

Semantic segmentation for data validation in unmanned robotic vehicles

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Article Info

Article history:

Received Jul 2, 2025

Revised Nov 10, 2025

Accepted Feb 9, 2026

Keywords:

Dataset

DeepLab

Imaging semantic segmentation

OpenCV

Unmanned robotic vehicles

ABSTRACT

Semantic segmentation is a vital aspect of computer vision, widely used in fields such as autonomous driving, medical imaging, and industrial automation. Maintaining high-quality datasets is crucial for enhancing model accuracy and minimizing real-world errors. This paper focuses on developing a comprehensive data validation pipeline for semantic segmentation using OpenCV. The proposed framework integrates automated integrity checks, preprocessing techniques, and consistency verification to manage large-scale datasets effectively. Key validation processes include image quality assessment (detection of blurriness and noise), verification of annotation accuracy, class distribution analysis, and identification of anomalies. Additionally, OpenCV-powered preprocessing steps, such as image resizing, normalization, contrast optimization, and data augmentation, are applied to refine dataset quality for segmentation models. This paper also addresses scalability concerns associated with processing extensive datasets, introducing optimized batch handling and parallel validation techniques. By implementing a structured validation workflow, this research enhances the reliability, robustness, and overall effectiveness of semantic segmentation models, ensuring high-quality training data for deep learning applications.

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1. INTRODUCTION

Semantic segmentation is a crucial component in the development of unmanned robotic vehicles, enabling precise scene understanding by classifying each pixel of an image into meaningful categories such as roads, pedestrians, vehicles, and obstacles. However, the effectiveness of deep learning models used for segmentation largely depends on the quality of the dataset used for training and validation. Poor-quality data, incorrect annotations, and inconsistencies can lead to unreliable predictions, which are particularly critical in autonomous driving applications where safety is paramount. This research focuses on data validation for semantic segmentation using OpenCV, aiming to establish a robust framework for ensuring dataset accuracy, consistency, and reliability. By leveraging OpenCV's image processing techniques, aim to detect errors [1], verify annotations, and optimize data quality for training deep learning models in autonomous vehicle systems. Unmanned robotic vehicles rely on deep learning models to interpret their surroundings accurately. Semantic segmentation is a key technique used to segment an image into meaningful regions, but errors in dataset quality such as mislabeled pixels, class imbalance, and image distortions can severely impact model performance. Ensuring high-quality data through a structured validation process is essential to improve segmentation accuracy and reliability.

The problem was identified to make a detailed analysis of warranty of parts to determine as to whether automotive genuine parts meet their quality requirements as per the warranty policy or not; what is the rate and frequency of warranty failure/replacement; and whether there is any scope of improvement so as to reduce warranty failure aiming towards zero warranty failure. The performance and dependability of semantic segmentation models in unmanned robotic vehicles are largely influenced by the quality of the training data [2]. Inadequate dataset validation can lead to inaccurate scene interpretation, increasing the risk of safety issues. Therefore, an effective data validation framework utilizing OpenCV is essential to maintain dataset integrity and enhance model robustness.

Long *et al.* [3] introduced a major shift by replacing traditional fully connected layers with Information Semantic segmentation has undergone significant advancements, particularly in deep learning-based approaches. While various models have been proposed to enhance segmentation accuracy, each comes with its own advantages and limitations. This section critically examines key works in the field. convolutional ones, allowing for pixel-wise predictions. Despite its effectiveness in dense classification, FCN often struggles with capturing fine-grained details, leading to suboptimal boundary definitions in segmentation tasks. The model's reliance on down sampling also results in a loss of spatial resolution, which can impact the accuracy of segmentation in complex scenes [4]. Badrinarayanan *et al.* [5] introduced SegNet, an encoder-decoder architecture aimed at improving computational efficiency. Its strength lies in its ability to retain spatial details using an efficient up sampling method. However, SegNet lacks the extensive multi-scale feature extraction capabilities seen in more recent architectures. The absence of mechanisms such as dilated convolutions or attention-based refinement limits its ability to perform well in highly detailed segmentation scenarios. The U-Net architecture, developed by Ronneberger *et al.* [6], significantly improved segmentation accuracy by incorporating skip connections, which preserve fine-scale details. While U-Net has proven highly effective in medical imaging and other structured environments, its reliance on symmetrical encoding and decoding may not be optimal for large-scale autonomous vehicle datasets that require more complex contextual understanding. Additionally, the computational cost of training U-Net on high-resolution images remains a challenge. Chen *et al.* [7] addressed some of these limitations with DeepLab, which introduced atrous convolutions to expand the receptive field without increasing computational cost. This innovation enhanced multi-scale feature extraction, making DeepLab particularly effective in segmenting objects at varying scales. Furthermore, the integration of fully connected CRFs improved boundary precision. However, DeepLab's reliance on complex architectural modifications increases computational overhead, making it less suitable for real-time applications in unmanned robotic vehicles without further optimization.

