Low Light Image Enhancement in License Plate and Recognition using Zero-DCE and TrOCR

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***Abstract*—Automatic License Plate Recognition (ALPR) is vital in intelligent transportation systems for traffic monitoring, law enforcement, and vehicle management. However, low-light conditions often degrade image quality and reduce recognition accuracy. This research presents a robust ALPR framework that combines Zero-DCE for enhancing low-light images, YOLOv8s for accurate license plate detection, and Microsoft's TrOCR-Large Printed model for high-precision character recognition. The proposed system significantly improves performance in challenging environments, as evaluated using accuracy, Normalized Edit Distance (1-NED), and inference time. This integrated approach demonstrates enhanced reliability and real-time potential for ALPR applications in diverse low-light scenarios.**

***Index Terms*—Keywords—Low-Light Image Enhancement (LLIE); License Plate Recognition (LPR); Image Quality Improvement; Traffic Monitoring**

I. Introduction

A. Background

Automatic License Plate Recognition (ALPR) is a crucial technology in modern transportation systems, enabling efficient vehicle identification and management. It supports law enforcement by detecting traffic violations such as speeding and unauthorized lane usage, and is widely used in smart parking and automated toll systems to improve traffic flow and reduce human intervention.

Beyond traffic management, ALPR enhances security by monitoring restricted areas, tracking stolen vehicles, and assisting in criminal investigations. Urban planners also rely on ALPR data to analyze traffic patterns and improve infrastructure.

However, the effectiveness of ALPR systems depends heavily on image quality. Low-light conditions—such as nighttime, fog, or poorly lit areas—often reduce image clarity, leading to detection and recognition errors.

To overcome these challenges, advanced image enhancement and deep learning techniques have been explored. Zero-DCE enhances low-light images without requiring paired data and is suitable for real-time use. For text recognition, Microsoft's TrOCR-Large Printed model, based on transformers, has shown superior performance over traditional OCR by leveraging visual and contextual understanding.

For license plate localization, YOLO-based object detection models are widely adopted, with the latest version, YOLOv8s, offering enhanced speed and accuracy, making it ideal for real-time detection in low-light conditions.

B. Problem Statement

While ALPR systems have achieved significant success in controlled lighting environments, their performance deteriorates under low-light conditions. Common issues include:

- Reduced contrast and color fidelity
- Motion blur and noise
- Glare from streetlights or headlights

These problems lead to poor license plate localization and misrecognition of characters, undermining the reliability of ALPR in real-world applications such as nighttime traffic monitoring or low-lit parking areas.

Traditional image enhancement techniques like histogram equalization or gamma correction often fall short in extreme low-light scenarios and may introduce visual artifacts. Likewise, conventional OCR engines struggle to recognize distorted, tilted, or low-contrast license plate characters.

Additionally, many current deep learning approaches either suffer from high computational costs, lack real-time performance, or require extensive labeled datasets for training, making them impractical for deployment in many real-world systems.

C. Objectives

This research aims to develop an advanced, efficient, and accurate ALPR framework optimized for low-light conditions. The specific objectives are:

- **Enhance Low-Light Image Quality**
  Apply Zero-DCE, a real-time, unsupervised image enhancement model, to improve brightness and contrast in poorly lit license plate images without introducing noise or artifacts.
- **Accurate License Plate Detection**
  Utilize YOLOv8s, a state-of-the-art lightweight object detection model, to robustly detect license plates in enhanced images with high speed and accuracy.
- **Robust Text Recognition**
  Integrate Microsoft's TrOCR-Large Printed OCR model to accurately recognize license plate characters, even under distortions, low contrast, and motion blur.

- **Evaluate Performance**
  Measure the system's effectiveness using evaluation metrics such as recognition accuracy, Normalized Edit Distance (1-NED), and inference time.

Through this integrated approach, the research seeks to improve the robustness and applicability of ALPR systems in diverse and challenging low-light environments.

II. Literature Review

A. Background

Automatic License Plate Recognition (ALPR) is extensively used in transportation systems for vehicle identification in law enforcement, traffic monitoring, toll collection, and parking management. These systems rely on capturing vehicle license plate images and applying image processing and recognition algorithms. However, performance is often degraded by environmental factors such as motion blur, occlusions, and particularly low-light conditions. Nighttime and poorly lit environments pose significant challenges, making specialized image enhancement and recognition methods essential for reliable ALPR performance.

