Enhancement by CLAHE for Traffic Light State Recognition Under Dynamic Weather

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**Abstract.** Traditional traffic light recognition methods, such as RGB thresholding and rule-based classifiers, offer computational efficiency but struggle with accuracy under dynamic lighting and weather conditions. Deep learning approaches, particularly convolutional neural networks, have significantly improved recognition accuracy. However, illumination variability remains a challenge, leading to misclassification in glare, low-light, and adverse weather conditions. This study aims to enhance the robustness of traffic light recognition by integrating Contrast-Limited Adaptive Histogram Equalization (CLAHE) as a preprocessing step with the YOLOv8 deep learning model. CLAHE improves image contrast, making traffic lights more distinguishable in challenging environments. The proposed method is evaluated using the LISA Traffic Light Dataset, which contains real-world traffic light images captured under diverse lighting and weather conditions. Performance is assessed by comparing model accuracy, precision, and recall with and without CLAHE preprocessing. In this paper we achieved 97.8% for precision and 97.4% for recall. These findings demonstrate that there is still opportunity to increase the accuracy. By incorporating CLAHE, it enhances feature visibility and improves detection performance, particularly in low-visibility scenarios. By addressing the gap in preprocessing techniques for traffic light recognition, this research provides a novel and scalable solution for improving detection robustness in autonomous driving systems. The integration of CLAHE with YOLOv8 still not being explored in other research, making this study a valuable contribution toward enhancing real-time traffic light recognition under dynamic conditions.

# INTRODUCTION

Traffic light recognition systems are becoming common in the technology implemented in the vehicles nowadays, enabling safer and greater efficiency of traffic flow. Traffic light recognition systems are crucial for autonomous vehicles, which has become increasingly popular research [1]. Autonomous vehicles rely on accurate and real-time recognition of any object on the road, especially traffic light states which are red, green and yellow to make decision to perform the autonomous driving. Traditional traffic light recognition methods, such as RGB thresholding and rule-based classifiers, have already been widely used due to their simplicity and computational efficiency [2]. However, these methods of traffic light recognition often lack in the dynamic lighting or weather conditions, such as glare, shadows, low-light environment and also bad weather, which can lead to misclassification and compromise the road safety [3 - 4].

Recent improvements in deep learning, particularly in convolutional neural networks (CNNs), have shown the confidence in improving the effectiveness and robustness of the system. Models that are based on YOLO such as the work by [5 - 6] are successful in real-time recognition. However, these models encounter difficulty with detection of small and distant objects such as traffic light color from a distance [7] and have challenges in handling illumination variability [8]. Hybrid models are proposed by [9] with the aim to simulate real-time traffic. Such models show improved model accuracy but also require high computational power. This research proposes to address these limitations. Our aim is to enhance and improve the preprocessing stage of the traffic light recognition systems by making it robust across dynamic lighting situation. This ensures the reliability of the classification it makes that leads to improve performance.

# METHODOLOGY

## CRISP-DM Framework

Figure 1 shows the Cross-Industry Standard Process for Data Mining (CRISP-DM) flowchart. CRISP-DM is a robust, industry-standard methodology that outlines a comprehensive, structured approach for data mining and machine learning projects. The framework consists of six distinct phases: problem understanding, data understanding, data preparation, modeling, evaluation, and deployment. Each phase is interconnected with iteration that allows for revisiting previous phase to ensure alignment with project objectives.

Problem Understanding

Data Understanding

Data Preparation

Modeling

Evaluation

Deployment

**FIGURE 1.** CRISP-DM framework

## Problem Understanding

Recognition of traffic light is essential for the development of autonomous vehicles and in the Advanced Driver Assistance Systems (ADAS). Both detects, classify, and interpret traffic light and its color for navigation. A reliable system must perform these tasks accurately. Even when the vehicles are under various challenging conditions such as glare, nighttime lighting, rain, fog, and occlusions, among others.

