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A Deep Learning Approach for Faded Road Marking Detection Using YOLOv8

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ABSTRACT

This study develops an automated system for detecting the fading level of road markings using a YOLOv8-based deep learning approach. A dataset of 2,049 images categorized into clear and faded markings was trained using four augmentation strategies: no augmentation, horizontal flip, saturation + exposure, and a combination of rotation, grayscale, saturation, and brightness. The results show that the saturation + exposure augmentation provides the highest performance, achieving 86% accuracy, 86% precision, 86% recall, and an 85% F1-score. These findings highlight the unique contribution of this work, demonstrating that color and illumination based augmentation significantly improves model generalization under real world lighting variations. The study provides an important step toward developing reliable automatic road marking monitoring systems to support road-safety management and intelligent transportation infrastructure.

Keywords: *YOLOv8, Object Detection, Road Markings, Deep Learning, Image Augmentation*

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INTRODUCTION

The quality of road infrastructure is a crucial factor in maintaining transportation safety and efficiency. Road markings, as one of the primary visual elements, serve to guide drivers to stay within safe lanes, avoid traffic conflicts, and make quick decisions (Erwin Kusnandar, 2016). However, in many regions of Indonesia, road marking maintenance remains suboptimal, causing the markings to fade and become difficult to recognize. This condition reduces driver visibility and increases the potential risk of traffic accidents (Rendy Fitra Adi Pratama, 2024). According to a report from the Ministry of Transportation, approximately 35% of traffic accidents are attributed to poor road infrastructure, including worn-out road markings. Environmental factors such as rainfall, sunlight exposure, and vehicle abrasion further accelerate the deterioration of road markings (Liusman Gaho, Ali, & Prakasa, 2024).

The core problem lies in the absence of an automated monitoring system capable of detecting and evaluating the condition of road markings quickly and accurately. Road marking inspections are generally performed manually, requiring significant time, cost, and labor. In the context of developing smart cities and intelligent transportation systems (ITS), the existence of an automated system is essential to support transportation efficiency and public safety (Liusman Gaho et al., 2024).

Recent advancements in artificial intelligence (AI) and computer vision have opened significant opportunities for automating road infrastructure analysis. Modern object detection methods, such as You Only Look Once version 8 (YOLOv8), are capable of recognizing objects rapidly and accurately in real time (Djulyansyah, Laxmi, & Agustian, 2023; Sasmito & Hadi, 2021). With this capability, YOLOv8 can be employed to identify and classify the condition of road markings either "clear" or "faded" based on image and video input. The integration of object detection models with image preprocessing techniques, such as contrast enhancement or jointly learned image restoration, has been proven to improve input feature quality and detection performance under challenging illumination conditions (Chen, Dewi, Zhuang, & Chen, 2023; Tual, Muzet, Foucher, Heinkelé, & Charbonnier, 2024).

This study aims to develop an automatic detection system for identifying faded road markings using a deep learning approach based on YOLOv8. The dataset used consists of 2,049 road marking images captured under various lighting conditions, categorized into two classes: "clear" and "faded." Through preprocessing, model training, and performance evaluation stages, this research is expected to produce an efficient and reliable detection system. The findings are anticipated to contribute to the development of intelligent transportation systems, enhance driving safety, and support the implementation of automated road infrastructure monitoring in Indonesia.

Although several studies have applied deep learning or object detection methods to road infrastructure assessment, most existing works still focus on general road defects, nighttime visibility enhancement, or surface damage classification. Only limited research specifically addresses the fading level of road markings, and even fewer evaluate the effect of different augmentation strategies on YOLOv8 performance for this task. This gap indicates the need for a systematic analysis of how augmentation techniques influence the model's ability to generalize across varying lighting and environmental conditions. Therefore, this study aims to develop a YOLOv8-based faded-road-marking detection system and evaluate multiple augmentation strategies to identify the most effective configuration for real-world deployment.

