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The Effect of Image Enhancement on Automatic Vehicle Detection Using Yolov8 Based on Jetson Nano Single Board Computer

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Abstract

Vehicle counting systems using image processing and deep learning have been widely studied. Using images captured by CCTV cameras makes vehicle counting effective and efficient. Although much research has been done, there are still challenges in direct application in the field. Object detection methods such as YOLO are widely chosen. In field applications, challenges are found such as rainy, nighttime, or foggy conditions and the use of appropriate hardware. In this study, the YOLOv8s and YOLOv8n object detection methods are proposed using Contrast Limited Adaptive Histogram Equalization (CLAHE) image enhancement in preprocessing and datasets and run using SBC Jetson Nano. From this study, the results obtained an increase in detection values of around 10% to 20% in dark image conditions and there was no improvement for bright images. The average accuracy is 0.873312 for YOLOv8s and 0.866906 for YOLOv8n with image enhancement. And the processing time on Jetson Nano is 59.5 ms for YOLOv8n.

Keywords: Vehicle Detection, Image Enhancement, YOLO, CLAHE

1 Introduction

Vehicle counting systems using image processing and deep learning have been widely studied. By using image processing from CCTV camera captures, automatic vehicle counting can be done effectively and efficiently. By using this mechanism, the devices used in the field are relatively simple in the form of CCTV cameras, either specially installed or already installed. The camera can still be used for its basic applications, for example for manual monitoring of road conditions.

Research has been conducted on vehicle counting using the r-CNN, YOLO, Deep Sort, SSD and color based methods. [1]–[8]. This model can also be applied to other applications such as to classify truck types based on the number of truck axles. [9]. Although much research has been done, there are still challenges in direct application in the field. In the application in the field, there will also be challenges of weather, whether rain, night or foggy. There are previous studies that use the Contrast Limited Adaptive Histogram Equalization (CLAHE) image enhancement method and variations of the use of the YOLO method. [10]. In this research, the detection results were improved but were still applied to personal computers with high specifications.

The use of embedded system devices that are suitable for image processing and deep learning is very important to ensure the system works in real time. Jetson Nano is one of the Single Board Computers (SBC) made by Nvidia that is dedicated to image processing with the most affordable price of the other Jetson series. With the lowest series, the implementation of deep learning used is also only capable of using lightweight methods. There is a study conducted using Jetson Nano for vehicle counting using MobileNet SSD v2 [11]. Image-based vehicle detection and tracking in varying weather conditions is also being researched [12], but has not discussed related to direct application. In this study, an object detection method is proposed with YOLOv8s and YOLOv8n variations using Contrast Limited Adaptive Histogram Equalization (CLAHE) image enhancement in preprocessing and dataset and run using SBC Jetson Nano. It is expected to improve vehicle detection results, especially during night conditions with uneven lighting and can be applied in the field in real time.

2 Material and Methods

In the proposed system there are two stages, namely training dataset and vehicle detection using YOLO. The object detection used is YOLOv8s and YOLOv8n. The dataset used consists of original images from CCTV cameras and datasets from original images that are augmented using the image enhancement model CLAHE. The dataset was obtained from collecting images from several CCTVs spread across Madiun, Semarang and Surakarta in Indonesia. Two types of datasets produce two types of datasets. In conducting the vehicle detection experiment, two variations were also used, namely the original image and the image that was preprocessed using the image enhancement CLAHE. The detection results from the dataset variations, YOLO models and image preprocessing will then be analyzed further. The research process flow is shown in Fig. 1.

The process flow is divided into two stages, the first is the training stage and the detection stage. In the training stage, the dataset consists of normal images and images enhanced with CLAHE. Each image is trained to produce model 1 with the original image dataset and model 2 with the original image dataset and images enhanced with CLAHE. Next is the process of testing the detection results with YOLO using original input images and images that have been enhanced with CLAHE. The output is obtained so that it can be compared and analyzed further.

2.1 Image Enhancement using CLAHE on LAB Color Space

Image enhancement is focused on improving nighttime captured images. Nighttime captured images tend to have characteristics that are dark or unevenly bright and dark. This makes objects or vehicles on the dark side difficult to recognize. The image enhancement used in this study is Contrast Limited Adaptive Histogram Equalization (CLAHE). Here CLAHE is applied to LAB Color Space [13]. The color space used in standard images and CCTV images is RGB. The first step is to convert RGB color space to LAB color space.