B. Low-Light Image Enhancement Techniques

Low-light enhancement techniques aim to improve image clarity and visibility in dark conditions to support accurate recognition. Traditional methods like histogram equalization and gamma correction apply global adjustments but often fail to preserve image details. Retinex-based methods improve illumination by mimicking human visual perception, better maintaining structural features. Deep learning models, such as U-Net and GAN-based approaches, offer state-of-the-art performance by learning complex mappings from low-light to well-lit images. These enhancements are critical for maintaining ALPR accuracy in nighttime or dim environments.

C. Character Recognition Techniques

Character recognition in ALPR involves extracting alphanumeric data from segmented license plate regions. While traditional OCR methods, such as template matching and rule-based segmentation, are limited by font variations and distortions, machine learning models like Support Vector Machines (SVM) and Hidden Markov Models (HMM) offer improved adaptability. Deep learning approaches, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), significantly enhance recognition accuracy. Advanced attention-based models such as CRNN and ASTER further improve performance by dynamically focusing on relevant text areas and correcting for distortions or complex backgrounds.

D. Novel Techniques in Low-Light Enhancement and Character Recognition

Zero-DCE is a deep learning model for low-light enhancement that estimates pixel-wise adjustment curves to adaptively improve image brightness and contrast. Notably, it requires no paired training data, making it practical for real-world ALPR. Zero-DCE effectively prevents overexposure and reduces noise, preserving plate details in dark scenes. For character recognition, TrOCR employs a transformer-based architecture that uses attention mechanisms to accurately recognize text even in blurred or distorted license plates, improving robustness compared to traditional methods. For vehicle and number plate detection, YOLOv8 delivers state-of-the-art performance with faster inference speed and higher accuracy than previous YOLO versions.

III. Methodology

The proposed ALPR system integrates low-light image enhancement, license plate detection, and character recognition in a sequential pipeline. The methodology is divided into four primary steps:

A. License Plate Detection with YOLOv8s

Following enhancement, license plates are localized using YOLOv8s, a lightweight and real-time object detection model. YOLOv8s is trained on the CCPD dataset, which contains annotated images with a single license plate per frame. The model is optimized for high precision, ensuring accurate detection in challenging environments.

The bounding box prediction is evaluated using the Intersection over Union (IoU):

$$\text{IoU} = \frac{A_{\text{pred}} \cap A_{\text{gt}}}{A_{\text{pred}} \cup A_{\text{gt}}} \tag{1}$$

Where:

- A_{pred} is the area of the predicted bounding box
- A_{gt} is the area of the ground truth bounding box

A detection is considered correct if,

$$\text{IoU} > 0.7$$

The detected plate region is then cropped and forwarded for preprocessing.

B. Image Enhancement with Zero-DCE

Zero-DCE (Zero-Reference Deep Curve Estimation) enhances low-light images by learning pixel-wise Light-Enhancement (LE) curves without requiring paired training data. The LE curve is applied directly to the RGB channels, allowing Zero-DCE to enhance brightness while maintaining natural color fidelity.

Let I be the original low-light image and α be the set of curve parameters predicted by the DCE-Net. The enhanced image I_{enh} is computed iteratively as:

$$I^{(t+1)} = I^{(t)} + \alpha^{(t)} \cdot I^{(t)} \cdot (1 - I^{(t)}), \quad t = 1, 2, \ldots, T$$

Where:

- $I^{(0)} = I \rightarrow$ Initial input is the original low-light image
- $T = 8 \rightarrow$ Number of enhancement iterations
- $\alpha^{(t)} \in \mathbb{R}^{H \times W \times 3} \rightarrow$ Learned enhancement parameters per RGB channel

To ensure suitable enhancement, a brightness threshold B_{th} is defined:

$$B = \frac{1}{N}\sum_{i=1}^{N}(0.299 \cdot R_i + 0.587 \cdot G_i + 0.114 \cdot B_i)$$

If $B < B_{\text{th}}$, the image is classified as low-light and passed through Zero-DCE. This check ensures that only necessary frames are enhanced, reducing computational overhead.

