



The Effect of Gamma Correction on the Accuracy of Vehicle Detection Using the YOLOv8 Algorithm

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Abstract

Accurate vehicle detection under low-light conditions is a significant challenge in traffic surveillance systems and computer vision applications. Although YOLOv8 performs well under normal illumination, its accuracy decreases when processing low-light images due to reduced contrast and limited visual details. This study proposes the integration of gamma correction as a preprocessing method to enhance image brightness and improve YOLOv8 detection performance. The dataset consists of real ATCS traffic camera recordings from Medan City under varying lighting conditions. Gamma correction with three values (0.5, 1.5, and 2.0) was applied to evaluate its effect on detection accuracy. The results show that gamma 1.5 provides the best improvement, increasing mAP@0.5 by 0.14% and mAP@0.5:0.95 by 0.74%, and achieving the highest confidence score of 0.9678 while also producing more stable training convergence. The novelty of this study lies in applying gamma correction to YOLOv8 using real-world ATCS low-light data, demonstrating that simple preprocessing can enhance detection robustness without modifying the model architecture.

Keywords: image preprocessing; gamma correction; low light; vehicle detection; YOLOv8

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1. Introduction

Vehicle detection is one of the fundamental aspects in the ever-evolving Intelligent Transportation Systems (ITS) intelligent traffic management system for modern mobility [1], [2]. As the number of vehicles on the road increases, there is a need for traffic monitoring systems that can work automatically and in real-time to reduce congestion, improve driving safety, and support decision-making in transportation management. Accurate and adaptive vehicle detection technology is needed to meet these needs [3].

Although CNN-based detectors such as YOLO achieve high accuracy, their performance significantly degrades under low-light conditions due to poor feature contrast, motivating the need for illumination-aware preprocessing strategies [4]. This limitation poses challenges for traffic surveillance systems, particularly those operating at night or during adverse weather conditions [5]. Therefore, illumination-aware preprocessing techniques, such as gamma correction, are required to enhance visual features prior to detection

and improve the robustness and stability of YOLO-based models in real-world ATCS environments [6], [7].

The latest version of this algorithm, YOLOv8, was released by Ultralytics with various performance improvements over previous versions [8]. YOLOv8 has higher detection accuracy than YOLOv5 and YOLOv6, despite using a similar number of parameters. The new architecture used in YOLOv8 is proven to be more efficient, enabling high-speed detection even on resource-constrained devices. YOLOv8 demonstrated stable performance and high precision in a variety of application scenarios, including traffic monitoring, security surveillance, and object detection on infrared images [9]. Like many other object detection models, YOLOv8 still faces problems in low-light conditions, such as at night, during bad weather, or when fog obstructs the visibility of the camera. These conditions lead to reduced image contrast and brightness, which in turn decreases vehicle detection accuracy [10].

To overcome this problem, image preprocessing techniques are required that can improve the visual quality before detection. One commonly used technique is Gamma Correction, which is a method of adjusting the brightness and contrast of images to improve visual details under various lighting conditions [11]. By setting the appropriate gamma parameters, images that were originally dark or too bright can be corrected so that objects are more easily recognized by the detection system [12]. Previous research has shown that Gamma Correction can improve image visibility in low-light conditions and result in higher detection accuracy without significantly increasing processing time. Gamma Correction has been widely used in various fields of image processing, including face recognition, object detection, and nighttime video processing [13].

There have been many previous studies on vehicle detection systems, such as background subtraction, edge detection, Hough transform, and morphological processing. One study used these approaches to count the number of vehicles and determine the level of traffic density on video images captured in real-time. The approach still has limitations, especially in poor lighting conditions where the image is dark and object information cannot be extracted properly [14]. This suggests that an integration between image quality enhancement techniques and object detection algorithms is needed for the system to work more reliably in various environmental conditions.

This research aims to develop a YOLOv8-based vehicle detection system combined with Gamma Correction techniques to improve vehicle detection accuracy in low lighting conditions. The data used are traffic videos from Medan City ATCS, focusing on the detection of four-wheeled vehicles such as cars, buses, and trucks. The application of this method is expected to produce a more adaptive, accurate, and efficient detection system, especially in environments with non-ideal lighting.

