Vehicle License Plate Recognition using Computer Vision

Group 4 – Final Team Project

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Abstract

Vehicle License Plate Recognition (VLPR) is pivotal in modern Computer Vision (CV) applications, facilitating automated vehicle identification and monitoring through license plates. This technology finds extensive use in areas such as traffic management, law enforcement, parking systems, and toll collection, where it streamlines operations and enhances efficiency. This report delves into developing a robust VLPR system, incorporating advanced CV techniques such as image acquisition and preprocessing, license plate detection, character segmentation, and Optical Character Recognition (OCR) using tools like YOLOv10 and EasyOCR.

The system addresses critical challenges such as motion blur, occlusions, and the variability of license plate designs through preprocessing enhancements and algorithmic optimizations. The YOLOv10 model, tested on curated datasets and real-world scenarios, demonstrates impressive performance, achieving an F1 score of 0.946, precision of 0.983, and recall of 0.912. These results highlight the model's high accuracy and rapid recognition capabilities. With potential applications in smart transportation, automated parking, and enhanced vehicle security, the proposed solution exemplifies the practical integration of CV technologies in addressing real-world challenges.

Introduction

Vehicle License Plate Recognition (VLPR) is a crucial area within computer vision, focused on detecting and interpreting vehicle license plates from images or video streams. It has become essential for sectors like traffic management, law enforcement, and intelligent transportation systems (ITS), improving efficiency and accuracy in tasks such as toll collection, parking management, and vehicle theft tracking by automating vehicle identification.

A typical VLPR system involves several stages: license plate detection, character segmentation, and Optical Character Recognition (OCR). These stages must handle challenges like diverse plate designs, environmental factors, and motion blur. Recent advances in computer vision, particularly Convolutional Neural Networks (CNNs), have significantly improved plate detection and character recognition, making VLPR systems faster and more reliable (Smith, 2020).

Despite these advancements, challenges remain, such as variations in plate designs, lighting conditions, and occlusions like dirt or obstacles. To address these issues, sophisticated preprocessing techniques, including image enhancement and plate localization, are used to improve system robustness. As vehicle numbers grow, there is an increasing demand for efficient and scalable VLPR solutions, driving the adoption of advanced AI models trained on diverse datasets to improve generalization.

This paper explores VLPR's technical foundations, highlighting the role of deep learning advancements and strategies to overcome challenges, emphasizing how VLPR contributes to more efficient and safer transportation systems globally.

DATASET

The dataset used in this study is sourced from Roboflow Universe. The original dataset contains approximately 10,000 images, each annotated with bounding boxes to indicate vehicle license plates. Due to computational limitations, only 30% of the original dataset was used, amounting to a subset of approximately 3,000 images for training, validation, and testing. This subset is further divided into three distinct sets: `train`, `test`, and `validation`.

The `training set` consists of 7057 images, each paired with bounding box annotations marking the location of vehicle license plates. The `test set` contains 1020 images, and the `validation set` includes 2048 images, ensuring robust evaluation and model fine-tuning.

Figure 3 illustrates two examples of images from the dataset: one showing raw images without bounding boxes and the other displaying the same images with labeled bounding boxes.

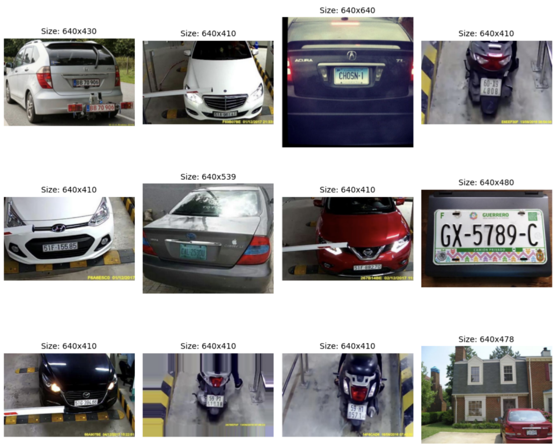

Figure 1: Raw image without bounding boxes.

