PROJECT REPORT

Title

Semantic Segmentation for Road Scene Understanding

Submitted By-

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ABSTRACT

Semantic segmentation assigns a label to every pixel in an image, which makes it really useful for understanding complex road scenes in computer vision. For this project, we focused on segmenting real-world driving environments using the Indian Driving Dataset (IDD). We used DeepLabV3+, which is a strong encoder-decoder model that uses atrous spatial pyramid pooling to capture different levels of context effectively.

The dataset includes a variety of challenging urban traffic scenes with 27 different classes like roads, cars, people, traffic signs, and sidewalks. We preprocessed all the images and created label masks by converting the polygon annotations into class ID masks that the model could use for training. The model was trained using Python and PyTorch, and we used Albumentations to help with data augmentation.

Even with tough conditions like changes in lighting and objects blocking each other, the model performed well. It was able to recognize key parts of the scene like roads, cars, trees, and the sky. We also created visualizations using color-coded overlays to make the predictions easier to understand.

The model is ready to be used in real-world applications like self-driving cars, traffic monitoring, lane detection, and avoiding obstacles. Some of the challenges we faced were dealing with class imbalance, the complexity of the annotations, and the need for a lot of computing power.

Overall, this project shows how useful semantic segmentation can be in helping machines understand road environments better, which can make autonomous navigation safer and more efficient.

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INTRODUCTION

Semantic segmentation is all about labeling each pixel in an image based on what object or class it belongs to. This kind of detailed understanding is super important for self-driving systems because the vehicle needs to fully understand what's happening around it in order to move safely and efficiently. Unlike regular object detection, which just finds and roughly outlines objects, semantic segmentation gives a much more accurate picture by capturing the exact shapes and positions of everything in the scene.

For our project, we worked on segmenting road scenes using the Indian Driving Dataset (IDD). This dataset is especially tough because it reflects the kind of traffic and road conditions you actually see in India. There's a huge variety of vehicles, people walking unpredictably, different types of roads, and sometimes even animals crossing. It's not as clean or organized as road scenes in datasets from places like Europe or the US.

To deal with this, we used DeepLabV3+, which is a high-performing semantic segmentation model. It combines something called Atrous Spatial Pyramid Pooling (ASPP) with an encoder-decoder structure. This helps it understand different levels of context in the image while still keeping the edges of objects clear and sharp. We trained the model on the IDD dataset, which has over 20,000 images split into 27 different classes like roads, cars, people, traffic signs, and other common elements in street scenes.

To see how well our model was doing, we used metrics like pixel accuracy and mean Intersection over Union (mIoU), which check how close the model's predictions are to the actual labeled data. The main goal is to build a system that can really understand complex road scenes in Indian traffic and help move toward safer and more reliable self-driving technology.

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OBJECTIVES

The main goal of this project is to use semantic segmentation to better understand road scenes by working with the Indian Driving Dataset (IDD) and training the DeepLabV3+ deep learning model. Here's what we set out to do:

- Understand how the **IDD dataset** is organized, especially how the **27 semantic classes** are labeled. These classes reflect the variety and complexity of real Indian road conditions.

- **Preprocess** the data by turning **polygon annotations** into clean, **pixel-wise segmentation masks**. This step was important to make sure the model had accurate and consistent data to learn from.

- Set up, train, and fine-tune the **DeepLabV3+ model**. The model uses **Atrous Spatial Pyramid Pooling (ASPP)** and an **encoder-decoder** structure, which help it pick up features at different scales and capture **object boundaries** more precisely.

- **Evaluate** how well the model performs using metrics like **pixel accuracy** and **mean Intersection over Union (mIoU)**, which tell us how close the model's outputs are to the ground truth.

- Look at how the model handles real-world challenges like **occlusions**, **lighting changes**, and a wide range of **objects** on the road. Based on that, figure out what could be improved.

- Show how this kind of **pixel-level scene understanding** can actually be used in **intelligent transportation systems**. With more accurate segmentation, systems like **autonomous vehicles** can become **safer** and more **reliable** in complex driving environments.