Traditionally traffic light system uses thresholding for color detection. Previous studies have shown that this method may lead to misclassification [2]. This is because, the change in ambient light can alter the perceived color of traffic lights under dynamic lighting and weather conditions. Modern approaches have moved towards using deep learning models. Such models are said to be capable of learning features directly from the data. Thus, the features are robust enough for working under these complex conditions.

The main objective of this research is to design a traffic light recognition model that is accurate. At the same time, the model is also able to perform under the dynamic lighting and weather conditions. In any tasks of visual analytics, they rely on preprocessing of visual data before being trained by the model. This may allow for an improvement in the accuracy of the recognition and the classification of the traffic light states.

YOLO (You Only Look Once) [10] is a deep learning model which has been very efficient and has worked accurately in image recognition tasks. Reduced performance has been seen when YOLO models were exposed to drastically varying lighting or adverse weather. This shows that YOLO models struggle to perform well under dynamic lighting and weather conditions. Therefore, our aim is to perform preprocessing step so that we can normalize the images. Preprocessing may also enhance key features before feeding them into the recognition models. We are proposing to use CLAHE (Contrast Limited Adaptive Histogram Equalization) [11] as a preprocessing technique.

## Data Understanding

The chosen dataset to be used for the model training is sourced from the LISA Traffic Light Dataset, which consists of real-world traffic light images captured under diverse lighting and weather conditions. This dataset is very suitable for achieving the objective of this research due to its data varies from many different lighting and weather conditions. The dataset consists of the daytime footages of the traffic light and nighttime footages of the traffic light with variations of lighting conditions, enable us to train the YOLOv8 deep learning model with dynamic lighting and weather conditions to get an insight of its performance and accuracy.

To ensure the relevance of this dataset to the research, we are focusing on improving the preprocessing techniques before the data being fed for model training. The preprocessing techniques can enhance the classification accuracy under dynamic lighting and weather conditions. Previous study has introduced the integration of median filtering [1], but very few studies have focused on the integration of CLAHE to the deep learning model such as YOLOv8 [12]. This research extends previous work by integrating CLAHE preprocessing techniques with the YOLOv8 deep learning model.

## Data Preparation with CLAHE (Contrast Limited Adaptive Histogram Equalization)

This phase consists of the organization of the dataset and ensuring that the dataset is ready to be used to train the deep learning model. The LISA Traffic Light Dataset is chosen for its wide variety of the lighting and weather conditions. This dataset is particularly suitable for this research due to variations in illumination and occlusions. Figure 2 shows the sample annotation from the dataset. We can see that the sky in the picture is overcast. This is one of the examples of the weather that will be used to train the traffic light state recognition model.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is an advanced image preprocessing technique designed to enhance the local contrast of images [5]. Unlike traditional histogram equalization, which operates globally on an image, CLAHE works on small regions (tiles) of the image. This localized adjustment enables better contrast in areas of low visibility while avoiding the over-amplification of noise.

CLAHE is particularly effective in conditions where lighting is non-uniform, making it ideal for enhancing traffic light visibility in real-world scenarios. By applying CLAHE to images prior to training and inference, the salient features of traffic lights (such as color and boundary) become more distinguishable to machine learning models, thereby improving recognition accuracy under dynamic lighting and weather conditions.

A traffic light on a street

AI-generated content may be incorrect.

**FIGURE 2.** Sample of annotation from the LISA traffic light dataset

Despite its potential, very few studies have explored the integration of CLAHE preprocessing with cutting-edge deep learning models like YOLOv8 for traffic light recognition. This research aims to bridge that gap by demonstrating how CLAHE can be combined with YOLOv8 to improve system robustness.

## Modelling with YOLOv8 Model

The development plan of this research shows the implementation steps that need to be taken, which are adaptive preprocessing techniques, model integration and performance evaluation. Adaptive preprocessing techniques develop and integrate the adaptive preprocessing techniques, such as CLAHE, with the YOLOv8 framework to enhance the performance of the traffic light recognition system under dynamic lighting and weather conditions. Model integration refines the YOLOv8 deep learning model to make it compatible with the CLAHE preprocessing techniques [. Performance evaluation conducts comprehensive evaluation based on the trained model using the standard metrics used in the deep learning project, such as accuracy, mean average precision (mAP), and the system’s performance under dynamic lighting and weather conditions.