2. Methods

The system overview in Figure 1 shows the flow of the research method consisting of five main stages, namely dataset collection and preparation, annotation process, preprocessing and data augmentation with gamma correction, YOLO model training, and model performance evaluation [15]. This research started with the collection of traffic vehicle image datasets from Medan City ATCS cameras, which consisted of 1400 960×720 pixel resolution images. This dataset was divided into two parts, 80% for training and 20% for validation. In addition, the test dataset was obtained directly from traffic image recordings with varying weather conditions such as rain, night and day lighting, and various shooting angles to ensure data diversity and model robustness in detecting objects in various real conditions.

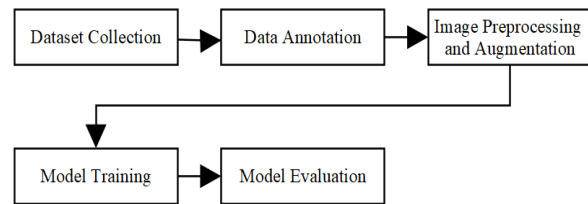


Figure 1. Flow of the research method

2.1 Data Annotation

The annotation process is performed by marking vehicle objects in the image using bounding boxes and labeling them according to their type, such as cars, trucks, and buses. The annotation is done manually using software and then saved in a format suitable for training the YOLO model. The results of this annotation are used so that the model can accurately recognize and distinguish vehicle objects [16].

In low-light traffic images, the annotation process presents several challenges, particularly in distinguishing vehicle boundaries due to poor contrast and illumination variability. Vehicles located far from the camera or partially occluded by shadows are prone to inaccurate bounding box placement. Annotation inconsistencies in such conditions may lead to imprecise localization during training, which directly affects the mAP and confidence stability of the YOLOv8 model. Therefore, careful manual verification was applied to ensure consistent bounding box quality, especially for vehicles captured at night or under rainy conditions.

2.2 Image Preprocessing and Augmentation Using Gamma Correction

This stage focuses on preprocessing and data augmentation to improve the quality and diversity of the vehicle image dataset, thereby strengthening the detection model performance. Augmentation is performed through rotation, cropping, and color change techniques to add visual diversity to the training data [17]. Meanwhile, preprocessing uses gamma correction to adjust the brightness of the image to make the lighting more balanced, whether the image is too bright or too dark. This technique helps the model recognize vehicle objects more accurately under various lighting conditions and viewing angles [18]. In addition, gamma correction also plays a role in reducing noise due to environmental factors, thereby improving the robustness and consistency of the model against real-world data variations [19].

The selection of gamma values 0.5, 1.5, and 2.0 in this study was intentional and based on their representation of different illumination enhancement levels. A gamma value of 0.5 provides mild brightening, allowing the evaluation of under-enhanced images. Gamma 1.5 was chosen as the mid-level enhancement because previous studies indicate that values around this range produce optimal visibility for low-light scenes without introducing artifacts. Meanwhile, gamma 2.0 represents

a strong enhancement level, allowing analysis of potential overexposure or loss of contrast. By testing these three levels, the study aims to observe how different intensities of illumination correction affect the YOLOv8 detection performance in low-light conditions.

2.3 YOLO Model Training and Evaluation

The training of the YOLO model is conducted using a dataset of vehicle images that have been annotated with labels and bounding boxes according to object types, such as cars, trucks, and buses. The YOLO model processes the entire image directly in one stage by dividing the image into grids, where each grid detects the objects within it [20]. The training process takes place over multiple epochs to optimize the parameters and minimize the loss which includes both detection and classification errors. Once training is complete, the model is evaluated using test data to measure detection performance using the metrics of precision, recall, mean Average Precision (mAP), and inference time. This evaluation aims to ensure the model's ability to detect objects accurately, quickly, and reliably even under varying lighting conditions or viewing angles [21].

Training YOLOv8 on low-light datasets introduces instability during early epochs due to uneven feature distribution and reduced object contrast. Without proper illumination normalization, the model tends to converge slowly and exhibits fluctuating loss values. The application of gamma correction aims to reduce this instability by enhancing visual features prior to training, thereby improving gradient consistency and accelerating convergence. This effect is evaluated by comparing mAP trends and confidence stability across different gamma configurations.