METHOD

1. Dataset

The dataset used in this study consists of 2,049 images of road markings collected through direct data acquisition using a GoPro Hero9 Black camera and a Poco X6 Pro smartphone. Data collection was conducted across various locations and environmental conditions to ensure dataset diversity, including variations in lighting (daylight, nighttime, dim), weather conditions (dry and wet), and road surface types (asphalt, dusty, or shaded).

The recorded videos were converted into images through frame extraction and uploaded to the Roboflow platform for annotation. Each image was manually labeled into two classes — “Clear” and “Faded” — and annotated with bounding boxes to support supervised learning. The dataset was then divided into three subsets: 70% for training, 20% for validation, and 10% for testing.

2. Research Stages

Figure ***1*** illustrates the research framework, which consists of five main stages in the development process of a faded road marking detection system using the YOLOv8 method. Each stage is interconnected to ensure that the final results are accurate, efficient, and applicable to real-world field conditions.

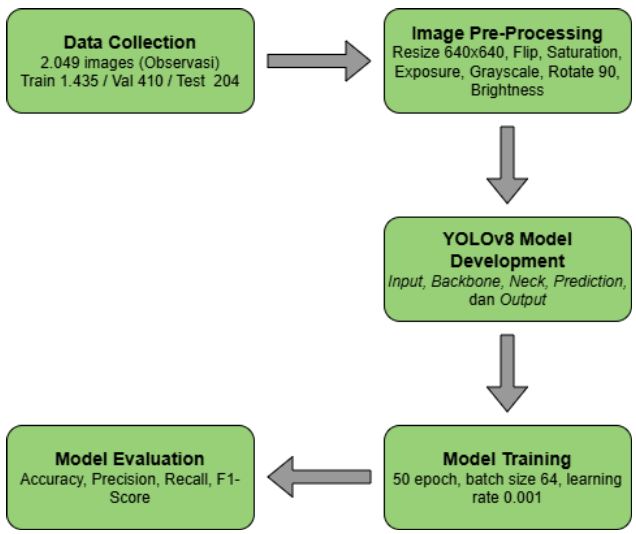

Figure 1 Research Stages

The first stage is Data Collection, which involves acquiring images of road markings under various environmental conditions. Data were obtained through direct image capture using a GoPro Hero9 Black camera and a Poco X6 Pro smartphone, considering variations in lighting (daytime, nighttime, dim), weather conditions (dry and wet), and road surface types (asphalt, dusty, or shaded). All images were categorized into two main classes, “Clear” and “Faded”, to support the supervised learning process.

The second stage is Image Pre-processing, consisting of two main steps: labeling and data augmentation. Labeling was performed manually using the Roboflow platform, where each road marking was annotated with a bounding box and an appropriate class label. Subsequently, data augmentation was applied to enhance the diversity and quantity of the dataset, using different techniques across separate folders:

a. Folder 1: No augmentation (original data)

b. Folder 2: Horizontal Flip to expand the image viewing perspective.
c. Folder 3: Saturation and Exposure Adjustment to simulate various lighting conditions in real-world scenarios.
d. Folder 4: Rotation (90°), Grayscale, Saturation, and Brightness to generate variations in orientation, color, and brightness, enabling the model to better adapt to camera position changes and diverse visual conditions in real environments.

The augmented images were then merged back into the main dataset and resized to 640×640 pixels to match the YOLOv8 input format.

The third stage is YOLOv8 Model Development. In this stage, an object detection architecture was designed using YOLOv8, which consists of five main components: Input, Backbone, Neck, Prediction, and Output. This model was selected for its capability to detect objects in real time with high accuracy (X. Wang, Gao, Jia, & Li, 2023). The architecture integrates Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) to capture features at multiple scales and employs an anchor-free detection approach for prediction efficiency (Yaseen, 2024).

The fourth stage is Model Training, conducted in the Google Colab environment using the Ultralytics YOLOv8 framework. The training process utilized the base model YOLOv8n, which had been pretrained on a large-scale dataset, and was subsequently fine-tuned using the road marking dataset. The training parameters were set as follows: 50 epochs, batch size = 64, and learning rate = 0.001. During the training process, the loss and accuracy curves were monitored to ensure stable convergence and to prevent overfitting.

