**Enhancing Road Boundary Detection in Autonomous Driving: The Impact of Targeted Image Augmentations on Model Robustness**

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**Abstract**

This study examines the impact of simple image augmentations on improving road boundary detection in autonomous driving AI under challenging conditions. Autonomous systems require robust recognition in varied lighting and weather, yet initial experiments using standard Albumentations transformations—HorizontalFlip, RandomSizedCrop, Compose, OneOf, and Resize—proved insufficient in handling shadows and adverse weather effects. To address this, we added RandomBrightnessContrast and HueSaturationValue augmentations, simulating brightness and color variations to improve the model’s adaptability to real-world conditions. These enhancements increased the UNet model's Intersection over Union (IoU) from 0.86 to 0.91, demonstrating a significant accuracy improvement in complex scenarios.

Our results highlight that targeted, minor adjustments in augmentations can substantially improve an autonomous model’s performance. This approach enhances resilience in self-driving systems, suggesting that even basic augmentations, when carefully chosen, can reduce recognition errors and contribute to safer autonomous operation. The study underscores the value of augmentation strategies in adapting AI for practical, real-world driving environments.

**Introduction**

Accurate road boundary detection is a critical component for safe autonomous driving, especially as autonomous vehicles encounter diverse real-world conditions.1-4 Variations in lighting, shadows, and weather changes can blur the distinction between road and non-road areas, increasing the risk of misinterpretation by autonomous driving AI.5-7 These visual ambiguities present a significant challenge, as traditional data augmentation techniques alone often fail to equip models with the robustness needed for consistent performance in such conditions.8, 9 In response, this study focuses on enhancing model resilience by incorporating targeted augmentations that adjust lighting and color, aiming to improve the model's capability to recognize road boundaries accurately under varying environmental factors.

Various data augmentation techniques have been explored to improve road boundary detection in autonomous driving AI. One commonly used approach is basic image transformations, including methods like HorizontalFlip and RandomSizedCrop.10, 11 These techniques add general diversity to the dataset, helping the model recognize roads from different angles and scales. However, they fall short in replicating complex real-world variations, such as dynamic lighting changes or adverse weather conditions. For example, in cases with shadsows across the road or dim lighting, these basic transformations alone are often insufficient to enhance the model's robustness in road detection. Another popular approach is adding noise or blurring effects to simulate certain types of visual noise that may occur in driving environments.12-14 This method aims to improve the model's resilience across various settings. However, it is often inadequate for extreme weather conditions, such as heavy rain or fog, where visibility is significantly impaired. In such cases, distinguishing between road and non-road areas becomes more challenging, and simple noise-based augmentations fail to provide the necessary support. Therefore, while traditional augmentation techniques offer some improvements, they are insufficient for addressing the complex visual challenges faced in real-world autonomous driving scenarios, highlighting the need for more targeted, environment-specific augmentation strategies.

The objective is to improve the robustness of autonomous driving AI models by making simple, yet effective adjustments to data augmentation techniques, enabling better handling of real-world visual challenges. While traditional augmentation methods offer some variability, they often struggle with more subtle yet impactful changes in lighting and weather, which can obscure road boundaries and reduce model accuracy.9, 15, 16 To address these limitations, minor adjustments were made to the augmentation strategy by adding basic brightness and color modifications using techniques like RandomBrightnessContrast and HueSaturationValue. These straightforward adjustments introduce slight variations in lighting and color, allowing the model to better adapt to common environmental shifts.17, 18 Despite the simplicity of these added augmentations, the model demonstrated an improved ability to recognize road boundaries under common visual disturbances, such as shadows or bright sunlight, leading to a measurable enhancement in its recognition accuracy. This approach shows that even minor modifications in augmentation can strengthen the model’s generalization capacity, resulting in higher precision and stability in road detection.19, 20 The findings suggest that small, targeted adjustments to data preprocessing can effectively support the reliability and safety of autonomous driving systems, highlighting that meaningful performance gains can be achieved without complex alterations.

This study demonstrates that even minor additions to data augmentation techniques can significantly improve the road boundary detection performance of autonomous driving AI. By incorporating simple brightness and color adjustment methods into basic augmentation techniques, the Intersection over Union (IoU) score increased from 0.86 to 0.97. This suggests that small changes can enhance the model's generalization ability and recognition accuracy in real-world environments. The research emphasizes the importance of data preprocessing that reflects complex environmental variations and proposes a simple yet effective approach that can contribute to strengthening the reliability and safety of autonomous driving AI.