2.4 Model Performance Evaluation Metrics

The performance of the proposed YOLOv8 model was evaluated using precision, recall, F1-score, and mean Average Precision (mAP). Precision is defined as the ratio of true positive detections to the total number of detected objects, expressed as $\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$, where TP denotes true positives and FP denotes false positives. Recall measures the ratio of true positive

detections to the total number of ground-truth objects and is defined as $\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$, where FN denotes false negatives. The F1-score represents the harmonic mean of precision and recall, calculated as $\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$. After defining these metrics, the overall detection performance is further evaluated using the mean Average Precision (mAP), which is commonly used to assess object detection accuracy across different confidence thresholds [22], [23].

In addition, mAP is used as an overall evaluation metric in the context of multi-class detection. mAP is calculated from the average of the Average Precision (AP) values for each object class, such as cars, trucks, and buses. The AP value itself is the area under the Precision-Recall curve (PR curve) that reflects the trade-off between the two metrics [24]. The model was tested using test datasets that reflect real-life conditions, such as variations in lighting, viewing angle, and object density. This evaluation aims to ensure that the model is able to accurately detect objects in various situations. If the precision, recall, F1 Score, and mAP values obtained are high, then the model is considered ready for implementation. Conversely, if the performance is still not optimal, then improvements can be made through the addition of data, parameter tuning, or model retraining.

2.5 Model Architecture Visualization Using the Keras API

To provide a clearer understanding of the YOLOv8 model architecture used in this study, a simplified structural visualization was created using the Keras API. Although YOLOv8 is originally implemented in the Ultralytics framework, the backbone-neck-head flow of the model can be represented using Keras layers for explanatory purposes. This visualization helps illustrate how feature extraction, multi-scale processing, and prediction occur within the model. A simplified Keras-based representation of a YOLO-style architecture is shown in Table 1. The simplified YOLOv8 architecture used in this study is summarized in Table 1.

Table 1. Model Architecture Summary Table

No	Layer / Type	Output Shape	Parameters
1	Input Layer	(None, 640 × 640 × 3)	0
2	Conv2D	(None, 320 × 320 × 32)	896
3	Batch Normalization	(None, 320 × 320 × 32)	128
4	LeakyReLU	(None, 320 × 320 × 32)	0
5	Conv2D	(None, 160 × 160 × 64)	18,496
6	Batch Normalization	(None, 160 × 160 × 64)	256
7	LeakyReLU	(None, 160 × 160 × 64)	0
8	Conv2D	(None, 80 × 80 × 128)	73,856
9	Batch Normalization	(None, 80 × 80 × 128)	512
10	LeakyReLU	(None, 80 × 80 × 128)	0
11	UpSampling2D	(None, 160 × 160 × 128)	0
12	Concatenate	(None, 160 × 160 × 192)	0
13	Conv2D (Head Layer)	(None, 160 × 160 × 18)	3,474
	Total Parameters		97,618

This visualization demonstrates the hierarchical processing pipeline typically found in YOLO-based detectors, enabling readers to understand how YOLOv8 extracts features at multiple spatial scales and generates bounding box predictions efficiently.

3. Results and Discussions

This section presents the experimental results and performance analysis of the proposed YOLOv8-based vehicle detection system under various gamma correction configurations.

The evaluation focuses on quantitative metrics, visual comparison, and field testing to assess the effectiveness of illumination preprocessing in low-light conditions.

3.1 Detection Evaluation Based on mAP50 Value

An evaluation was conducted to assess the performance of YOLOv8 in detecting vehicles under various lighting conditions with and without gamma correction. Assessment using the mAP50 metric shows that the application of gamma correction, specifically with a gamma value of 1.5, gives the best results with an mAP50 of 0.941 at the 29th epoch. This result shows that gamma correction can improve detection accuracy under low illumination conditions.

The evaluation results of YOLOv8 performance under different lighting conditions and gamma correction configurations based on the mAP50 metric are summarized in Table 2.