IMPLEMENTATION

We used the DeepLabV3+ model to do semantic segmentation for road scenes, and we ran everything on Google Colab since it offers free GPU support which helped speed up the training process. For this project, we used the Indian Driving Dataset (IDD) Segmentation Part 2. This dataset has detailed annotations of road scenes that are specific to Indian traffic conditions, which made it a good fit for what we were trying to do. The whole process of setting up and running the model can be broken down into a few main stages.

1. Environment Setup

We started the implementation on Google Colab since it's a great cloud-based setup for testing deep learning models. We turned on GPU acceleration to make the training process faster. To keep everything organized and make sure we didn't lose progress between sessions, we also connected Google Drive. That's where we stored the dataset and saved model checkpoints so we could pick up right where we left off if needed.

2. Dataset Preparation

We used the IDD Segmentation Part 2 dataset from Kaggle, which has urban road images and their matching grayscale segmentation masks. Each pixel in the mask represents a specific object like a road, car, or person. We organized everything into folders and used a custom data loader to make sure each image matched with the right mask.

- Download **IDD Part 2** from Kaggle.
- Organize the dataset into folders: images/ and masks/.
- Ensure that each image has a corresponding segmentation mask.

3. Data Preprocessing and Augmentation

All images and masks were resized to 256×256 for consistency. We normalized the images using ImageNet stats to help the model learn better. The mask values were kept unchanged to preserve labels, and we used data augmentation to mimic different lighting and scene conditions.

- Resize all input images and masks to **256x256** resolution.
- Normalize pixel values (e.g., scale to 0–1 or mean-std normalization).
- Convert masks to **class labels** (0–25), ensuring correct mapping.

4. Model Selection and Configuration

For the semantic segmentation task, the **DeepLabV3+** architecture was chosen due to its strong performance in preserving object boundaries and capturing context at multiple scales. The model utilized a **ResNet50** backbone pre-trained on ImageNet. To suit the IDD dataset, which includes **26 semantic classes**, the final classifier layer of the model was modified to produce 26 output channels.

5. Training Strategy

The dataset was divided into training and validation subsets. Training involved passing the preprocessed images through the model in mini-batches. The **CrossEntropyLoss** function was used to calculate the error between the predicted and true class labels. The **Adam optimizer** was used to update model weights during backpropagation. The training loop was run for a few epochs initially to verify correctness, with plans for further training to improve accuracy.

- Loss Function: CrossEntropyLoss with ignore_index=255
- Optimizer: Adam, learning rate = 0.0001
- Platform: Trained on Google Colab GPU
- Batching: Used DataLoader for efficient loading and preprocessing
- Epochs: Ran for 2 epochs
- Logging: Recorded training loss per epoch

6. Model Evaluation

The evaluation was conducted on the validation set with all predictions and ground truths resized to **1280×720 resolution**, in line with the AutoNUE benchmark format.