**Method**

To enable effective training on the KITTI segmentation dataset, a custom data generator, KittiGenerator, was developed using TensorFlow's Sequence API. This generator facilitates structured parsing, batch loading, and preprocessing of images and corresponding labels, specifically adapted for an input size of (224, 224, 3) and output size of (224, 224).

Dataset Preparation and Loading

The KittiGenerator initializes by accepting key parameters, including the dataset directory, batch size, input and output dimensions, an indicator of training mode, and an optional augmentation function. Upon initialization, the generator identifies and loads image paths and corresponding label paths from the specified directory, arranging these into a dataset split. When set to training mode, the generator partitions the data, reserving a subset of images exclusively for testing. This organized setup enables controlled access to images and labels, ensuring that the model receives a structured input-output mapping for semantic segmentation.

Batch Construction and Augmentation

Within each batch, the generator loads and preprocesses images and labels as defined in the \_\_getitem\_\_ function. Each input image is resized to match the model's specifications, and basic augmentations are applied when augmentation functions are provided. Label images are processed into binary masks focusing on the target class by assigning specific pixel values, thereby ensuring consistency across segmentation tasks. The normalized images and corresponding masks are then prepared for input to the model, promoting enhanced learning across varied visual conditions.

Training Variability and Shuffling

To support effective model generalization, the on\_epoch\_end function shuffles data at the end of each epoch when in training mode, introducing randomization that reduces overfitting. This shuffling ensures that each epoch presents a different sequence of data, contributing to the model’s robustness over time. This approach enables a streamlined and efficient handling of the KITTI dataset, providing the model with a well-prepared input stream for real-time augmentation and segmentation-based training in autonomous driving applications.

Model Architecture and Optimization

The UNet model was selected for its suitability in pixel-level segmentation tasks like road boundary detection. The architecture consists of an encoder-decoder structure with skip connections linking corresponding layers. The encoder includes four blocks, each with two 3x3 convolutional layers (64, 128, 256, 512 filters, respectively), followed by a 2x2 max pooling layer, capturing progressively detailed features. The decoder mirrors this structure with four upsampling blocks, each including a 2x2 transposed convolution layer to restore spatial resolution, followed by two 3x3 convolutions (512, 256, 128, 64 filters, respectively). Skip connections concatenate feature maps from the encoder to their matching decoder layers. The final output layer applies a 1x1 convolution to reduce the channel dimension to the number of classes (2 for road and non-road) and uses a softmax activation function, generating pixel-wise probability maps for segmentation.

The model was optimized using the Adam optimizer with an initial learning rate of 0.001, coupled with learning rate decay to ensure stable convergence. Binary cross-entropy served as the primary loss function, appropriate for binary segmentation, with IoU monitored as a secondary metric to capture boundary accuracy. Early stopping based on validation loss was employed to prevent overfitting, ensuring efficient training without compromising generalization. This combination of UNet architecture and optimized training parameters supported effective road boundary segmentation in the KITTI dataset.

Data Augmentation

To enhance model robustness against real-world variations, targeted data augmentation techniques were applied, focusing on subtle yet impactful environmental changes often encountered in autonomous driving. In addition to standard transformations, minor augmentations were introduced to simulate variations in lighting and color that mimic real driving conditions. This combination aimed to improve the model’s adaptability to visual disruptions, such as shadows, reflections, and weather-induced shifts.

Basic Augmentations

Basic augmentations included horizontal flipping with a 0.5 probability to introduce directional variability, and random cropping with resizing, where images were cropped within a height range of 300 to 370 pixels, maintaining a width-to-height ratio of 370/1242, and then resized to 224x224 with a 0.5 probability. This cropping emulated different viewpoints by focusing on varied image sections. All images were finally resized to 224x224 to meet model input requirements. For the test set, only resizing was applied to maintain consistency without additional transformations.

Targeted Lighting and Color Adjustments

Targeted lighting and color adjustments included brightness and contrast modifications through RandomBrightnessContrast, with brightness and contrast limits set to ±0.2 to simulate conditions such as shadows or intense sunlight. HueSaturationValue was applied with hue, saturation, and value limits of ±10, ±20, and ±20, respectively, to introduce subtle color shifts reflecting environmental changes like reflections or surrounding objects. These controlled ranges were chosen to avoid drastic alterations while enhancing the model’s adaptability to common outdoor driving variations.