C. Preprocessing the Cropped License Plate Image

The following sequence of operations is applied to enhance the quality of the license plate images before feeding them into the recognition model:

- **Cropping** → The left portion of the image (approximately 20% of the width) is removed. This is typically where the province or emblem appears, which is irrelevant for character recognition.
- **Upscaling** → The cropped image is upscaled by a factor of 2 using bicubic interpolation. This increases the resolution, making fine character details more discernible.
- **Grayscale Conversion** → The RGB image is converted to a single-channel grayscale image to simplify further processing and reduce computational complexity.
- **Histogram Equalization** → Enhances contrast by redistributing pixel intensities, improving visibility of features in poorly lit or unevenly exposed regions.
- **Gaussian Blur** → A small blur (kernel size 3×3) is applied to reduce noise and smoothen the image, aiding in removing minor artifacts.
- **Sharpening** → The blurred image is sharpened to enhance edges and improve the clarity of character boundaries.
- **Contrast Enhancement** → The overall contrast of the image is increased to make characters stand out more distinctly from the background.
- **RGB Conversion** → The final processed image is converted back to RGB format, suitable for models expecting three-channel input.

D. Character Recognition using Microsoft's TrOCR-Large Printed

For character recognition, this system uses Microsoft's TrOCR-Large Printed, a transformer-based OCR model that processes printed text with high accuracy—even under blur, low contrast, or perspective distortions.

TrOCR consists of:

- **Vision Transformer (ViT) encoder:** Extracts visual features from the input image.
- **Transformer decoder:** Generates the output character sequence from the visual tokens.

This end-to-end sequence-to-sequence model does not require explicit character segmentation, allowing it to process the entire license plate string holistically. The model's attention mechanism dynamically focuses on the most relevant parts of the image, enhancing its robustness to different lighting conditions, character spacing, fonts, and plate layouts.

In some countries, license plates may contain one or two lines of text (e.g., upper and lower lines of characters). Before sending the image to TrOCR, the system checks whether the plate contains two lines using horizontal projection profiling.

Line Splitting Logic:

- The preprocessed license plate image is first binarized (black and white).
- Then, the system computes a horizontal projection by summing black pixels along each row.
- A dynamic threshold (30% of the maximum row sum) is used to detect which rows likely belong to text regions.
- The algorithm scans the rows, grouping contiguous regions of text and skipping small gaps.
- It extracts each detected text block as a separate image line (up to two lines).

If the system detects two lines, it processes both lines individually through TrOCR and concatenates the results. If only one line is detected, that single image is passed directly to the model. This preprocessing ensures that the model receives well-aligned character sequences, improving recognition accuracy on vertically stacked plates.

IV. Experiments and Results

A. Datasets

In this research, a variety of datasets were employed to train and evaluate different components of the system, including vehicle detection, number plate detection, and low-light enhancement. Each dataset was chosen or created to reflect real-world traffic conditions and ensure practical applicability.

For vehicle detection involving cars, motorbikes, and vans, the YOLOv8s model was trained on a combination of publicly available datasets and additional annotated images. These datasets covered diverse scenarios to improve the model's performance across different environments. For number plate detection, a custom dataset was developed containing only Sri Lankan number plates. This dataset included a wide range of plate formats used locally, with manually annotated bounding boxes to enhance detection accuracy in regional contexts.

To train the Zero-DCE model for low-light enhancement, we compiled a dataset of vehicle images captured in poorly lit conditions. Images with an average brightness below 60 were classified as dark, resulting in a set of approximately 3,000 low-light vehicle images. These included night-time, rainy, and shaded scenarios, enabling the enhancement model to significantly improve image clarity and support better recognition in challenging conditions.

B. Results

1) Number Plate Localization

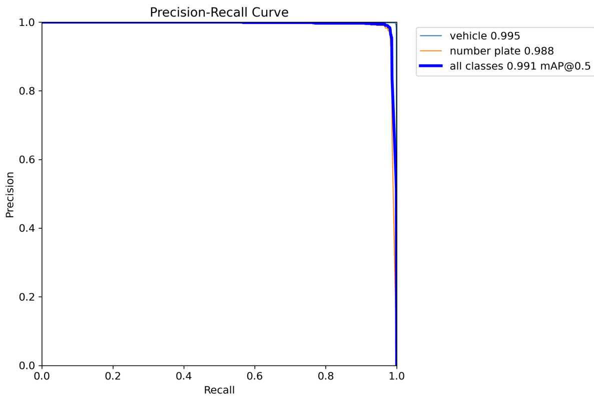


Fig. 1: Precision-Recall (PR) curveacross classes

This curve illustrates the trade-off between precision and recall across different classes using the Precision-Recall (PR) curve. A higher area under the curve reflects better model performance. In our results, the model achieves a mean Average Precision (mAP@0.5) of 0.995 for vehicles, 0.988 for number plates, and an overall mAP@0.5 of 0.991.