Table 2. Model Evaluation Results Based on mAP50 Value

Condition	Best Epoch	Highest mAP50
Clear	49	0.925
Low Light	49	0.940
Gamma = 0.5	49	0.940
Gamma = 1.5	29	0.941
Gamma = 2.0	49	0.940

The detailed evaluation results of YOLOv8 performance under different lighting conditions and gamma correction configurations based on the mAP50 metric are summarized in Table 2. In the early epochs, gamma correction also showed significant results, where Gamma 2.0 resulted in an mAP50 of 0.874, higher than the condition without gamma. This proves that gamma correction is effective in improving the accuracy and acceleration of YOLOv8 model training.

3.2 Visualization of the Effect of Gamma Correction

Gamma correction is used to improve the visibility of objects in low-light images without losing important visual details. Tests were conducted at three different gamma values (0.5; 1.5; and 2.0) to evaluate their effect on the visual results of the vehicle image. A gamma value of 1.0 was not used as it does not change the pixel intensity.

The visual results are shown in Figure 2, which shows that the original image is dark and objects are difficult to recognize. Gamma 0.5 slightly increases the brightness but is still not optimal. Gamma 1.5 gives the

best results with balanced lighting and clear object details. While gamma 2.0 makes the image very bright, it starts to lose contrast in certain areas. The visual comparison of gamma correction effects under different gamma values is illustrated in Figure 2.

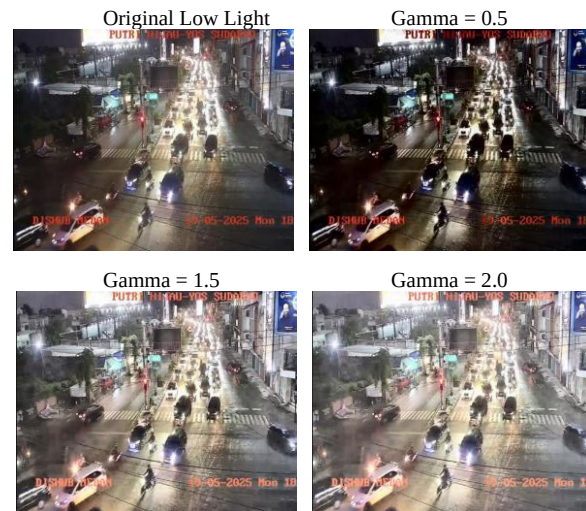


Figure 2. Comparison of Visual Gamma Correction Results with Different Gamma Values

Based on the visualization results, a gamma value of 1.5 proved to be the most effective in improving image quality without causing overexposure. This shows that a proper gamma correction configuration can improve the visibility and accuracy of the object detection model, especially under low-light conditions.

3.3 Implementation and Visualization of YOLOv8 Detection Results

The YOLOv8 model was implemented using the Ultralytics framework and trained for 50 epochs on four different scenarios, namely without gamma correction, and with gamma correction using gamma values of 0.5; 1.5; and 2.0, respectively. The purpose of this comparison is to evaluate the effect of gamma correction preprocessing on object detection performance under low-light conditions.

The vehicle detection results produced by YOLOv8 under different gamma correction configurations are shown in Figure 3.

Figure 3 shows the results of vehicle detection in the low light image. Without gamma correction, only a small number of vehicles are detected and the confidence value is low. After applying gamma 0.5, there is an increase in the number of detections although it is not consistent. Gamma 1.5 gives the best results with almost all vehicles detected accurately and high confidence. Gamma 2.0 also improves detection, but there is an overexposure effect in parts of the image. Based on these results, gamma 1.5 is considered the most optimal configuration in improving the detection accuracy of YOLOv8 in low light conditions.