The final stage is Model Evaluation, aimed at measuring the system's performance in detecting faded road markings. The evaluation employed four primary metrics: Accuracy, Precision, Recall, and F1-Score.

a. Accuracy

A Accuracy measures how many predictions made by the model are correct compared to the total number of tested data. It represents the degree of closeness between the values predicted by the system and the actual ground truth values (Palupi, Ihsanto, & Nugroho, 2023). The accuracy can be calculated using Equation (1):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where:
a. TP (True Positive): Number of positive samples correctly identified.
b. FP (False Positive): Number of negative samples incorrectly identified as positive.
c. FN (False Negative): Number of positive samples incorrectly identified as negative.
d. TN (True Negative): Number of negative samples correctly identified.

b. Precision

Precision is a parameter that measures the proportion of correctly predicted positive instances among all instances predicted as positive. It indicates how reliable the model is when making positive predictions (Palupi et al., 2023). The precision can be calculated using Equation (2):

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Where:

a. TP (True Positive): Number of positive samples correctly identified.
b. FP (False Positive): Number of negative samples incorrectly identified as positiv

c. Recall

Recall measures how many actual positive samples are correctly classified by the model. It represents the model's ability to identify all positive instances within the dataset (Palupi et al., 2023). The recall is computed using Equation (3):

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

Where:

a. TP (True Positive): Number of positive samples correctly identified.
b. FN (False Negative): Number of positive samples incorrectly identified as negative.

d. F1-Score

The F1-Score is the harmonic mean between precision and recall, used to balance both metrics in a single measurement. Its best possible value is 1, indicating perfect precision and recall, while the worst value is 0 (Palupi et al., 2023). The F1-Score can be calculated using Equation (4):

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Where:

a. Precision: Measures the accuracy of the algorithm in identifying positive instances.
b. Recall: Measures the completeness of the algorithm in capturing all positive instances..

3. Preprocessing

The preprocessing stage was carried out to ensure data uniformity and enhance data quality prior to model training. This process consists of two main steps: labeling and image augmentation.

In the labeling step, each road marking image was manually annotated using the Roboflow platform. Every road marking object was assigned a bounding box and classified into two categories: “Clear” and “Faded.” An example of the dataset showing both clear and faded road markings is presented in

Figure ***2***.

Figure 2 Faded (Left) and Clear (Right) Dataset Examples

The subsequent stage involves image augmentation, which aims to enhance both the diversity and volume of the training dataset. The augmentation process was independently applied to each dataset folder to generate a broader spectrum of visual variations.

This folder-based augmentation strategy was designed to improve the model’s adaptability to various real-world scenarios, including changes in illumination, shadow effects, and surface degradation of road markings. In computer vision tasks, augmentation techniques that simulate lighting variations, shadow interference, or visual deterioration have been demonstrated to strengthen model robustness against real-world environmental conditions (Mazhar & Kober, 2021; S. Wang, Veldhuis, Brune, & Strisciuglio, 2023). Upon completion, the augmented images were reintegrated into the primary dataset and subsequently utilized during the training phase of the YOLOv8 model.

4. YOLO Architecture

This study employs the YOLOv8 (You Only Look Once, version 8) algorithm as the primary method for object detection. The YOLOv8 architecture comprises five main components: Input, Backbone, Neck, Prediction, and Output (Yaseen, 2024).

a. Input Layer: Receives an image with a resolution of 640×640 pixels.
b. Backbone: Extracts essential visual features using convolutional layers and C2f blocks to identify key visual patterns.
c. Neck: Combines multi-scale features through the Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) to strengthen feature representation.
d. Prediction Head: Produces bounding boxes and class probabilities using an anchor-free detection mechanism, providing higher efficiency and accuracy.

e. Output Layer: Displays the detection results in the form of bounding boxes and class labels, categorized as “Clear” or “Faded”.