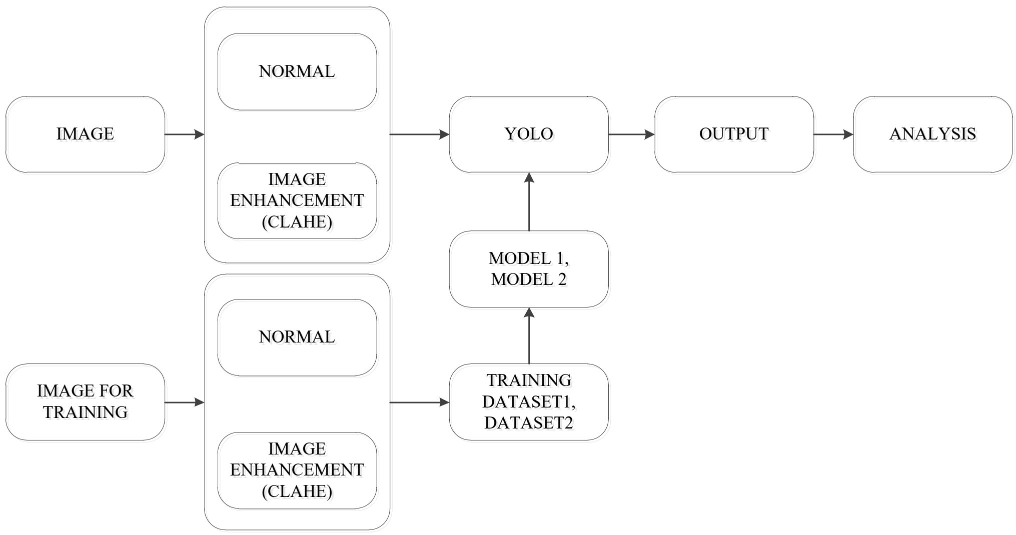

Figure 1. Research Process Flow

This is done because LAB color space consists of L (lightness), A (red/green value), B (blue/yellow value). By utilizing the L section to perform CLAHE enhancement, it is expected to correct uneven light and dark conditions in night images. After CLAHE is performed on the L section, the L, A and B sections are combined again and converted back to RGB color space. The flow of the CLAHE image enhancement process on the color image is shown in Fig. 2.

2.2 Dataset and Experiment Specification

The dataset for training the YOLO model consists of a combination. Dataset 1 is a dataset consisting of original images captured by the camera without any modification. Dataset 2 is a dataset consisting of a combination of original images captured by the camera and images captured by the camera that have been augmented with CLAHE image enhancement. The combination of datasets is shown in Table 1. The parameter settings for training the YOLOv8 model are shown in Table 2. The image size is set to 640 and Epoch 100 for each training dataset.

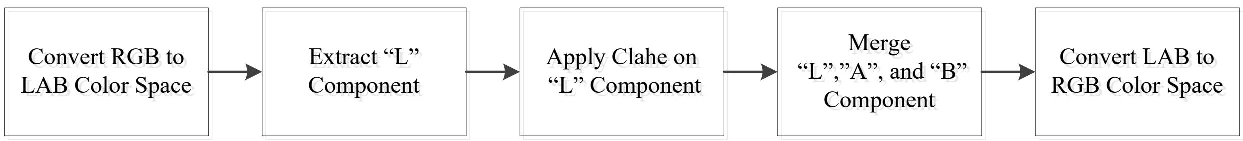

Figure 2. Color Image Enhancement Process Flow using CLAHE

Table 1. Dataset Combination Setting

Dataset	**Original Image**	**Image Enhancement CLAHE**
Dataset 1	√	
Dataset 2	√	√