YOLOv8, developed by Ultralytics, represents a significant advancement in the YOLO series of object detection models. Unlike its predecessors, YOLOv8 adopts an anchor-free architecture, which simplifies training and inference, and offers faster performance without sacrificing accuracy [6].

Key improvements in YOLOv8 include anchor-free detection which reduces the complexity of bounding box prediction. YOLOv8 also equipped with enhanced backbone and neck networks that provide better feature extraction and aggregation. Training YOLOv8 model is also flexible since it supports classification, detection and segmentation tasks. The computational efficiency of YOLOv8 is also improved to allows deployment on resource-constrained devices.

YOLOv8 is particularly suited for traffic light recognition tasks due to its real-time detection capability and high mean average precision (mAP). However, as with most computer vision models, its performance can degrade under extreme lighting variations if images are not appropriately preprocessed. This research explores how applying CLAHE to the input images can further elevate YOLOv8’s performance in detecting traffic lights across diverse environmental conditions.

## Evaluation

This phase focuses on measuring the result from the data training using the YOLOv8 model. This will act as a control to the traffic light recognition system that integrates the CLAHE preprocessing techniques. Firstly, we want to analyse the classification accuracy to set a control and the following values:

1. **Accuracy:** Analyse the classification accuracy to set a control and see the performance of YOLOv8 model without preprocessing.
2. **Mean Average Precision (mAP):** Assess the real-time accuracy of the YOLOv8 model using the other dataset that consists of optimal lighting and weather conditions.
3. **Recall and F1-score:** Evaluate the precision and recall under dynamic lighting and weather conditions.

# RESULTS AND DISCUSSION

## Training and Validation Loss Analysis

From Figure 3, the training loss is slightly higher compared to the validation loss. This indicates that there is minor overlifting. By integrating CLAHE as the preprocessing techniques, the noise can be reduced, and the feature extraction can be improved. This will lead to lower validation loss and improved generalization.

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| A group of graphs showing the results of a loss  AI-generated content may be incorrect.  **FIGURE 3.** Graphs of training and validation loss |

As can be seen in Figure 3, the training process was tracked using these primary loss components:

1. Box Loss: This component calculates the predicted bounding box coordinates error compared to the ground truth.
2. Classification Loss: This component measures the misclassification of the traffic light states by the model.
3. Distribution Focal Loss (DFL): A refinement loss to improve the localization accuracy.

## Precision and Recall

From Figure 4, the traffic light recognition model maintains its high-precision even as the recall is increasing. If the traffic light recognition system is paired with preprocessing techniques such as CLAHE, the recall can be further enhanced. This is because when the preprocessing techniques are integrated with the traffic light recognition model, it will improve the contrast in low-light images, ensuring more traffic lights are correctly classified.

Figure 5 indicates that the mAP performance is strong. However, it can be improved further using preprocessing techniques. CLAHE has been proven to enhance object detection models in low-contrast conditions, leading to better bounding box predictions and higher overall accuracy [7].

A graph of a graph

AI-generated content may be incorrect.

**FIGURE 4.** Precision-recall curve

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| A group of graphs showing the results of a loss  AI-generated content may be incorrect.  **FIGURE 5.** Graphs of mean average precision (mAP) |

# CONCLUSION

The traffic light recognition model trained without the integration of preprocessing techniques has a good performance, but its performance under dynamic lighting and weather conditions can be improved with the integration of preprocessing techniques. By integrating preprocessing techniques such as CLAHE, classification accuracy, precision-recall balance, and mean average precision (mAP) can be further enhanced. Future iterations of traffic light recognition model training will integrate preprocessing techniques and the results will be compared to the traffic light recognition model without the integration of preprocessing techniques.

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