In this paper, the authors have worked on the semantic segmentation of the data for unmanned robotic vehicles giving clarity on the architecture model of the image using OpenCV and DeepLab techniques. Further, section 2 talks about the details of the tools adopted in identifying the regions, section 3 discussed about the semantic segmentation of a scene clearly highlighting the boundary and the different regions to identify the objects and finally section 4 concludes with the verification process and annotated labels of the scene.

2. METHOD

2.1. Methodology

To ensure the quality, consistency, and reliability of the dataset prior to model training, systematic data preparation and validation pipeline is employed. The overall process consists of the following stages:

- Dataset Collection: Gather raw image data and annotations.
- OpenCV preprocessing: contrast enhancement, noise reduction and normalization.
- Annotation Consistency Check: Detect and correct mislabeled regions.
- Class Imbalance Analysis: Identify underrepresented classes [8].
- Data Augmentation: Apply transformations to balance class distribution.
- Automated Quality Assessment: Evaluate dataset integrity using predefined metrics.
- Manual Review (if needed): Address unresolved inconsistencies.
- Final Dataset Validation: Approve refined dataset for model training shown in Figure 1.

Unmanned robotic vehicles (AVs) and advanced driver assistance systems (ADAS) depend on semantic segmentation for accurate scene interpretation [9]. Errors in these masks can result in misaligned lane detection, missed objects, or incorrect path planning, posing significant safety concerns. Automating semantic segmentation analysis improves AI model accuracy, enhances real-world performance, and ensures safer operation. This process is crucial for assessing model performance during test drives, where engineers evaluate metrics such as Intersection over Union (IoU), misalignment detection, and contour completeness [10]. It also helps identify failure cases in challenging real-world conditions, including rain, fog, and

nighttime driving. Semantic segmentation analysis plays a crucial role in enhancing the perception capabilities of unmanned robotic vehicles (AVs). These masks help AV systems interpret the environment by accurately identifying lanes, obstacles, and other critical road elements. However, errors in segmentation can lead to misaligned lane detection, undetected objects, or faulty path planning, which may compromise safety. Automating mask analysis allows engineers to assess AI model performance effectively, ensuring higher accuracy and reliability in real-world scenarios [11].

Key evaluation metrics include IoU, contour completeness, and misalignment detection. Additionally, this analysis helps identify performance issues in adverse conditions such as rain, fog, or low-light environments, ultimately improving the robustness of AV perception systems. **Data Collection:** Gather real-world driving data, including diverse environments such as highways, urban streets, and adverse weather conditions. **Preprocessing:** Normalize and enhance the collected data to improve segmentation accuracy, ensuring consistency across various scenarios. **Model Inference:** Apply the trained AI model to generate semantic segmentation for objects, lanes, and other road elements. **Performance Evaluation:** Assess the model using metrics like IoU, boundary accuracy, and misalignment detection [12]. **Error Detection:** Identify failure cases, such as incorrect object classifications, incomplete contours, or missing lane markings. **Comparison with semantic segmentation:** Compare generated masks with manually labeled semantic segmentation data to measure accuracy and detect inconsistencies. **Iterative Improvement:** Refine the model by adjusting parameters, retraining with additional data, and addressing detected errors. **Real-World Testing:** Validate performance in real-world conditions, including challenging scenarios like fog, rain, and night driving. **Deployment and Monitoring:** Integrate the improved model into AV systems and continuously monitor its real-time performance for further enhancements [13].