Table 2. YOLOv8 Series model training parameter values

Parameter	YOLO8s
Size of Input Images	640
Epoch	100

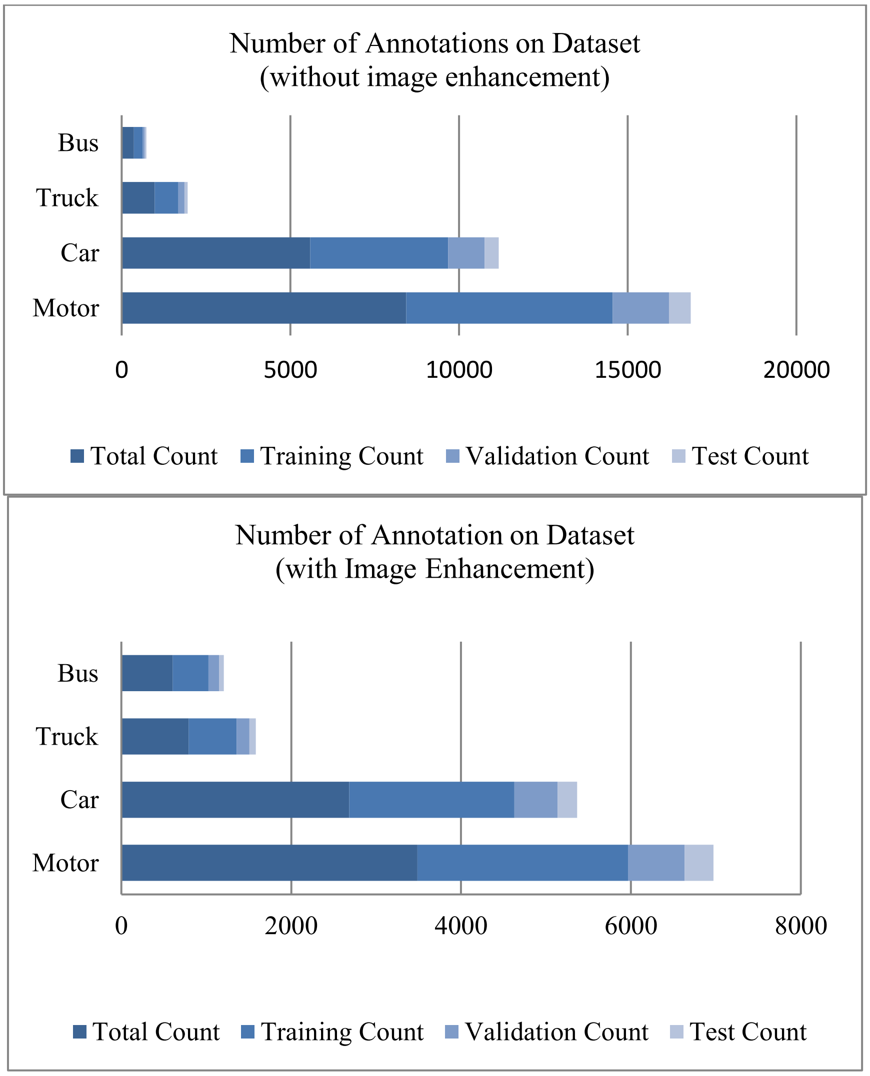

Figure 3. Graphic of Number of Annotation on Dataset (with and without Image Enhancement)

The dataset itself consists of captured images from several CCTV points in Indonesia during day, night and rainy conditions. The number of datasets used for Dataset 1 and Dataset 2 is shown in Table 3 and Fig. 3. The dataset consists of four classes, namely bus, truck, car and motorbike. There is a difference in the number of datasets 1 and 2 due to the difficulty in equalizing and balancing the number of images used. Training is done with the help of Google Colab with a training time of approximately 2 hours.

The hardware setup to be tested is shown in Fig. 4. It consists of the main processor in the form of a Jetson Nano single board computer, a switch/hub with POE and IP Camera. The specifications of Jetson Nano are shown in Table 4. Jetson Nano is the most economical SBC series from Nvidia which is specifically designed for processing images and AI. Nvidia Jetson Nano itself supports the use of TensorRT. NVIDIA TensorR is an SDK for high-performance deep learning inference. It already contains a deep learning inference optimizer and runtime that can provide processing speed for deep learning more efficiently. TensorRT-based applications have a performance 40X faster than CPU usage during inference. TensorRT is built on CUDA®, NVIDIA's parallel programming model, and allows for optimizing libraries that leverage inference, development tools, and technologies in CUDA-X ™ for artificial intelligence, autonomous machines, high-performance computing, and graphics. With TensorRT, developers can focus on creating new AI-powered applications rather than tuning performance for inference applications.