**Results and Discussion**

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**Figure 1.** Examples of data augmentation applied to the KITTI dataset. Images within black boxes represent the original resized images (224x224). Images within blue boxes show results of basic augmentations, including horizontal flip and random cropping. Images within red boxes demonstrate additional augmentations with brightness, contrast, hue, and saturation adjustments.

Figure 1 illustrates the effects of data augmentation applied to the KITTI dataset to enhance the model's ability to handle diverse visual conditions in autonomous driving scenarios. The images in black boxes represent the original, resized dataset images (224x224), which serve as the baseline input for the model. To introduce variability and improve generalization, two stages of augmentation were employed. The images within the blue boxes show the results of basic augmentations, including horizontal flipping and random cropping. These transformations expose the model to different perspectives and compositions, allowing it to learn from slight variations in image orientation and scale. However, while beneficial, these basic augmentations alone are often insufficient for addressing complex environmental factors like lighting and color shifts, which are common in real-world driving conditions. To address this gap, additional augmentations—displayed in the red boxes—were applied to simulate subtle but impactful environmental changes. Adjustments to brightness, contrast, hue, and saturation were incorporated to emulate various lighting scenarios, such as shadowed regions, direct sunlight, and ambient reflections. This targeted approach is intended to help the model adapt to the unpredictable visual disruptions that occur in outdoor environments, enhancing its resilience to real-world variability. These augmentations collectively aim to improve the model’s robustness by diversifying the dataset with controlled variations that mimic realistic conditions, setting a stronger foundation for accurate segmentation performance under challenging visual settings.

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**Figure 2.** Comparison of segmentation results with different augmentation techniques. (a) Segmentation results using basic augmentation methods. (b) Segmentation results with additional targeted augmentations applied. Green areas indicate correct segmentation, red represents false negatives, and blue indicates false positives.

As shown in Figure 2. the impact of different augmentation strategies on segmentation performance. Panel (a) shows the segmentation results obtained with basic augmentations, while panel (b) displays results after applying additional targeted augmentations, including brightness, contrast, hue, and saturation adjustments. In both panels, green areas correspond to correct segmentation predictions, red indicates false negatives (missed detections), and blue represents false positives (incorrectly predicted areas). The basic augmentations in (a) provide a baseline performance, with visible false positives and false negatives along boundary regions, particularly in areas affected by shadows or changes in surface texture. In contrast, the results in (b), generated using the enhanced augmentation approach, show reduced false positives and false negatives, particularly around complex boundary regions. The targeted adjustments in lighting and color enabled the model to better generalize to varied environmental conditions, effectively capturing road boundaries even under challenging visual changes. This improvement suggests that incorporating these simple but focused augmentations contributes significantly to the model’s robustness, enhancing its ability to accurately delineate road areas in real-world scenarios.

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**Figure 3**. IoU comparison between Advanced Augmentation and Basic Augmentation across sample images. The blue line represents IoU values for Advanced Augmentation, while the orange line shows IoU values for Basic Augmentation.

The maximum IoU achieved with Advanced Augmentation is higher than that of Basic Augmentation, reflecting the enhanced segmentation accuracy provided by the targeted augmentations. (**Figure 3.**) While both augmentation strategies show fluctuations in IoU, Advanced Augmentation consistently yields higher values, indicating its effectiveness in improving the model's robustness to challenging visual conditions. This result suggests that the inclusion of additional adjustments, such as brightness, contrast, and color shifts, contributes positively to the model’s ability to generalize across diverse environmental variations, ultimately leading to more reliable road boundary detection.

**Conclusion**

In this study, we explored the impact of data augmentation strategies on improving road boundary detection in autonomous driving AI models. By comparing basic augmentations with advanced techniques that included targeted adjustments in brightness, contrast, and color, we demonstrated that even simple enhancements in augmentation can lead to significant gains in segmentation performance. The results showed that Advanced Augmentation not only achieved a higher maximum IoU but also maintained more consistent accuracy across varied sample images, highlighting its role in enhancing model robustness under diverse environmental conditions. This approach emphasizes the importance of thoughtful augmentation in preparing models for real-world challenges, where lighting and color variations are prevalent. Overall, our findings suggest that incorporating targeted augmentations can substantially improve the reliability and accuracy of autonomous driving systems, paving the way for safer and more adaptable AI in complex driving scenarios.

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