The training process was conducted on Google Colab using the Ultralytics YOLOv8 framework with the following parameters: 50 epochs, batch size of 64, and a learning rate of 0.001. A pretrained YOLOv8n model was fine-tuned using the road marking dataset to adapt it for the specific detection task. During training, loss and accuracy metrics were continuously monitored to ensure model convergence and prevent overfitting. The overall YOLOv8 architecture is illustrated in Figure 3 below.

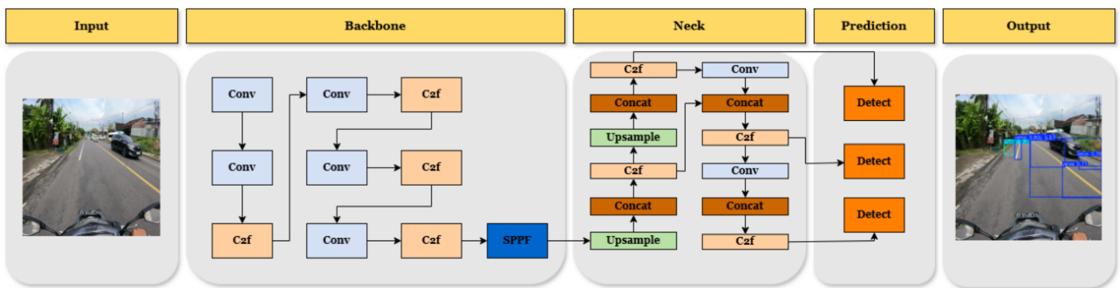

Figure 3 YOLO Architecture

FINDING AND DISCUSSION

RESEARCH RESULT

1. Images Before and After Augmentation

Examples of images before augmentation and the various augmentation techniques applied in this study are presented in Figure 4 below.