Table 3. Number of Annotation on Dataset

Class Name	**without Image Enhancement**				**With Image Enhancement**			
	Total Count	Training Count	Validation Count	Test Count	Total Count	Training Count	Validation Count	Test Count
Motor	8433	6122	1665	646	3485	2480	669	336
Car	5587	4094	1080	413	2684	1944	509	231
Truck	977	700	183	94	791	566	151	74
Bus	365	261	58	46	604	420	124	60

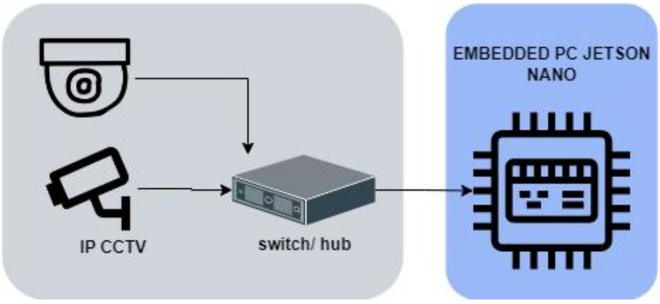

Figure 4. Hardware Setup

Table 4. Experiment Specification on Jetson Nano 4GB

Name	Specification
OS	Jetpack 4.6
CPU	Quad-core Arm A57 processor @ 1.43 GHz
GPU	128-core Maxwell GPU 4GB
RAM	System Memory – 4GB 64-bit LPDDR4 @ 25.6 GB/s

3 Results and Discussions

Night photo images have low brightness and contrast. The brightness level is sometimes uneven so that objects on the dark side become unclear and difficult to recognize. As a result, image enhancement is carried out to obtain an image with a clear image. This is done on the dataset image or as a preprocessing stage before object detection. The results of the image enhancement process and the original image are shown in Fig. 5. It can be seen that the image from the image enhancement process with CLAHE gets a brighter image and even contrast for the night image. A comparison of the histogram of the original image and the results of the process with CLAHE image enhancement is shown in Fig. 6. This histogram is a histogram of the image converted into grayscale image space to make it easier to compare. From the histogram, it can be seen that after the image enhancement process, the distribution of color brightness is more even.

Figure 5. Original Image (Left) and Result of Image Enhancement using CLAHE (Right)

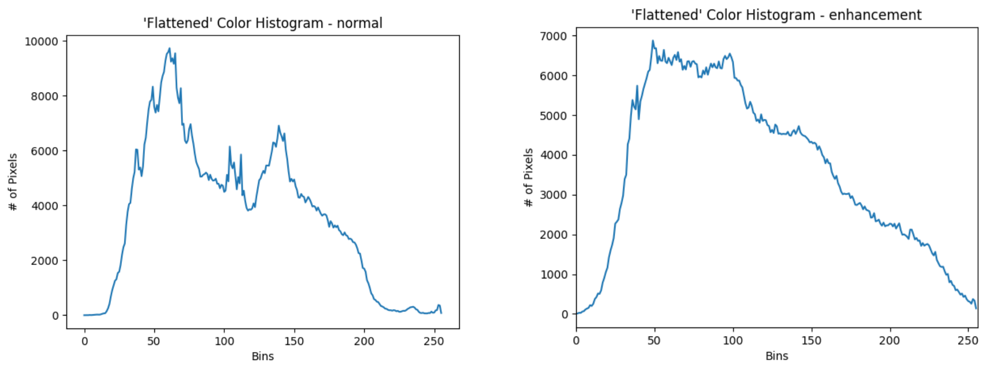

Figure 6. Histogram of Original Image (Left) and Result of Image Enhancement using CLAHE (Right)

In the dataset and testing, images captured by cameras from various regions in Indonesia were used. Training was carried out for the YOLOv8s and YOLOv8n object detection models to compare the performance that is suitable for use on the Jetson Nano. The test results for images in day and night conditions using the mode obtained an average accuracy result for the YOLOv8s model of 0.87, higher than YOLOv8n 0.86. Although YOLOv8s is superior, the difference that occurs is not too significant. This comparison can be seen in Table 5.

The results of the comparison of object detection using YOLOv8s with dataset 1 for training for the original image and the image that was image enhanced are shown in Fig. 7. The image used is in night conditions. There appears to be an improvement in the detection rate for several vehicles. After image enhancement, there are also vehicles that were previously undetected that are detected.

In the experiment using the YOLOv8s model and training using dataset 2. The results of the image comparison are shown in Fig. 8. In this model, it is trained with the original image dataset and added with augmented images with CLAHE image enhancement. From this experiment, there is no difference in the detection rate for the original image or the image that was image enhanced with CLAHE. This is because during the training process, image enhancement has been carried out so that the training dataset is balanced between the original image and the improved image.

