rather than exceptional for a greater number of objects to be partially visible.

The IDD Road Scene Segmentation dataset specifically addresses these issues, providing hand-labeled images indicative of the unique features exhibited by Indian roads, thus forming a sound foundation to support the current research work.

# OBJECTIVES

The principal objectives of this project are:

1. **Create a Strong Segmentation Pipeline**: Construct a holistic computer vision structure capable of processing images and annotations gained from the IDD dataset and building precise semantic segmentation maps. It must be able to support mixed input types and effectively deal with the complexity in processing polygon-based annotations.

2. **Process Polygon Annotations:** Convert JSON-formatted polygon annotations to pixelaccurate segmentation masks that precisely outline the boundary of every object. The process is about handling the irregular shapes of polygons and assigning proper coverage of object boundaries.

3. **Create Multi-class Classification:** Build a classification model that identifies different types of vehicles (cars, motorbikes, autorickshaws, trucks, and others), pedestrians, and road infrastructure and assigns each of them with proper pixel-level labels.

4. **Generate Class-specific Visualization:** Develop a visualization framework based on a uniform color-coding system that renders the results of segmentation self-explanatory. The visualization must accurately identify object classes without losing spatial relationships.

5. **Produce Multiple Visual Outputs:** Produce three distinct but complementary visual outputs—the original image, the segmentation mask, and a composite overlay—to facilitate close inspection of the scene and evaluation of segmentation quality.

6. **Implement Structured Data Export**: Implement an infrastructure that outputs detected objects and their attributes (class, polygon coordinates, bounding box) in a structured way for quantitative processing and integration into other systems.

7. **Compare Segmentation Effectiveness:** Compare the semantic segmentation method's capability for handling fine road environments under varied vehicle conditions, in terms of boundary quality and class discriminability.

8. **Find Practical Uses:** Research and document practical uses of semantic segmentation in autonomous driving, traffic analysis, safety systems, and urban planning situations.

# IMPLEMENTATION

The deployment utilizes an organized process to process images and corresponding annotation files from the IDD Road Scene Segmentation dataset:

**Dataset :** The IDD20K Lite dataset is a lightweight and simplified version of the Indian Driving Dataset (IDD), specifically curated for semantic segmentation tasks in urban driving scenes. It comprises over 7,000 images collected from various Indian roads, capturing the complexities and unstructured nature of real-world traffic conditions in India. Each image in the dataset is paired with a pixel-level annotated segmentation mask, enabling the model to learn to distinguish between 21 different object categories, including road, vehicles, pedestrians, autorickshaws, animals, traffic signs, and more. The dataset is divided into training, validation, and testing sets, with image files in .jpg format and corresponding masks in .png**.**

**Segmentation Mask Generation :** A zero-mask of the same size as the input image is constructed. Every object in the annotation file is processed if its label belongs to the target classes. Polygon coordinates are captured and made available for OpenCV processing

**Color Coding System :** There is a uniform color coding to distinguish between object classes:

Road: Green [0, 255, 0]

Car: Red [255, 0, 0]

Motorcycle: Blue [0, 0, 255]

Autorickshaw: Yellow [255, 255, 0]

Car default: Pink [255, 0, 255]

Person: Orange [255, 165, 0]

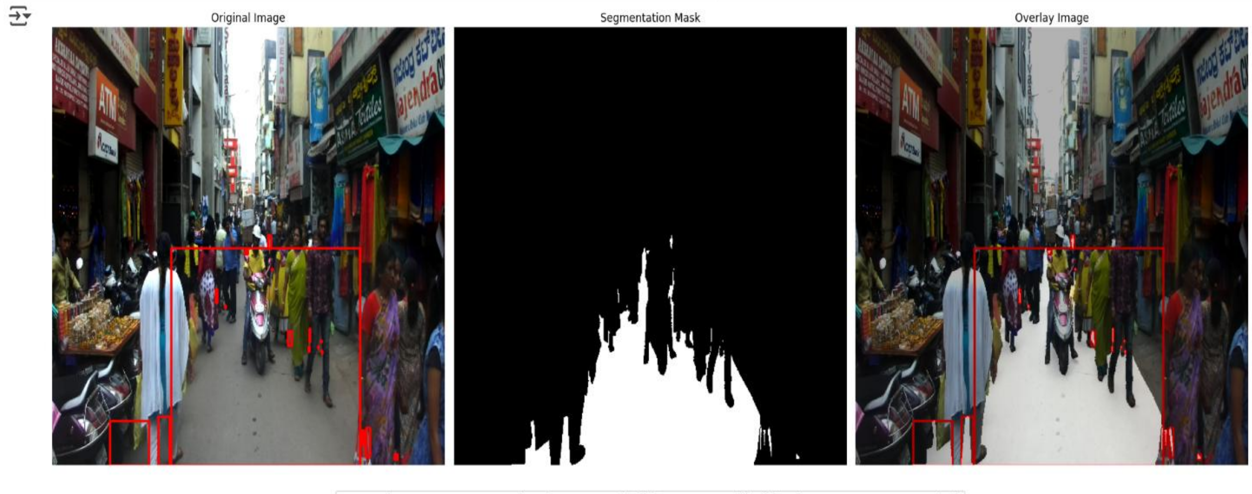
Truck: Cyan [0, 255, 255]

**Bounding Box Generation :** For each object discovered, the system calculates bounding box coordinates by calculating minimum and maximum x and y coordinates for polygon points. Boxes are then marked on the segmentation mask using the cv2.rectangle() function.