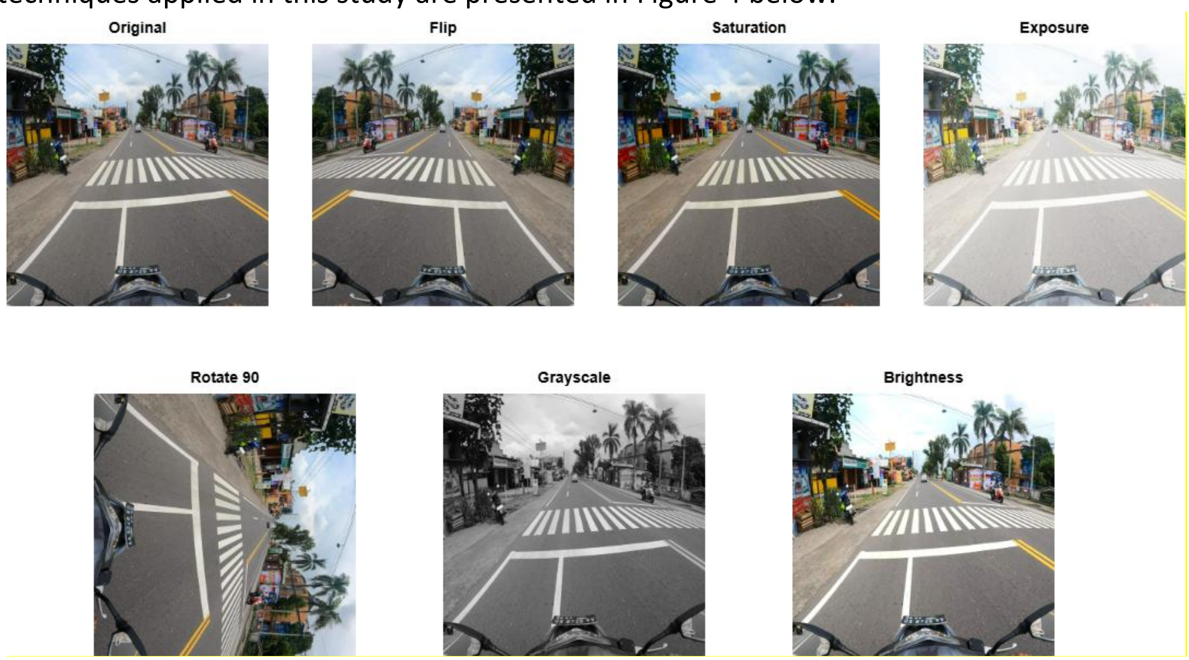

Figure 4 Original Image and Some Augmentations used

2. Model Evaluation

The performance evaluation of the YOLOv8 model was conducted in two testing stages: object detection between road markings and the background, and classification of the fading level of the markings into "faded" and "clear" categories. For each stage, the prediction results were visualized using a confusion matrix to illustrate the distribution between the actual data and the model's predicted outcomes.

In the initial evaluation phase, the YOLOv8 model's capability to distinguish between road marking objects and the background was tested. Based on the confusion matrix results shown in Figure 5, the model demonstrated excellent performance in detecting road marking objects.

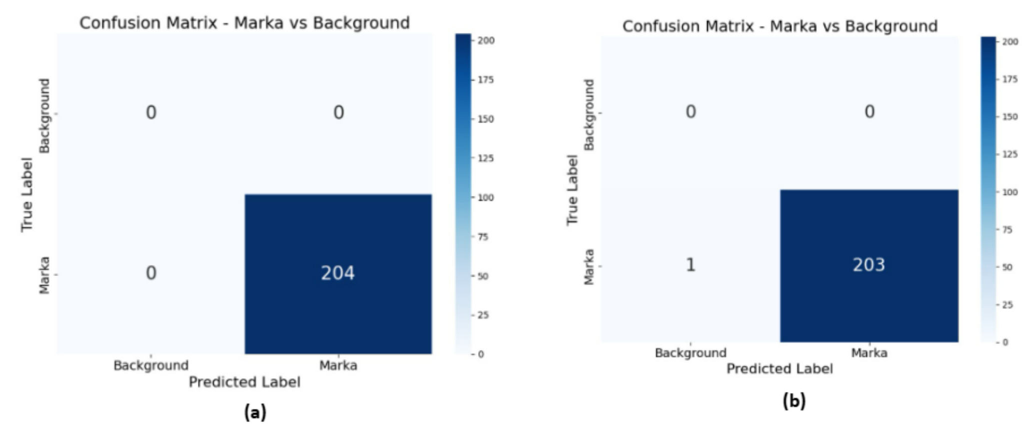

Figure 5 Confusion Matrix of Marker and Background Detection

In the model without augmentation and the model with saturation + exposure augmentation, all road marking images were correctly detected as marking objects without any misclassification into the background class, as shown in Figure 5a, where all 204 actual data samples were perfectly classified as "Marking" (100% accuracy). Meanwhile, in the models employing horizontal flip and the combination of four augmentations (rotation 90°, grayscale, saturation, and brightness), the detection results showed a minor misclassification, with one road marking image detected as background, as illustrated in Figure 5b. Nevertheless, the overall model performance remained remarkably high, achieving 99.5% accuracy, indicating that the model consistently recognized road marking objects across various augmentation conditions.

The second evaluation phase focused on classifying the degree of road marking fading, distinguishing between the "Faded" and "Clear" categories. Figure 6 presents the confusion matrices of each model, namely: (a) without augmentation, (b) with horizontal flip, (c) with saturation + exposure, and (d) with the combination of four augmentations (rotation 90°, grayscale, saturation, and brightness)