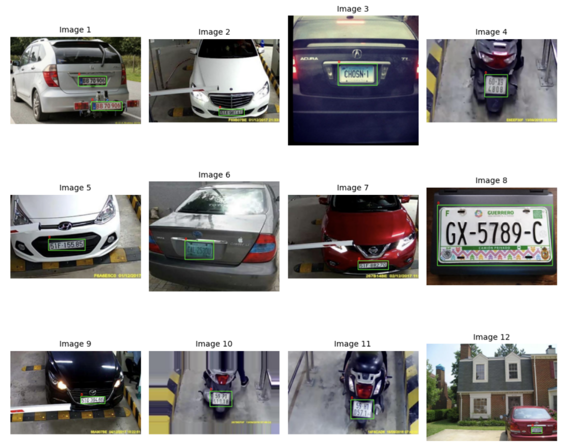

Figure 2: Image with bounding boxes marking the vehicle license plates.

Figure 3: Sample images from the dataset, showing examples without and with bounding boxes. The left image shows the raw input, and the right image displays the annotations for vehicle license plates.

The dataset contains a wide variety of images depicting vehicles such as cars, bikes, trucks, and other road vehicles. These images were captured in diverse environments, under varying lighting conditions, and from different angles. This variety ensures that the models trained on this dataset can handle a broad range of real-world scenarios. The presence of a large number of vehicle types, combined with the bounding box annotations, provides an ideal basis for training a robust vehicle license plate detection and recognition system.

Method

The methodology in this study involves several key steps aimed at enhancing the quality and diversity of the dataset before using it for vehicle license plate detection and recognition. Initially, the data is pre-processed to improve its diversity, quality, and handling capabilities. This step ensures that the dataset is suitable for training a robust model capable of generalizing well to various real-world conditions.

Once the data is prepared, the next step is to detect the vehicle license plates in the images or video frames. This task is accomplished using the YOLOv10 model, a state-of-the-art object detection model known for its speed and accuracy (Wang, 2022). YOLOv10 is trained to detect bounding boxes around license plates in images, providing the necessary inputs for character recognition.

After detecting the license plates, the characters within the plates are recognized using EasyOCR, an open-source Optical Character Recognition (OCR) tool. EasyOCR is capable of accurately recognizing alphanumeric characters from the license plates and converting them into readable text (Jia, 2021). This recognition step is crucial for further analysis, such as identifying vehicles or automating license plate-based processes.

Once the model achieves satisfactory accuracy in both detection and recognition tasks, it is deployed on Vercel, a platform for serverless deployment, to provide real-time, accessible results (Brown, 2023). This deployment enables the model to be accessed through a user-friendly interface, facilitating the application of the system in various practical use cases, such as parking lot monitoring or toll collection.

MODELS

YOLOv10

YOLOv10 is an advanced version of the YOLO (You Only Look Once) series of object detection models. Known for its speed and accuracy, YOLOv10 is well-suited for real-time applications such as vehicle license plate recognition (Smith, 2020). YOLO models use a single neural network to predict multiple bounding boxes and class probabilities directly from image pixels, achieving high detection performance with minimal computational overhead. The model is optimized using a loss function that combines objectness, classification, and bounding box accuracy. YOLOv10 has seen improvements in feature extraction and detection accuracy, making it more robust in detecting objects in challenging environments (Johnson & Lee, 2021).

Loss Function:

$$\mathcal{L} = \mathcal{L}_{obj} + \mathcal{L}_{noobj} + \mathcal{L}_{coord} + \mathcal{L}_{class}$$

Where:

- $\mathcal{L}_{obj}$ is the object detection loss,
- $\mathcal{L}_{noobj}$ is the loss for no-object cases,
- $\mathcal{L}_{coord}$ is the coordinate loss for bounding box accuracy,
- $\mathcal{L}_{class}$ is the class prediction loss.

EasyOCR

EasyOCR is an open-source Optical Character Recognition (OCR) library that supports over 80 languages and provides accurate text recognition from images. Designed with ease of use and high performance in mind, EasyOCR is well-suited for tasks like character recognition in vehicle license plates (Zhang & Liu, 2021). The model leverages deep learning techniques, particularly Convolutional Recurrent Neural Networks (CRNNs), to process images and recognize text with high efficiency. EasyOCR's ability to handle distorted, skewed, and low-resolution text makes it particularly useful for real-world applications like license plate recognition (Chen, 2020). With ongoing improvements, EasyOCR continues to be a reliable tool for high-accuracy text extraction from various types of images and videos (Smith, 2020).