- **Pixel Accuracy**
- **Mean IoU**

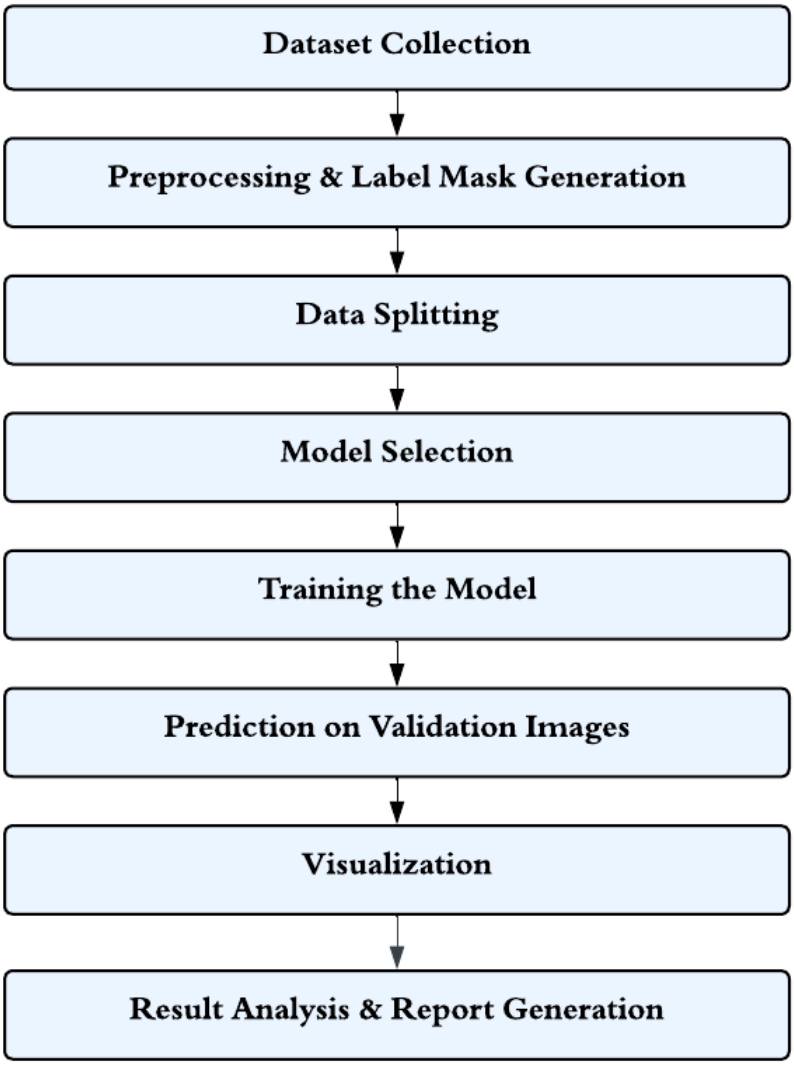
These metrics indicate that the model was able to reliably distinguish between various elements of the road scene, such as vehicles, roads, pedestrians, and buildings, even in unstructured and cluttered environments.

7. Visualization and Result Analysis

To see how well the model was working, we overlaid the predicted masks on the original images. This made it easier to tell if the model was picking up on the right areas, especially in busy street scenes like the ones you'd find on Indian roads. The results looked solid, with the model doing a good job of picking out small details and keeping edges clear, which really matters for things like self-driving tech or traffic analysis.

Overlay predicted masks on original images using **OpenCV**.
Assign distinct colors to each class for better interpretation.
Display side-by-side:

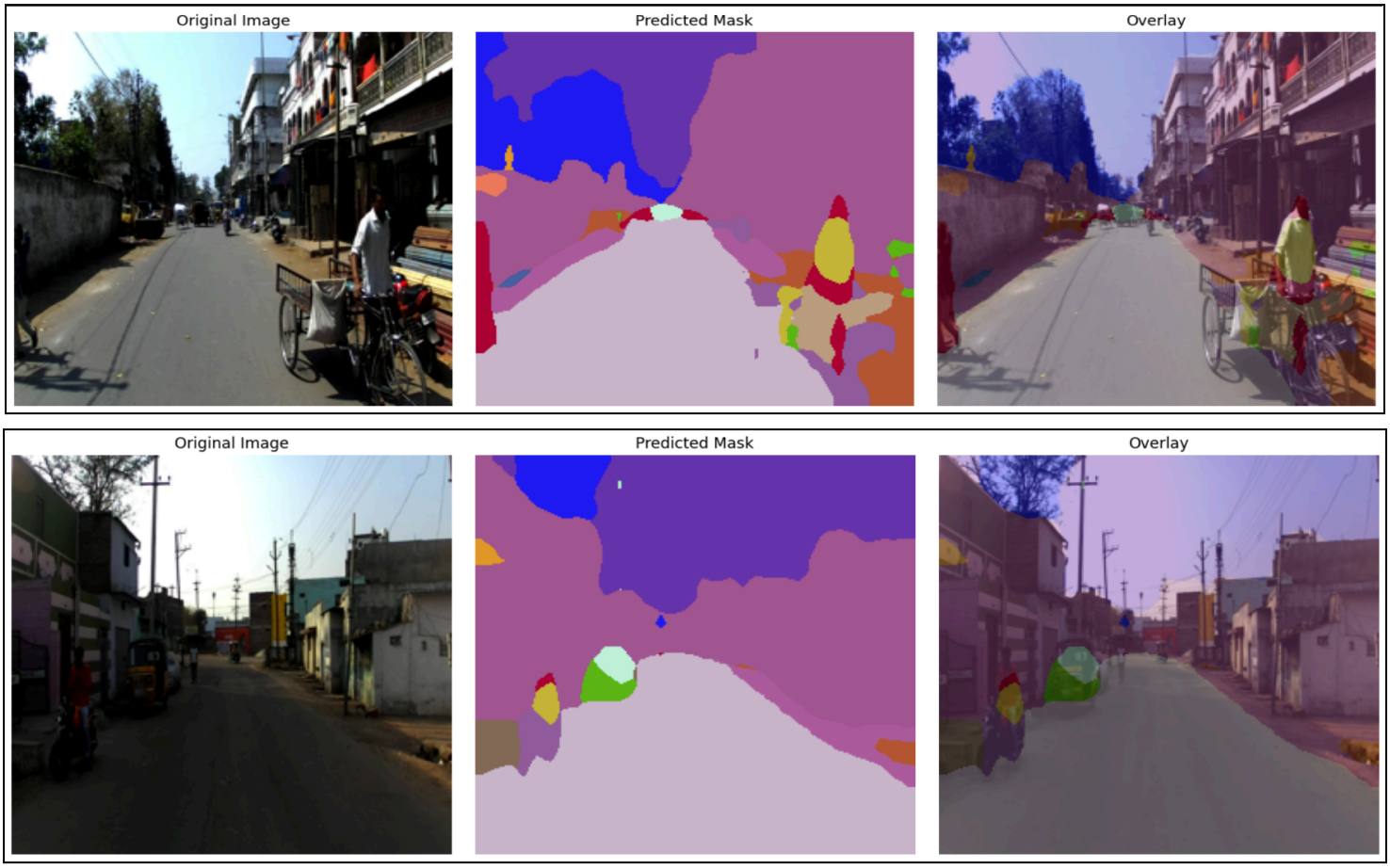
- Original Image
- Ground Truth Mask
- Predicted Segmentation Overlay