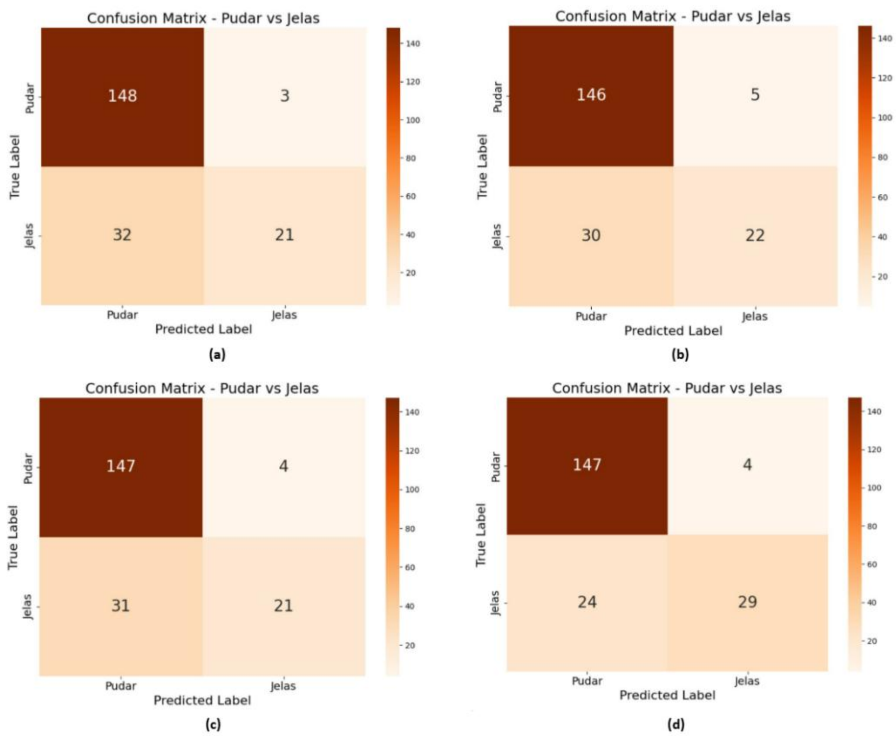

Figure 6 Confusion Matrix for Classification of Faded and Clear Road Markings

Meanwhile, Table 1 presents the quantitative results in terms of accuracy, precision, recall, and F1-score for each training scenario.

Table 1 training results

Augmentation Pattern	Accuracy	Precision	Recall	F1-Score
No Augmentation	83	84	83	80
Flip Augmentation	83	83	83	81
Saturation + Exposure Augmentation	86	86	86	85
90° Rotate, Grayscale, Saturation, and Brightness Augmentation	83	83	83	80

Based on the results in Table 1, the model without augmentation achieved an accuracy of 83%, with 84% precision, 83% recall, and an F1-score of 80%. These values indicate that the baseline model was able to classify the road markings reasonably well, although some faded markings were still misclassified as clear. The model trained with horizontal flip augmentation achieved a similar performance, with 83% accuracy, precision, and recall, and a slightly improved F1-score of 81%, suggesting a minor enhancement in the balance between precision and recall.

A more significant improvement was observed in the model trained with saturation and exposure augmentation, where all metrics reached 86% (accuracy, precision, and recall) and the F1-score rose to 85%. This indicates that adjusting saturation and exposure effectively helped the model recognize variations in lighting conditions and color intensity of the markings more accurately. Meanwhile, the model trained with a combination of four augmentations (90° rotation, grayscale, saturation, and brightness) achieved stable performance with 83% accuracy and an F1-score of 80%, although it did not surpass the performance of the saturation + exposure model.

Overall, the evaluation results demonstrate that saturation and exposure augmentation provided the most substantial contribution to improving the YOLOv8 model’s ability to distinguish between faded and clear road markings. This finding confirms that light- and color-based augmentations have a greater impact on model generalization than spatial transformations such as rotation or flipping.

DISCUSSION

The baseline YOLO model trained without any data augmentation demonstrated satisfactory performance, achieving 83% accuracy, 84% precision, 83% recall, and an F1-score of 80%. These results indicate that the model successfully captured key visual patterns of road markings, particularly for the clear class, which exhibits high-contrast characteristics. However, the relatively high rate of misclassification in the faded class suggests that the model was not fully robust to variations in lighting and color saturation. This phenomenon reflects a limitation of YOLO models when trained on homogeneous data, as the network tends to learn overly specific patterns from the training distribution. According to (Anhar & Putra, 2023), such conditions often lead to overfitting, where the model performs well on training data but struggles to generalize to unseen data. Therefore, implementing data augmentation strategies becomes crucial to increase visual feature diversity and strengthen the model’s generalization capability.