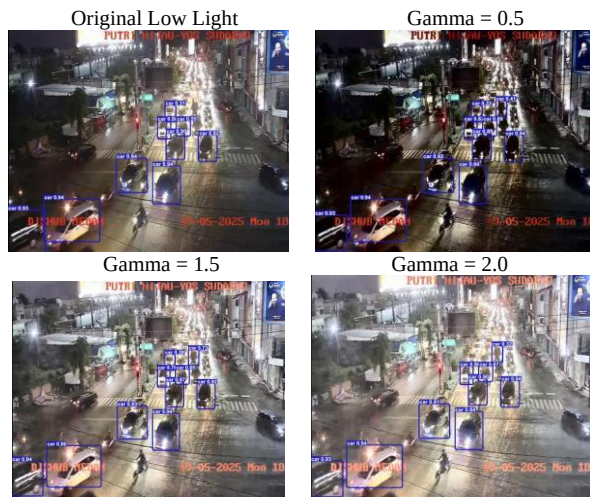


Figure 3. YoloV8 Object Detection Results after Gamma Correction with Different Gamma Values

3.4 Effect of Gamma Correction on Object Detection Accuracy

An initial evaluation was conducted to analyze the performance of vehicle object detection by YOLOv8 on

low light images before and after gamma correction preprocessing. Based on Table 2, the highest confidence value in the original condition (without gamma) is 0.9455. The application of gamma correction 0.5 increases the confidence to 0.9489, and gamma 1.5 provides the most significant increase to 0.9678. In contrast, gamma 2.0 decreased to 0.9426, which indicates over-enhancement.

The comparison of maximum confidence values under different gamma correction configurations is presented in Table 3.

Table 3. Comparison of Maximum Confidence Values

Conditions	Highest Confidence
Original Low Light	0.9455
Gamma Correction 0.5	0.9489
Gamma Correction 1.5	0.9678
Gamma Correction 2.0	0.9426

In addition to confidence, the visual graph in Figure 4 reinforces that gamma 1.5 produces the most stable and high confidence values in most detections.

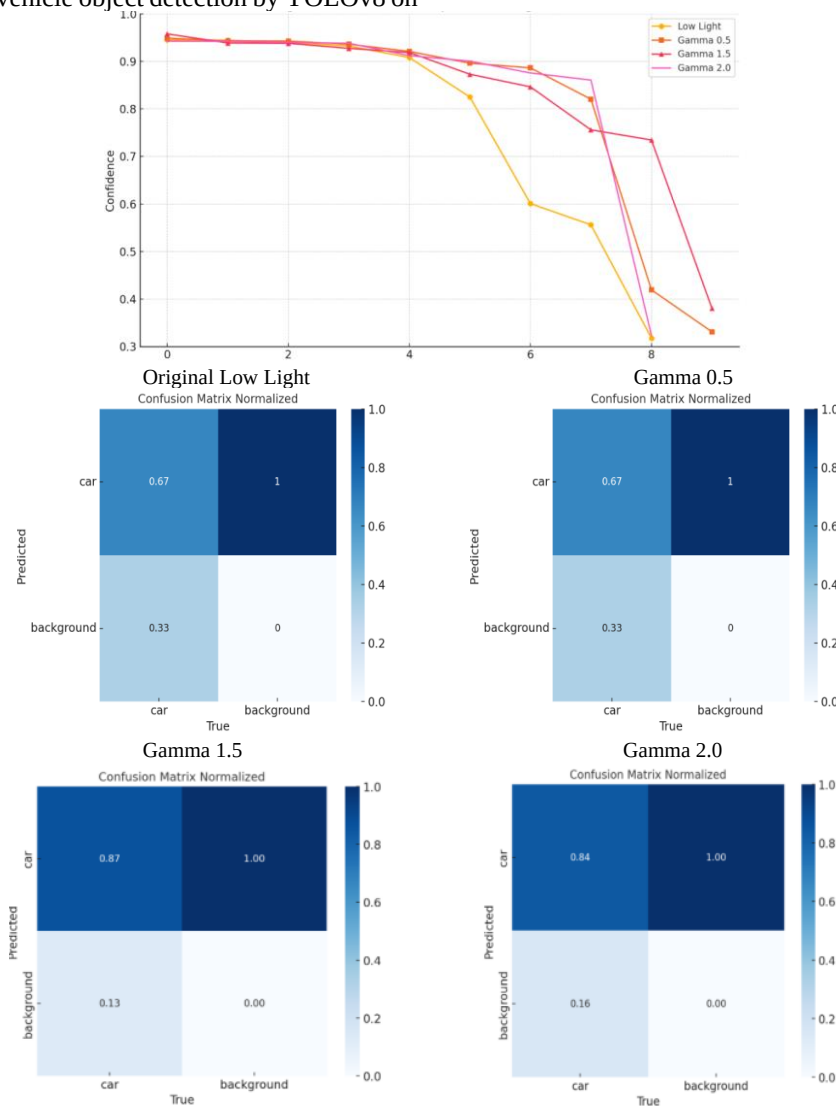


Figure 4. Confidence Graph and Confusion Matrix

The confusion matrix also shows that gamma 1.5 has the highest proportion of correct classifications, indicating the stability of the model in various vehicle classes. The confidence distribution and confusion matrix results for different gamma configurations are illustrated in Figure 4.