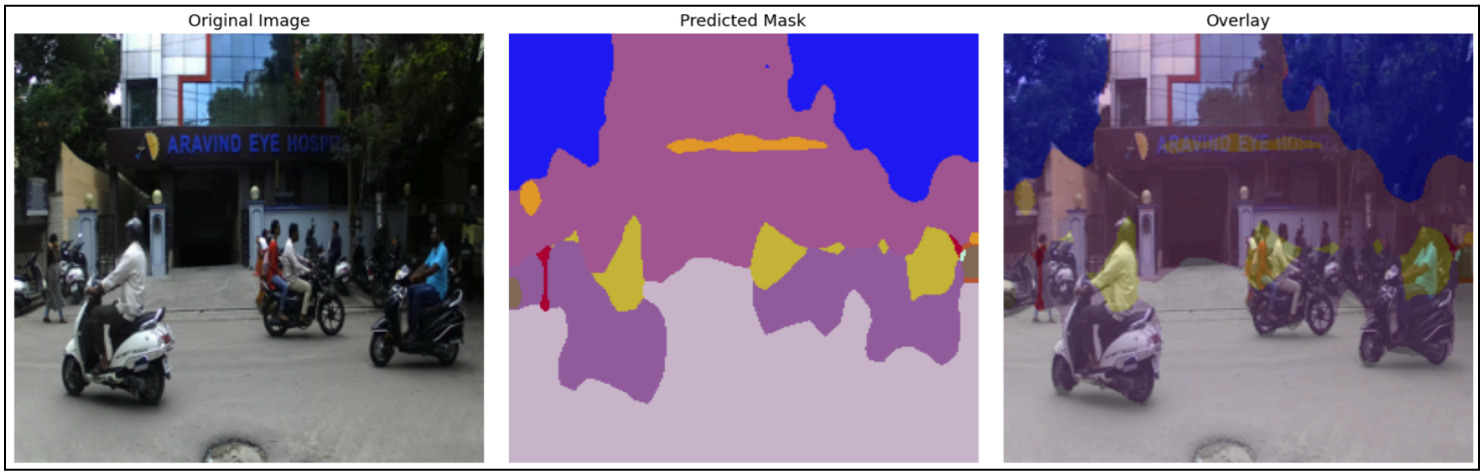


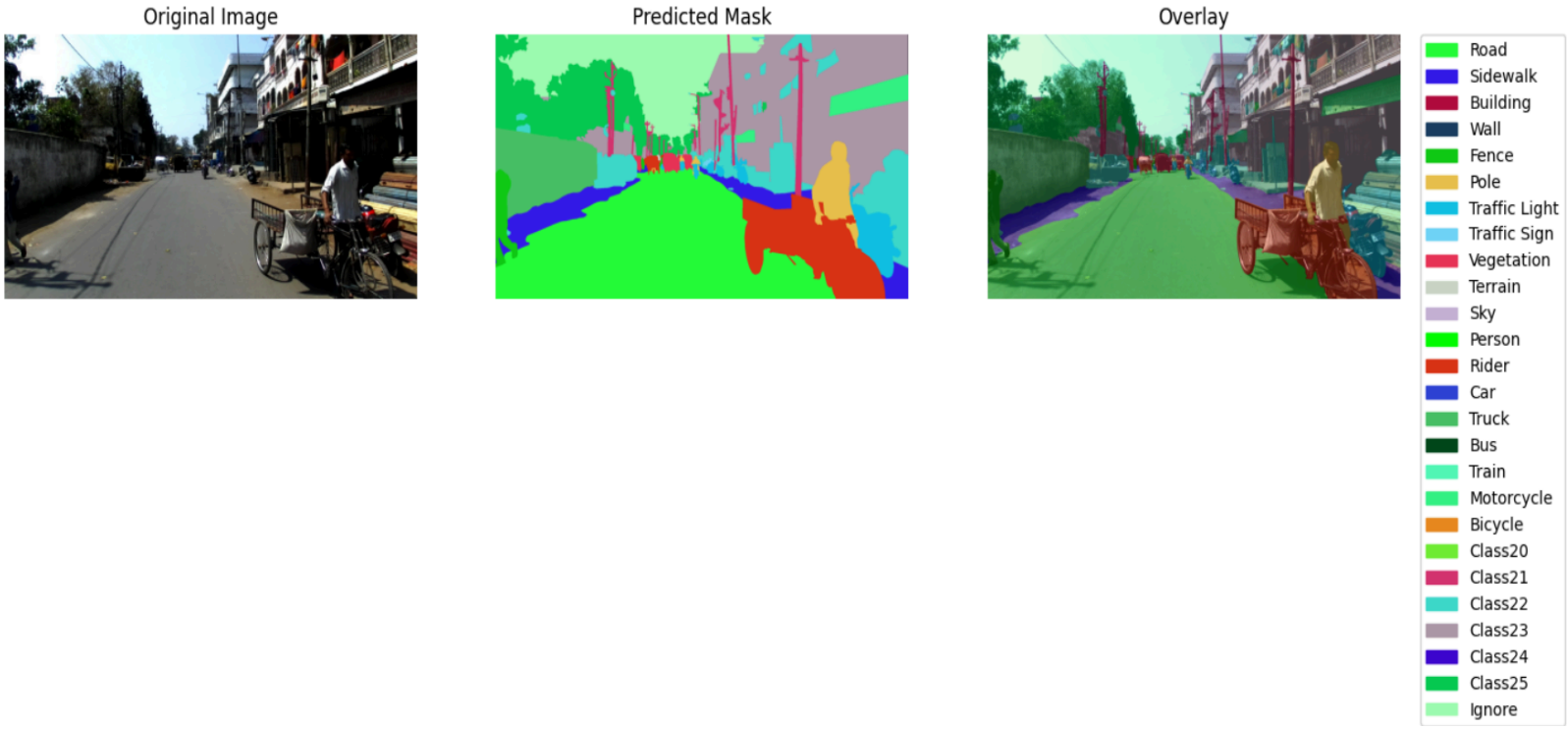
RESULT

We tested our **DeepLabV3+ (ResNet-101)** model on real images from the **IDD Part-2 dataset** using **Google Colab (GPU)**. Visual results included:

- **Left**: Original road image
- **Center**: Predicted segmentation mask (26 classes)
- **Right**: Overlay of prediction on original image




Original Image
Predicted Mask
Overlay


Original Image
Predicted Mask
Overlay
Road
Sidewalk
Building
Wall
Fence
Pole
Traffic Light
Traffic Sign
Vegetation
Terrain
Sky
Person
Rider
Car
Truck
Bus
Train
Motorcycle
Bicycle
Class20
Class21
Class22
Class23
Class24
Class25
Ignore

Performance Metrics

- Pixel Accuracy: 0.8291 (82.91%)
- Mean IoU: 0.3529 (35.29%)

The model effectively segmented key elements like roads, vehicles, pedestrians, and maintained sharp object boundaries. Visual overlays clearly showed its ability to handle Indian traffic complexity, proving useful for autonomous driving systems.

APPLICATIONS

Using DeepLabV3+ for semantic segmentation in road scenes actually has a lot of real-world uses, especially when it comes to smart transportation and self-driving tech. Here are some of the ways it can make a difference:

Autonomous Driving Systems

It helps self-driving cars better understand what's around them by separating roads, cars, people, signs, and other stuff in the scene. This makes things like lane detection, avoiding obstacles, and planning routes way more accurate and reliable.

Advanced Driver Assistance Systems (ADAS)

It also supports important features like keeping the car in the right lane, helping avoid crashes, and recognizing traffic signs. All of this helps drivers stay safer and more aware while they're on the road.

Smart City Infrastructure