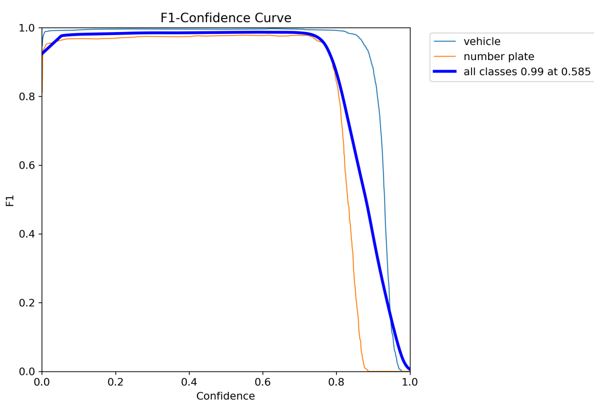


Fig. 2: F1-score vs. Confidence

This curve shows the model's F1-score at various confidence thresholds. The peak F1-score of 0.99 occurs at a threshold of 0.585, demonstrating the model's strong balance between precision and recall across detection classes.

TABLE I: Evaluation metrics of the best-performing model (highest mAP@0.5) on the validation set.

Metric	Value
Precision	0.9876
Recall	0.9858
mAP@0.5	0.9942
mAP@0.5:0.95	0.7780

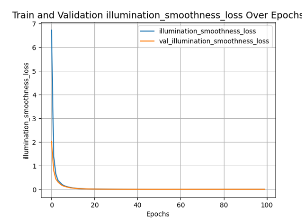
The table above presents the key performance metrics of the trained YOLOv8 model evaluated on the validation set. The model achieved a high precision of 0.9876 and a recall of 0.9858, indicating accurate and consistent detection across classes. The mAP@0.5, which measures the average precision at an IoU threshold of 0.5, reached 0.9942, highlighting the model's strong detection capability. Additionally, the more rigorous mAP@0.5:0.95 score, which averages performance across multiple IoU thresholds, was 0.7780 — showing the model's robustness across varying localization strictness levels.

The number plate detection pipeline is shown in Fig. 3, beginning from the original violation image, through cropping, to the final enhanced image ready for OCR processing.

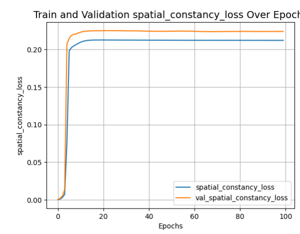
(a) Violated image (b) Cropped image (c) Processed image

Fig. 3: Pipeline for license plate extraction from raw violation frame.

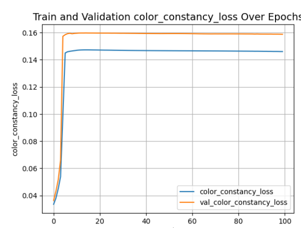
2) Zero-DCE for Low Light Image Enhancement