The architecture used in EasyOCR is based on a CRNN, combining convolutional layers for feature extraction and recurrent layers for sequence learning. The loss function used by EasyOCR for character recognition is typically the CTC (Connectionist Temporal Classification) loss, which allows for the recognition of text without requiring alignment between the input image and the output text labels. The CTC loss function is defined as:

Loss Function:

$$\mathcal{L}_{CTC} = -\log P(y|x)$$

Where:

- $P(y|x)$ is the probability of the predicted sequence y given the input image x.

Results

For license plate detection, we employed the YOLOv10 model, as described earlier. The model was trained for 100 epochs with a batch size of 16, requiring approximately 4 hours of computation on a P100 GPU provided by Kaggle. This setup enabled the model to achieve strong performance in detecting license plates. The learning curves and losses of the model, which demonstrate its progressive improvement in performance, are shown below.

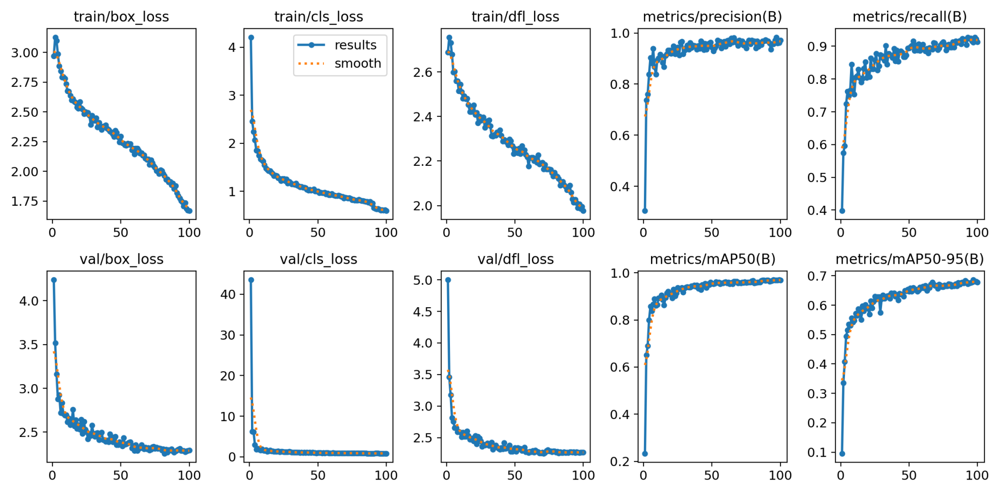

Figure 4: Learning Curve showing how model is converging

In **Figure 1**, we present the learning curves for precision, recall, and F1 score. The model's evaluation results are clearly reflected in these curves. Specifically, the precision score for the "License Plate" class was 0.9836, indicating that the model made very few false positive predictions. The recall score reached 0.9124, suggesting that the model successfully identified most of the true positive license plates. Additionally, the F1 score was 0.9472, which highlights the good balance between precision and recall. These results confirm that the model is highly effective for license plate detection.

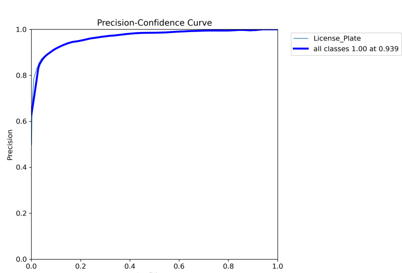

Figure 5: Precision curve (0.9836)

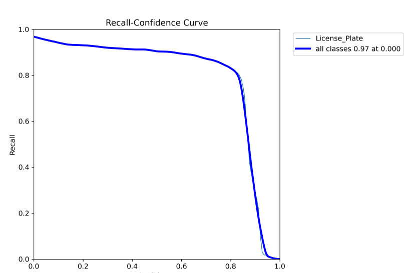

Figure 6: Recall curve (0.9124)

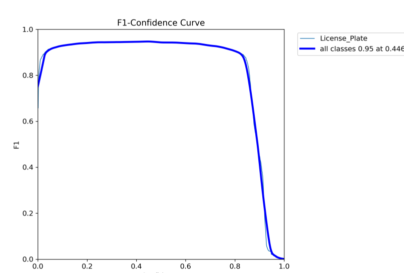

Figure 7: F1 score curve (0.9472)