In cities, it can be used for monitoring traffic, managing congestion, and automatically spotting accidents using surveillance cameras. It's also useful when planning new roads or figuring out where repairs are needed.

Robotics and Drones

It helps robots and drones move through streets and city areas without running into things, which is especially useful in crowded or complex environments.

Augmented Reality Navigation

For AR navigation, it helps by detecting roads and landmarks in real time so useful info can be shown right on the driving scene.

Simulation and Training Platforms

It's also used in virtual driving sims and AI training setups. It helps create more realistic environments for testing and teaching AI how to handle real-world driving situations.

Traffic Law Enforcement

On the law enforcement side, it can be used to catch things like illegal parking or people cutting lanes by analyzing live video footage.

CONCLUSION

In this project, we successfully implemented semantic segmentation of road scenes using the DeepLabV3+ architecture. By leveraging a pre-trained deep learning model and a well-structured dataset, we were able to classify each pixel of the input images into meaningful categories such as roads, vehicles, pedestrians, and other infrastructure components. The DeepLabV3+ model provided accurate and detailed segmentation maps, which are crucial for real-time decision-making in applications like autonomous driving and intelligent transportation systems. The preprocessing, training, and prediction pipeline was executed step-by-step, resulting in grayscale segmentation outputs that conform to the required format. Overall, this project demonstrates the power of semantic segmentation in enhancing the visual understanding capabilities of machines and serves as a foundational step towards building safer and smarter AI-driven transportation solutions.

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