Table 5. Experiment Result on YOLOv8s and YOLOv8n

Object	YOLOv8s	YOLOv8n
Bus	0.931437	0.91791
Car	0.837073	0.829733
Motor	0.798421	0.794073
Truck	0.926316	0.925907
Average Accuracy	0.873312	0.866906

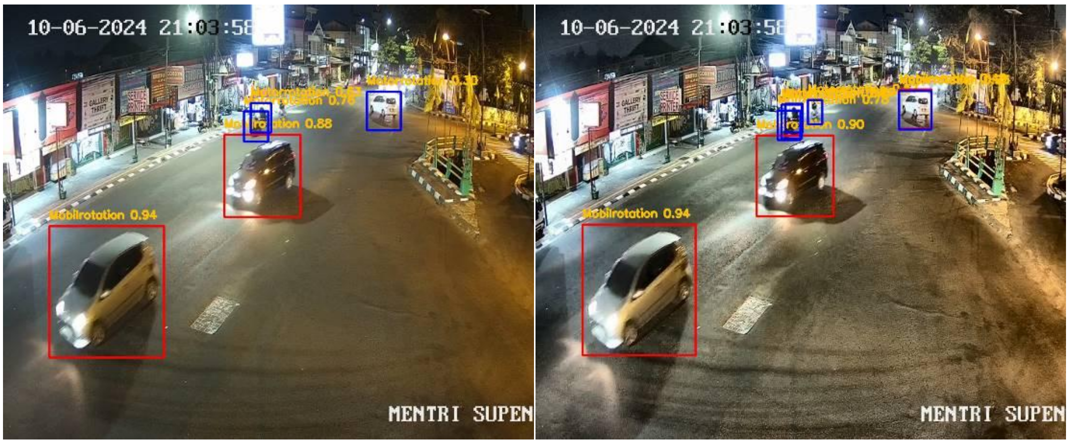

Figure 7. YOLOv8s on dataset 1 and original image test (Left) YOLOv8s on dataset 1 and modified image test using CLAHE (Right)

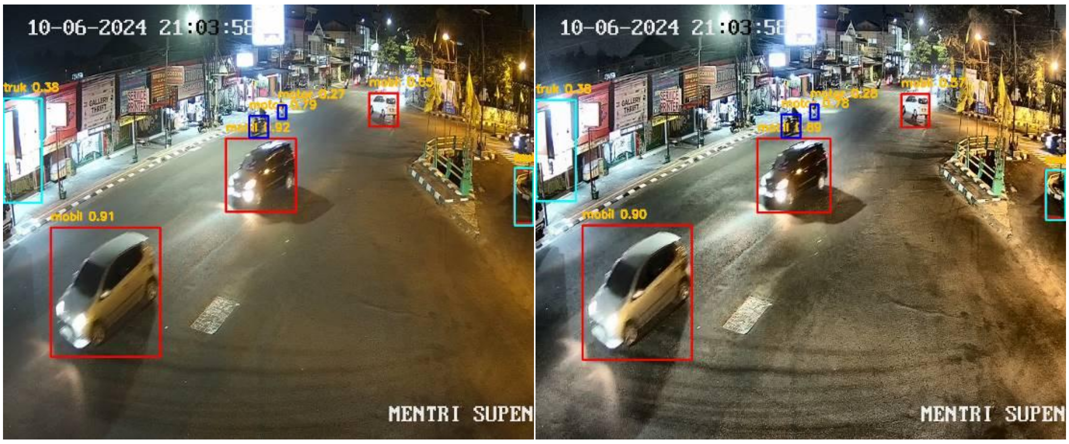

Figure 8. YOLOv8s on dataset 2 and original image test (Left) YOLOv8s on dataset 2 and modified image test using CLAHE (Right)

In the third experiment, the YOLOv8n model was used and training was done using dataset 2. The results of the image comparison are shown in Fig. 9. In this model, it was trained with the original image dataset and added with augmented images with CLAHE image enhancement. From this experiment, there was no difference in the detection rate for the original image or the image that was image enhanced with CLAHE. The detection rate performance decreased slightly when compared to using the YOLOv8s model.