The application of horizontal flip augmentation resulted in performance comparable to the baseline model, with 83% accuracy, precision, and recall, and a slightly improved F1-score of 81%. Although the improvement was not significant, this result indicates that flipping provided a positive effect by expanding the range of image orientations without disrupting the original data distribution. The slight decline in precision may be due to orientation changes that are not always relevant for road markings, which generally follow uniform directions. Nevertheless, from a robustness perspective, flip augmentation remains beneficial because it prevents the model from overfitting to a single viewpoint. This finding is consistent with previous studies showing that simple augmentations such as rotation and flipping help object detection models handle camera orientation variations, although improvements are often marginal for symmetric patterns like road markings (Alin, Kusrini, & Yuana, 2023; Mumuni & Mumuni, 2022).

Training the model with saturation and exposure augmentation yielded the most significant performance improvement, reaching 86% accuracy, precision, and recall, along with an F1-score of 85%. This augmentation technique enhanced the model's adaptability to varying illumination and color intensity in real-world environments. The improvement suggests that adjusting saturation and exposure plays an important role in helping YOLO recognize road marking patterns more consistently. This aligns with previous findings indicating that color-based augmentations, such as saturation and exposure adjustments, improve object detection models' robustness against extreme weather and lighting variations, making them more adaptive to real-world conditions (Aloufi, Alnori, Thayananthan, & Basuhail, 2023; Wozniak et al., 2023). Thus, color-focused augmentation can be regarded as an effective strategy for improving image detection performance in real-world environments.

Conversely, the complex augmentation combination (90° rotation, grayscale, saturation, and brightness) produced lower results, with 83% accuracy, precision, and recall, and an F1-score of 80%. Although this combination increased the diversity of training data, the findings suggest that excessive augmentation variation can disrupt the consistency of essential features needed for road marking classification. This may be due to information loss from the grayscale process, which reduces the model's sensitivity to differences in color saturation between faded and clear markings. However, in terms of model resilience to visual variations, this approach still adds value. These results are consistent with studies reporting that multi-variant data augmentation can enhance object detection generalization, even under non-uniform data distributions (M. Abdulghani, M. Abdulghani, L. Walters, & H. Abed, 2023).

The improvement observed in the saturation + exposure augmentation aligns with findings from (Aloufi et al., 2023) and (Wozniak et al., 2023), who highlight that illumination-oriented augmentations improve robustness in object detection under challenging lighting conditions. Similarly, the enhancement of color-based augmentation is consistent with the conclusions of (Kim, Kim, Lee, & Kim, 2021), who demonstrated that color-related variations help models overcome data deficiency and illumination imbalance. However, the limited improvement from geometric augmentation (flip and rotation) supports the observations of (Alin et al., 2023) that spatial transformations may offer minimal benefits when object orientation is already consistent, as is the case with road markings. These comparisons reinforce the contribution of this work by confirming that illumination-based augmentation is more influential than geometric transformations for faded-marking classification.

CONCLUSION

This study successfully developed an automatic detection system to identify the level of road marking fading using a deep learning approach based on YOLOv8, with evaluations conducted on several data augmentation strategies. Based on the experimental results, the model trained with saturation and exposure augmentations achieved the best performance, obtaining an accuracy of 86%, precision of 86%, recall of 86%, and F1-score of 85%. These findings demonstrate that color- and lighting-based augmentation variations can enrich data representation and improve the model's generalization capability under diverse visual conditions in real-world environments. However, this research is still limited by the relatively small dataset size (2,049 images) and the restricted number of classes, which only include "clear" and "faded" categories. For future work, it is recommended to expand the dataset to cover more complex environmental conditions—such as low lighting, extreme weather, or damaged road markings—and to apply transfer learning or attention mechanisms to further enhance the accuracy and robustness of the YOLOv8 model in real-time road marking detection across various real-world scenarios.

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