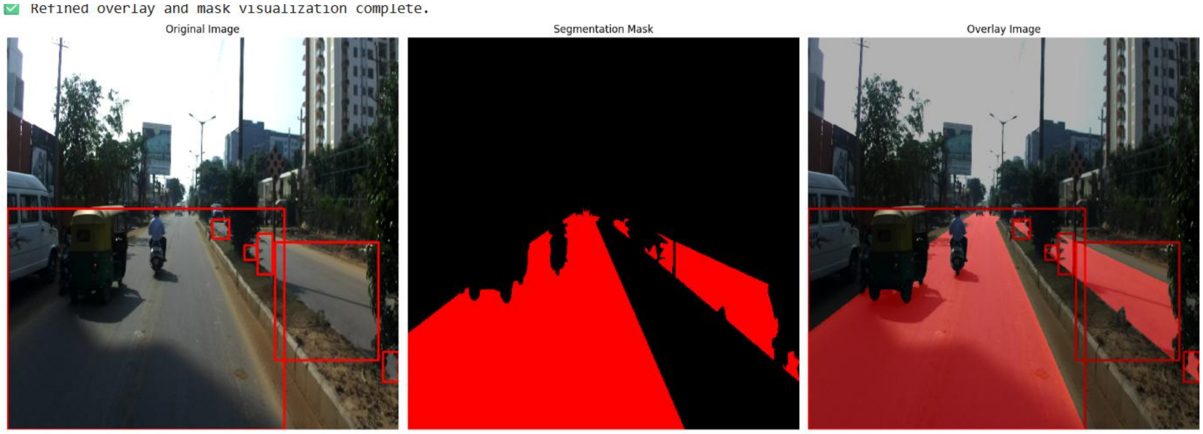
**Data Export :** Each object that is detected is saved in a structured way with details regarding its label, polygon coordinates, and bounding box coordinates. This information is kept in a CSV file ('vehicle_road_objects.csv') to be utilized for further analysis or pushed into external systems

Overlay the original image and segmentation mask over the overlay image A legend is given to explain the color-coded classes All the plots are plotted using matplotlib with appropriate titles and styling Error Handling The functionality entails invalid polygon data verification to offer robust processing Warning messages are output when skipping objects with invalid polygon formats