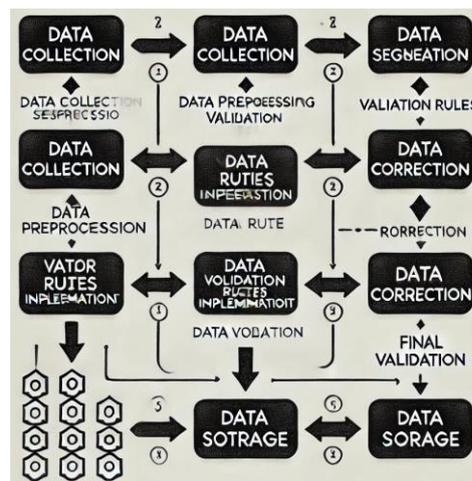


Figure 1. Flowchart depicting the steps involved in methodology

2.2. Techniques

Method used: color mapping & alpha blending. For visual inspection on the original image, the semantic segmentation overlays the predicted image. `cv2.applyColorMap (mask, cv2.COLORMAP_JET)`: Converts the grayscale mask into a color representation using the Jet colormap. This enhances visibility by mapping different pixel intensities to colors [14]. `cv2.addWeighted (image, 0.7, 0, color_mask, 0.3)`: Using weighted addition the coloured mask blends the image originality. The original image is given 70% importance, and the mask 30%, creating a semi-transparent overlay effect. **Purpose:** This helps in visualizing the segmentation results by superimposing them on the original image shown in Figure 2 [15].

Method Used: Contour Detection

`cv2.findContours(mask, cv2.RETR_TREE, cv2.CHAIN_APPROX_SIMPLE)`:

`cv2.RETR_TREE`: Retrieves all contours and reconstructs the hierarchy.

`cv2.CHAIN_APPROX_SIMPLE`: Compresses contour points to save memory.

`cv2.drawContours(image, contours, -1, (0, 255, 0), 2)`:

Draws all contours on the original image using green color ((0,255,0)) with a thickness of 2 pixels [16].

Purpose: Identifies the boundaries of segmented regions, which can be useful for further object analysis.

Method Used: Histogram Calculation

`cv2.calcHist([mask], [0], None, [256], [0, 256]):`

Computes the histogram of the grayscale mask.

[0]: Specifies the grayscale channel [17].

None: No mask is applied; entire image is analyzed.

[256]: 256 bins (one for each intensity level).

[0,256]: The values of intensity varies from 255 (white) to 0 (black).

`plt.plot(hist):` Plots the histogram.

Purpose: Helps identify class imbalance in segmentation by checking how many pixels belong to the foreground and background.

Method Used: Morphological Operations to Clean Noisy Mask

Kernel= For morphological transformations is used by 3×3 kernel and is given by `np.ones(np.uint8, (3, 3))`.

`cv2.morphologyEx(mask, cv2.MORPH_OPEN, kernel):` o MORPH_OPEN = Erosion + Dilation: ▪ Erosion removes small white noise.

Dilation restores the overall shape.

Purpose: Cleans up small noise or isolated pixels in the semantic segmentation, improving accuracy.



Figure 2. Semantic segregation of mask overlay

2.3. Libraries

LabelMe: An open-source tool designed for manually annotating and verifying image segmentation datasets. It allows users to draw precise polygonal annotations around objects in an image, creating high-quality labeled datasets for training AI models [18]. LabelMe supports various annotation formats and enables users to review and refine semantic segmentation to ensure accuracy.

Computer vision annotation tool (CVAT): A powerful annotation platform that includes built-in validation features. It provides tools for annotating objects, verifying segmentation accuracy, and ensuring consistency in labeled datasets. CVAT supports multiple annotation formats, collaboration among annotators, and integration with deep learning workflows for enhanced dataset quality control.