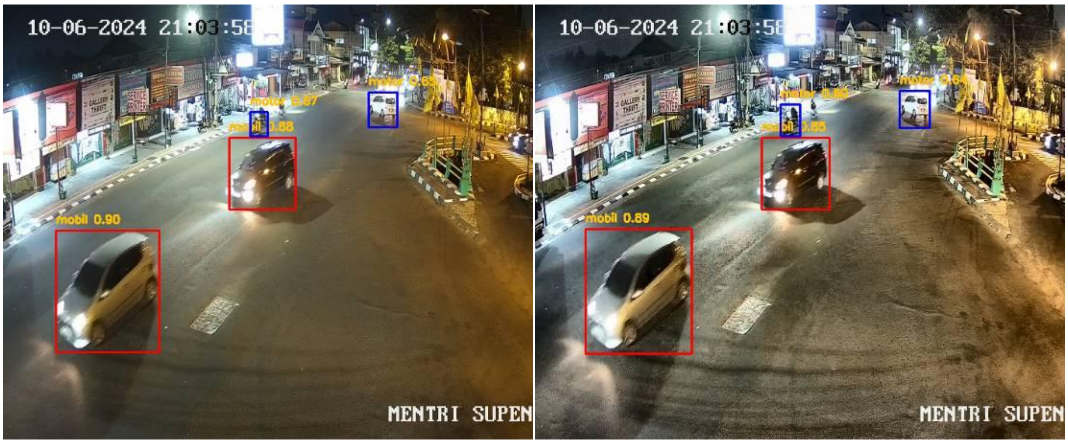

Figure 9. YOLOv8n on dataset 2 and original image test (Left) YOLOv8n on dataset 2 and modified image test using CLAHE (Right)

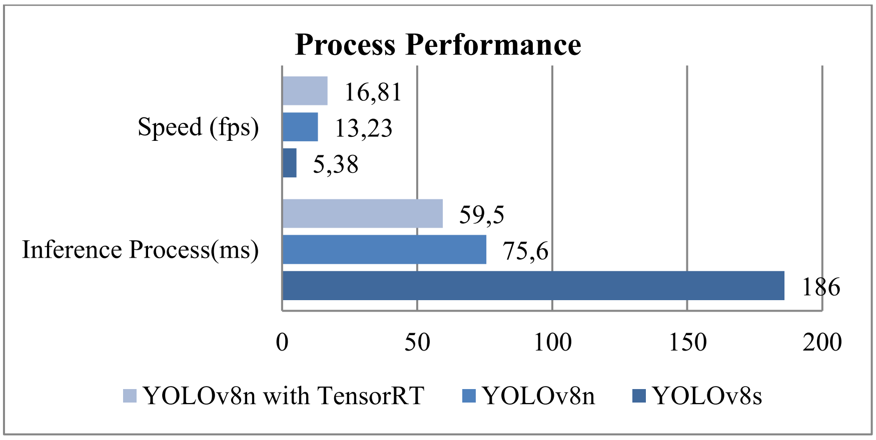

Figure 10. Process Performance Test on Jetson Nano

The last experiment is an experiment to determine the performance of each model to be applied to the SBC Jetson Nano as shown in Fig. 10. This is done to determine the appropriate model to choose. Small inference processes or high FPS are better to use. This is because it is very important for real-time applications in the field. Especially later for vehicle calculations which require an image tracking process there. If the processing speed is low, it means that many vehicles will be missed to be counted. The experiment itself compares the YOLOv8s and YOLOv8n models and YOLOv8n by applying the tensorRT feature to the Jetson Nano. The results of this test can be seen in Figure 10. The process performance between YOLOv8s and YOLOv8n is very far. In this case, YOLOv8n excels in processing speed with a level of accuracy that is not too significant. The use of the tensorRT feature on the Jetson Nano can increase the processing speed by 21% better.

4 Conclusions

This paper focuses on the effect of using CLAHE image enhancement on the level of vehicle detection at night with the YOLOv8 detection model that is suitable for application on Jetson Nano. We use two types of datasets with object detection models YOLOv8s and YOLOv8n. From the experimental results, it is obtained that night images that are processed with CLAHE image enhancement produce images that are brighter and clearer visually when compared to the original image. For models using only the original image dataset, there is also an improvement in the level of detection when the processed image is preprocessed with CLAHE image enhancement. The level of vehicle detection using YOLOv8n is not significantly lower than YOLOv8s but with a much better processing speed on Jetson Nano. The use of TensorRT on Jetson Nano also improves the processing speed by up to 21% at an inference speed of 59.5 ms. From the experiment, it can be concluded that the YOLOv8n model with CLAHE image enhancement and the use of TensorRT is the optimal choice. By using image enhancement CLAHE can improve vehicle detection with deep learning models, especially in dark or night conditions. Future work is to count the number of vehicles on the highway by adding a tracking process. The processing speed results are limited to the image enhancement process and vehicle detection without tracking processes and others. The use of Jetson SBCs with higher specifications is recommended so that faster processing can be applied in the field.

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