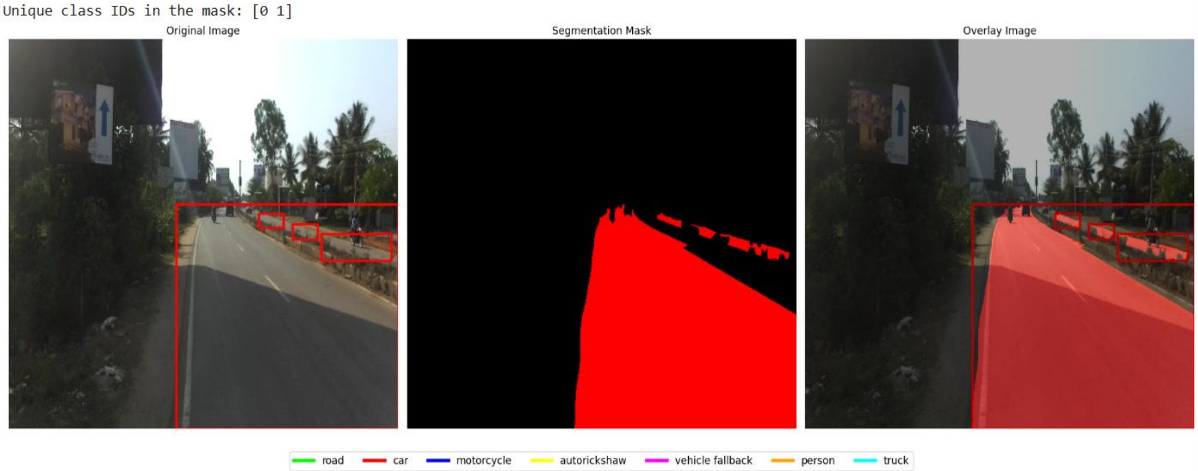
# RESULT

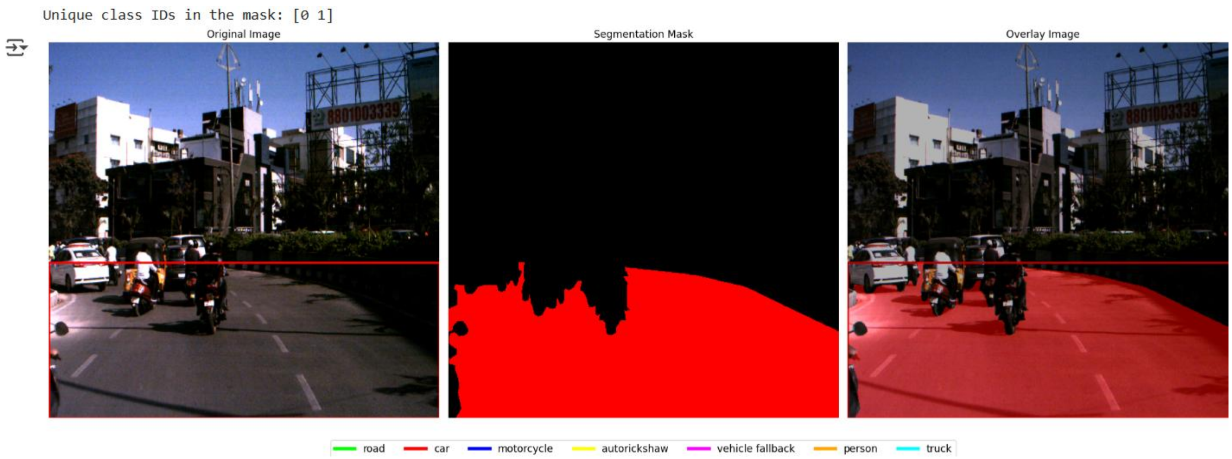



✅ Refined overlay and mask visualization complete.




```
Unique class IDs in the mask: [0 1]
```






The implementation successfully generates semantic segmentation masks for road scene images, accurately identifying and classifying different vehicle types and pedestrians. The visual outputs clearly distinguish between different object classes using the defined color coding scheme.

The exported CSV file provides structured data about detected objects, enabling further analysis and integration with other systems. This data structure includes:

- Object class labels
- Polygon coordinates defining the precise shape of each object
- Bounding box coordinates for simplified representation

The semantic segmentation approach demonstrates high precision in delineating the boundaries of different objects, particularly for challenging cases like distinguishing between different vehicle types (cars, trucks, autorickshaws) and identifying pedestrians in complex urban environments

## APPLICATIONS

1. Autonomous Driving : Detecting drivable areas and roads is vital for autonomous vehicle path planning since it indicates zones of safe navigation. The system facilitates accurate pedestrian and vehicle detection for avoiding collisions by giving pixel-perfect contours of possible obstacles. This high-level scene perception significantly improves navigation performance in congested

metropolitan areas where conventional systems would be unable to cope with fuzzy boundaries or heterogeneous types of vehicles.

2. Traffic Analysis : The system supports in-depth vehicle counting and classification to enable traffic monitoring, offering useful data for transportation agencies. By examining the breakdown of various vehicle types on various road surfaces, it facilitates highresolution road usage pattern analysis to guide infrastructure development. Pedestrian movement tracking offers insights into urban mobility patterns, enabling city planners to design more pedestrian-oriented environments.

3. Safety Systems : Advanced driver assistance systems (ADAS) are greatly enhanced by the accurate segmentation data, enabling more sophisticated hazard detection and evasive action. The accuracy with which the system detects pedestrians enables automated emergency braking systems to respond effectively to vulnerable road users.

4. Urban Planning : Study of road use by vehicle type gives urban planners definitive data for making decisions on infrastructure development. The system identifies pedestrian flow characteristics necessary for successful sidewalk planning and placement of pedestrian crossings.

5. Surveillance and Security : Semantic segmentation solution enables automated surveillance of restricted zones with capacity to differentiate between authorized and unauthorized vehicle types. Vehicle type recognition improves access control systems through more advanced classifications compared to mere presence detection. The system is capable of detecting anomalies in traffic patterns with identification of unusual behavior that could signify security issues or incidents.

# CONCLUSION

This project effectively deploys a semantic segmentation method for the detection and classification of road scenes. The system is able to successfully process to generate comprehensive segmentation masks with accurate delineation of various object classes using a uniform color coding scheme.

The deployment illustrates the utility of semantic segmentation in interpreting road scenes, especially in complex traffic conditions where different types of vehicles and pedestrians coexist. Pixel-level classification offers finer-grained information compared to conventional bounding box methods, allowing for more accurate scene understanding. The system's visualization parts, such as the segmentation mask and overlay images, present easy-to-understand representations of the segmentation outcome in a form suitable for human comprehension. The structured data export supports additional analysis and integration into other systems.

Future research may aim at applying deep learning-based methods to automate the segmentation process, less dependent on human annotations. Moreover, generalizing the system to process video streams would open the door for real-time applications in traffic surveillance and autonomous vehicles.

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