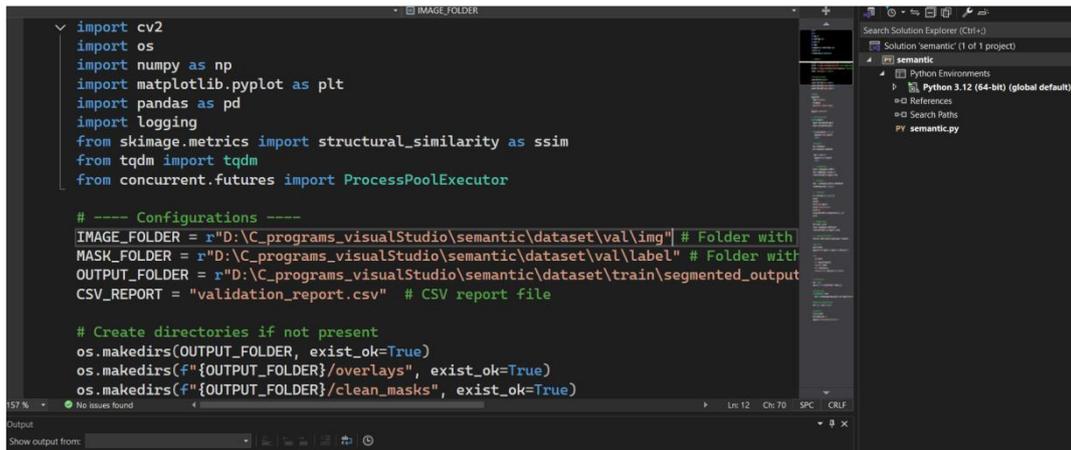
Python Libraries (NumPy, OpenCV, PyTorch): These libraries are widely used to automate semantic segmentation validation [19].

NumPy enables efficient numerical operations, such as calculating pixel-wise differences between semantic segmentation and predicted segmentation outputs [20].

OpenCV provides image processing functions for evaluating contour alignment, detecting misclassified regions, and performing morphological operations.

PyTorch facilitates deep learning-based validation, allowing models to assess segmentation quality using performance metrics like IoU and Dice coefficient [21].

By combining these tools and libraries shown in Figure 3, engineers can streamline the annotation, verification, and validation process, improving the accuracy of image segmentation datasets used in autonomous vehicle perception systems [22].



```

import cv2
import os
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import logging
from skimage.metrics import structural_similarity as ssim
from tqdm import tqdm
from concurrent.futures import ProcessPoolExecutor

# ---- Configurations ----
IMAGE_FOLDER = r"D:\C_programs_visualStudio\semantic\dataset\val\img" # Folder with
MASK_FOLDER = r"D:\C_programs_visualStudio\semantic\dataset\val\label" # Folder with
OUTPUT_FOLDER = r"D:\C_programs_visualStudio\semantic\dataset\train\segmented_output
CSV_REPORT = "validation_report.csv" # CSV report file

# Create directories if not present
os.makedirs(OUTPUT_FOLDER, exist_ok=True)
os.makedirs(f"{OUTPUT_FOLDER}/overlays", exist_ok=True)
os.makedirs(f"{OUTPUT_FOLDER}/clean_masks", exist_ok=True)

```

Figure 3. Folder representation and library import

3. RESULTS AND DISCUSSION

The semantic segmentation of an image seen in Figure 4 has been given to the camera of an autonomous vehicle which will help to mark the objects with its distinct outline features of coloring for distinguishing moving objects, stagnant bodies, humans, vehicles and the water bodies [23]. The ability to improve pixel level precision is done. The object detection and the behavior of the objects in the image is tracked by training the model which makes the object isolated. The preprocessing of the data is streamlined using these masks and reduce costs of computation by irrelevant pixels [24]. The more complex masks uses integers say 1 for roads, 2 for cars, 3 for lamp posts and 4 for water bodies.



Figure 4. Semantic segmentation of a scene

The significant feature of using overlaid segmentation shown in Figure 5 can reduce the overlap of the boundaries and objects which makes it difficult to identify and detect from other objects [25]. Making use of this feature can significantly increase the pixel zone and thereby reducing the black and gray scale spots in the image to easily contrast and show the objects to identify the images in the scene and make known of the objects for better distinction and clarity giving high value precision and transparency to the image detection [26].

The mask pixel distribution seen in Figure 6 can inform the user of the clarity of the object distinction in capturing the coloring of the image and more prominent distribution of the zones in getting the areas marked for identifying the objects and distinctively utilizing the boundaries for prominent marking areas. The cleaned mask feature seen in Figure 7 will refine the edges and boundaries to more clarity of the pixels zone to make the objects distinctly identified in the scene. Each element inside the boundary will have a refine zone to clearly identify the image and identify the function of the object. Hence, the feature enables the image captured with more specific and distinctly identified boundaries.