3.5 Evaluation of YOLOv8 Model and Gamma Correction Effectiveness

The training and testing results show that gamma correction 1.5 produces a better trend of loss reduction and improvement in mAP50 and mAP50-95 than other configurations. Figures 5 and 6 show that the gamma 1.5 model is more stable and accurate than gamma 0.5, which shows fluctuations and lower mAP values.

The final performance evaluation of the YOLOv8 model with and without gamma correction is reported in Table 4.

Table 4. Final Evaluation of Model Performance

Metric	Original	Gamma 1.5	Δ (%)
Precision	84.29%	82.79%	-1.78%
Recall	89.60%	89.60%	0.00%
F1-Score	86.90%	86.09%	-0.93%
mAP@0.5	93.31%	93.44%	+0.14%
mAP@0.5:0.95	79.84%	80.58%	+0.74%

In the field tests at various locations, gamma 1.5 showed increased confidence in most objects compared to the other configurations, as shown in Table 5. However, in some locations, gamma 1.5 had results that were equivalent to or slightly below the baseline, indicating that the effectiveness of gamma correction depends on the visual characteristics of the environment. The average detection confidence

obtained from field tests at several locations is summarized in Table 5.

Table 5. Average Confidence at Several Test Sites

Location	Best Gamma (Average Confidence)
HM Thamrin – YP. Sutomo	Gamma 1.5 (0.741)
MT Haryono – Irian Barat	Gamma 1.5 (0.59)
Pengadilan – Maulana Lubis	Gamma 1.5 = Original (0.57)
Cipto – Masdulhak	Original & Gamma 1.5 (0.75)
Imam Bonjol – Zainal Arifin	Gamma 2.0 & Original (0.545)

Overall, gamma 1.5 proved to be the most effective in improving luminance quality, sharpening visual features, and producing high and stable detection accuracy, especially under low lighting conditions. The use of gamma correction 1.5 was also shown to support the efficiency of the training process and reduce detection noise. The F1-score value reached 0.89 based on field tests, with no false positives and only two undetected vehicles

3.6 Baseline Comparison.

To evaluate the effectiveness of the proposed gamma correction preprocessing, a comparative analysis was conducted between the baseline YOLOv8 model (without gamma correction) and the models trained using gamma values of 0.5, 1.5, and 2.0. The comparison includes key performance metrics such as mAP@0.5, mAP@0.5:0.95, precision, recall, F1-score, and maximum confidence values. A comparative analysis between the baseline YOLOv8 model and gamma-corrected model variants is detailed in Table 6.

Table 6. Baseline vs. Gamma-Corrected Model Performance

Condition / Model Variant	Precision	Recall	F1-Score	mAP@0.5	mAP@0.5:0.95	Max Confidence
Baseline (No Gamma)	84.29%	89.60%	86.90%	93.31%	79.84%	0.9455
Gamma 0.5	—	—	—	94.00%	—	0.9489
Gamma 1.5 (Best)	82.79%	89.60%	86.09%	93.44%	80.58%	0.9678
Gamma 2.0	—	—	—	94.00%	—	0.9426

The results demonstrate that gamma correction provides measurable improvements over the baseline model, particularly in terms of detection confidence, mAP stability, and robustness in low-light environments. Among all configurations, Gamma 1.5 produces the best overall performance, yielding the highest maximum confidence (0.9678) and the highest mAP@0.5:0.95 (80.58%). Although the baseline model achieves similar recall, the gamma-enhanced model shows better illumination normalization, resulting in clearer feature representation and more stable training convergence.