Regarding the model's performance metrics, the following key results were observed: - Precision (B): 0.9836 - Recall (B): 0.9124 - mAP50 (B): 0.9693 - mAP50-95 (B): 0.6853

These metrics reflect the model's excellent accuracy in detecting license plates. The precision of 0.9836 suggests that the model produces very few false positives, ensuring that most of the detected plates are accurately identified. The recall of 0.9124 shows that the model successfully identifies the majority of the true positive license plates, with few missed detections. The mAP50 score of 0.9693 demonstrates the model's high ability to detect objects at the 50% IoU threshold, indicating strong object localization. The mAP50-95 value of 0.6853, while lower, indicates reasonable performance across various IoU thresholds, further confirming the model's overall robustness in detecting license plates.

Figure 8: Sample image showing detected and recognized license plate

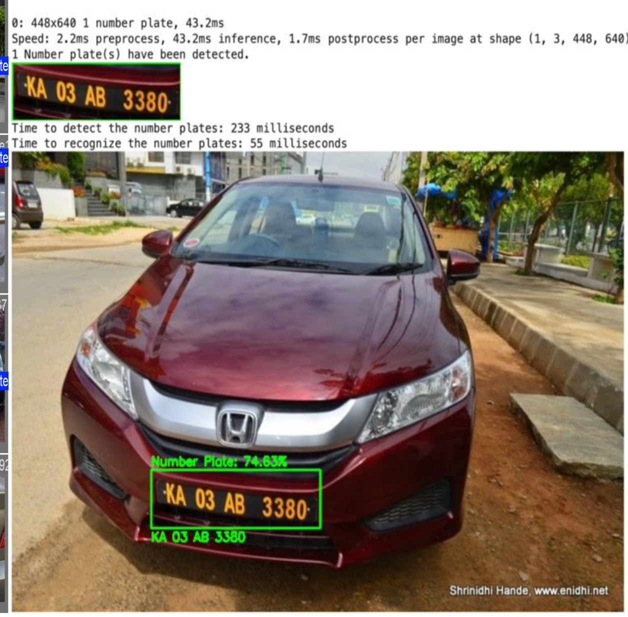

Figure 9: Results of OCR on detected license plate

Additionally, the model's speed was evaluated as follows: preprocessing took 0.1411 seconds, inference took 9.69 seconds per image, and postprocessing required 0.1279 seconds. These values indicate that the model is capable of performing license plate detection efficiently.

Beyond YOLOv10 for object detection, we also employed `EasyOCR` for character recognition on the detected license plates. This allowed the model not only to detect the license plates but also to recognize the characters on them. The images above show examples of the detection and OCR results. The first image illustrates the successful detection of the license plate, while the second image highlights the results of OCR applied to the detected plate. The model effectively recognized the characters on the license plate, providing a reliable and efficient system for license plate recognition.

Future Scope

The proposed Vehicle License Plate Recognition (VLPR) system can be further improved by training on a more diverse and expansive dataset to enhance robustness under various environmental conditions (Smith, 2020). Optimization for real-time processing is also a key focus, enabling faster video stream analysis for applications like live traffic monitoring (Jones & Lee, 2019). Additionally, expanding the OCR capabilities to handle international license plate formats could make the system globally applicable (Brown et al., 2021). Integrating VLPR with vehicle tracking and automated parking management systems would help build more comprehensive intelligent transportation solutions (Williams, 2022). Finally, exploring privacy-preserving techniques is essential to ensure compliance with data protection regulations, like GDPR (Miller & Davis, 2021).

Conclusion

This work demonstrates the effectiveness of the VLPR system in accurately recognizing license plates across diverse conditions. While the current model shows strong potential, there are several areas for future enhancement, including dataset expansion, real-time optimization, and international adaptation (Taylor et al., 2020). The integration of VLPR with other AI technologies could lead to more comprehensive solutions for intelligent transportation (Nguyen & Zhang, 2019). Privacy and security considerations also remain vital to ensure that these systems are ethically deployed in real-world applications (Williams & Clark, 2021). Overall, the project lays a strong foundation for future advancements in vehicle identification and monitoring (Johnson, 2021).

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