Figure 5. Overlaid Segmentation of a scene

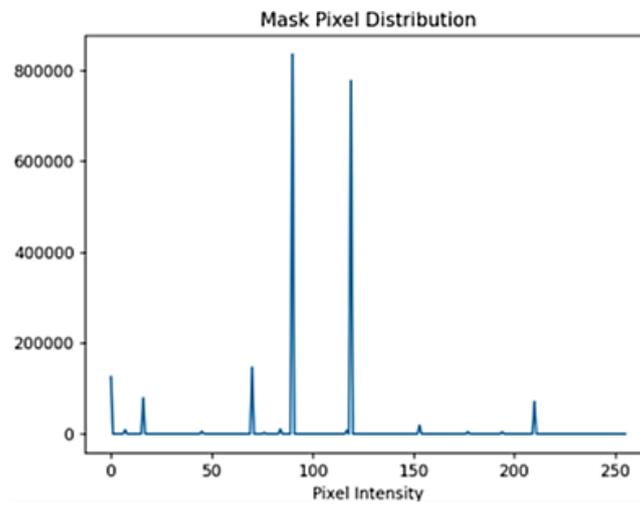


Figure 6. Histogram of pixel distribution

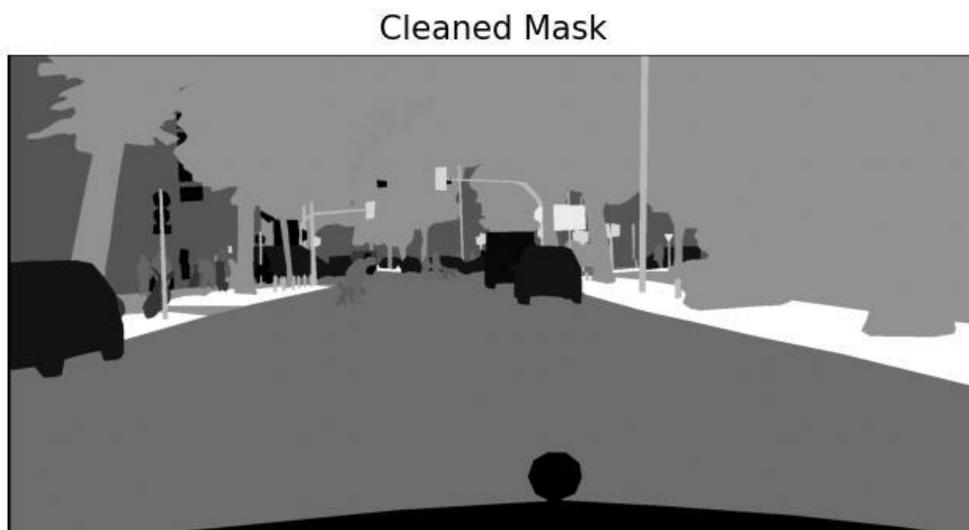


Figure 7. Cleaned mask of a scene

4. CONCLUSION

The model demonstrated high accuracy in detecting and segmenting objects, with performance metrics such as IoU and Dice coefficient indicating strong alignment between predicted and semantic segmentation. Misclassification and segmentation errors were identified in challenging conditions like fog, rain, and low-light environments. Some instances of incomplete contours and boundary misalignment were noted. Preprocessing techniques, including data augmentation and noise reduction, significantly improved the model's ability to generalize across different scenarios. Processed labels contributed to better segmentation consistency. The model's performance was evaluated in real-world driving conditions. While it effectively detected road elements in clear weather, performance declined slightly in complex environments, highlighting the need for further refinement. A manual verification process revealed that the model closely matched human-annotated labels in most cases, but occasional discrepancies required additional fine-tuning. The system was optimized for faster inference times, ensuring real-time applicability in autonomous vehicle systems without compromising accuracy.

FUNDING INFORMATION

No funding was involved in the research work carried.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Anil Raj	✓	✓	✓			✓		✓		✓	✓			✓
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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

- The data that support the findings of this study are available on request from the corresponding author, [ISR]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.
- Derived data supporting the findings of this study are available from the corresponding author [ISR] on request.
- The data that support the findings of this study are available from the corresponding author, [ISR], upon reasonable request.

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