Gamma 0.5 and gamma 2.0 also improve the mAP@0.5 compared to the baseline, but their confidence values are lower than gamma 1.5, indicating that under- or over-enhancement can reduce model certainty. These findings confirm that gamma correction—especially at 1.5—is an effective preprocessing technique that

enhances YOLOv8 performance without modifying the model architecture.

The application of gamma correction is proven to improve the accuracy and consistency of vehicle detection under low illumination conditions. In this study, the use of gamma 1.5 resulted in the highest detection confidence value (0.9678), outperforming other gamma variations as well as the original image. This finding is in line with Viviana Fransisca and Handri Santoso (2023) who showed that applying gamma correction (e.g. gamma = 2) to YOLOv5 increased the average accuracy from 0.846 to 0.918 [25]. This supports that gamma correction is able to clarify the visual features of vehicles in dark conditions, thereby improving the detection capability of the model.

The Dark YOLO approach by (Jiang et al., 2023) aimed at object detection in low-light environments with CSPDarkNet53 backbone and attention modules,

successfully improved the mAP by 4.10% over YOLOv4 on the ExDark dataset. This confirms that specialized image processing for low-light is essential, and the gamma correction technique is a simple yet effective form of improving the visual representation before inference [26]. The model with a gamma of 1.5 is not only more accurate, but also shows faster convergence and a more stable training curve, with consistent mAP and loss compared to other gamma. This is consistent with the study on 3LYOLO that synthesized dark images with gamma manipulation between 2.0 to 5.0 to train vehicle detection, thus extending the generalization ability of the model under varied conditions [27].

Literature such as the evaluation of YOLOv5 with image enhancement (including EnlightenGAN) shows that not all enhancement methods improve detection performance; some even decrease mAP due to the addition of irrelevant visual noise [28]. Therefore, it is important to choose the optimal gamma value so that visual improvements do not cause artifacts that interfere with detection features.

The results of the study indicate that gamma correction settings, particularly gamma 1.5, provide optimal effects in improving image visual quality and YOLOv8 training stability, while strengthening model generalization in low-light conditions without increasing the risk of disruptive noise.

4. Conclusions

The results of this study demonstrate that gamma correction is an effective and lightweight preprocessing technique for enhancing YOLOv8 performance in low-light vehicle detection. Among the tested variations, gamma 1.5 produced the most consistent improvements, particularly in terms of visual clarity, model stability, and detection confidence. This configuration achieved the highest mAP@0.5:0.95 value (80.58%) and the highest maximum confidence (0.9678), indicating that illumination normalization plays a significant role in strengthening the feature extraction capability of YOLOv8 under challenging lighting conditions.

These findings show that gamma correction does not necessarily increase all evaluation metrics simultaneously; however, it provides meaningful gains in overall robustness and consistency, especially in real ATCS environments where lighting conditions vary significantly throughout the day. This emphasizes the practical relevance of gamma preprocessing for traffic monitoring systems, allowing existing models to perform more reliably without modifying architecture or increasing computational cost.

The implications of this study extend beyond the specific ATCS dataset used. The approach can be applied to various intelligent transportation applications, such as automated traffic monitoring, congestion analysis, and safety surveillance under low

illumination. Moreover, the results confirm observations from prior literature that specialized low-light image enhancement when optimally tuned can significantly improve object detection quality.

Despite these contributions, several open challenges remain. Gamma correction may not always provide improvements in environments with excessive noise, glare, or extreme contrast. Additionally, only three gamma values were explored, and no adaptive or dynamic enhancement method was applied. Future research should investigate automated gamma selection, integration with advanced low-light enhancement models (e.g., Retinex-based, Zero-DCE, or deep learning illumination networks), and testing across broader datasets and more diverse lighting conditions. Further evaluation using newer model architectures, such as YOLOv9 or YOLOv10, may also reveal additional performance benefits.

In conclusion, this study provides evidence that gamma correction particularly at value 1.5 is a simple yet effective preprocessing strategy for improving vehicle detection in low-light conditions. The approach enhances detection accuracy, stabilizes model convergence, and offers practical value for real-time traffic monitoring systems, contributing to more reliable intelligent transportation infrastructure.

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