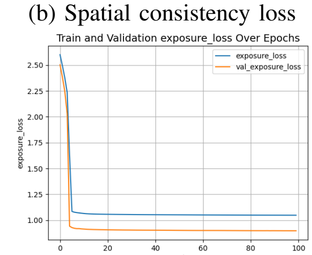
(a) Illumination smoothness loss



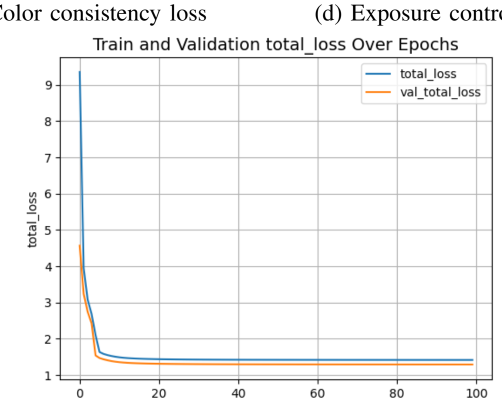
(b) Spatial consistency loss



(c) Color consistency loss



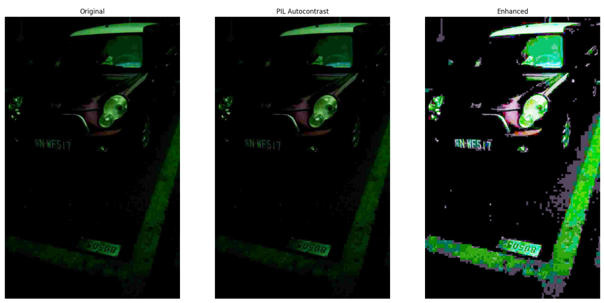
(d) Exposure control loss



(e) Training and validation total loss

Fig. 4: Training and validation loss curves for the Zero-DCE model.

Figure 4 presents the training and validation loss curves for the Zero-DCE model across different loss components. Subfigure (a) shows the total loss decreasing steadily, confirming effective learning. Subfigures (b), (c), and (d) represent component-wise loss functions—illumination smoothness, spatial consistency, and color consistency respectively. These component losses stabilize as training progresses, indicating that the model learns to enhance illumination while preserving structural and color fidelity.



(a) Comparison Example 1

(b) Comparison Example 2

Fig. 5: Each image displays a side-by-side comparison of the original (left) and enhanced (right) outputs. The model effectively improves illumination while preserving details and natural colors.

V. Discussion

This research presents an integrated and efficient pipeline for Automatic License Plate Recognition (ALPR) optimized for low-light and complex real-world conditions. By employing YOLOv8s, the latest lightweight and accurate object detection architecture, the system achieves fast and reliable localization of license plates even in cluttered or dimly lit environments. YOLOv8s's improvements over earlier YOLO versions are evident in its ability to maintain high precision and recall while reducing computational overhead, which is crucial for real-time applications.

For character recognition, the transformer-based Microsoft TrOCR-Large Printed model offers significant advantages over conventional OCR techniques. Its attention-based sequence-to-sequence architecture allows it to handle distortions, varying font styles, motion blur, and low-contrast characters without the need for explicit character segmentation. This robustness translates into higher recognition accuracy and adaptability across diverse license plate designs.

A key enhancement of this system is the inclusion of a line-segmentation preprocessing step, which analyzes horizontal pixel projections in binarized images to detect whether license plates contain one or two lines of text. This enables the model to accurately process multi-line plates by splitting and recognizing each line independently before concatenating the results. This preprocessing improves recognition performance for countries or regions where license plates commonly have stacked character layouts.

Overall, the combination of advanced detection, preprocessing, and transformer-based recognition creates a powerful ALPR framework suitable for deployment in intelligent transportation systems, parking management, toll collection, and security monitoring. The modular nature of the system also facilitates further adaptations and scalability.

VI. Conclusion and Future Work

In conclusion, this research successfully develops a robust ALPR system tailored to handle the challenges posed by low-light conditions and diverse license plate formats. The use of YOLOv8s significantly improves detection speed and accuracy, enabling real-time processing, while Microsoft's TrOCR-Large Printed model offers superior character recognition performance, even on degraded or distorted images.

The integration of line detection and segmentation further enhances the system's flexibility, allowing it to effectively recognize plates with single or multiple text lines without requiring manual intervention or complex layout assumptions.

Future work will focus on several promising directions to further advance this system:

- Multilingual and Multiscript Recognition: Extending the OCR capability to support various languages and scripts prevalent in different regions will broaden the applicability of the system globally.
- Model Optimization: Investigating lightweight transformer models or pruning techniques to reduce computational cost and enable deployment on edge devices such as embedded systems or mobile platforms.
- Advanced Preprocessing: Incorporating geometric correction, super-resolution, and adaptive noise reduction to further improve image quality and recognition accuracy under extreme conditions.
- System Integration: Building interfaces for integration with traffic management databases, law enforcement systems, and parking or tolling infrastructure to enable end-to-end intelligent vehicle monitoring solutions.

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