Automatic Number Plate Recognition Using YOLOv8

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Abstract

This paper presents a deep learning-based Automatic Number Plate Recognition (ANPR) framework leveraging the YOLOv8 architecture. The system integrates YOLOv8 for fast and accurate license plate localization, combined with EasyOCR for optical character recognition. The framework demonstrates 89.29% accuracy across varied conditions such as lighting, angles, and plate formats, validating its real-time applicability in traffic automation, law enforcement, and smart surveillance. Future work focuses on optimizing inference for edge devices and enhancing text recognition under challenging conditions.

1. Introduction

The demand for intelligent transportation systems has led to the rise of vision-based applications such as Automatic Number Plate Recognition (ANPR). Urban congestion, vehicle theft, toll automation, and smart parking systems all require robust license plate identification under real-time constraints.

Traditional ANPR systems often rely on handcrafted features or fixed-angle cameras, making them unreliable in uncontrolled environments. With the emergence of real-time object detection networks, YOLOv8 offers a promising solution with speed, accuracy, and adaptability. This research proposes an integrated YOLOv8-based ANPR system complemented by EasyOCR for character decoding.

2. Related Work

Earlier ANPR systems used edge detection, morphological operations, and Haar cascades, but lacked robustness. Deep learning–based approaches using CNNs improved accuracy, but often required high computational overhead.

Recent studies combined object detection with OCR pipelines. Works such as Sharma et al. (2022) applied YOLO with KNN, while others used Mask R-CNN or Faster R-CNN. However, YOLOv8's lightweight architecture and improved anchor-free design offer better real-time performance, which this work utilizes for ANPR in diverse conditions.

3. Proposed Framework

3.1. YOLOv8 for Plate Detection

YOLOv8, developed by Ultralytics, is a cutting-edge, anchor-free object detector. Its architecture balances speed and accuracy, enabling real-time detection on mid-range hardware. For this ANPR task, it was fine-tuned on a curated dataset of Indian license plates with augmentation techniques such as motion blur and contrast shifts.

3.2. OCR with EasyOCR

EasyOCR was selected for its language flexibility and ease of deployment. After YOLOv8 detects and crops the license plate region, EasyOCR performs character recognition. Although limited by plate distortions and font stylizations, it provides a practical balance between accuracy and computational cost.

3.3. System Pipeline

1. Input from video stream or image source.
2. YOLOv8 localizes plate region.
3. Plate is cropped and passed to OCR.
4. Extracted text is post-processed and stored.

4. Dataset and Preprocessing

The dataset comprises 200 labeled vehicle images sourced from Indian roads, parking lots, and garages. It includes diverse scenarios—angled plates, night-time shots, and motion blur.

4.1. Preprocessing

- Resizing images to 640x640 px.
- Label formatting for YOLO annotation style.
- Data augmentation with Gaussian noise, rotation, brightness shifts.

5. Experimental Setup

5.1. Environment

The model was trained on a machine with NVIDIA GTX 1660 GPU using PyTorch and Ultralytics' YOLOv8 implementation. EasyOCR was integrated using OpenCV and Tesseract fallback.

5.2. Training Details

- Epochs: 100
- Batch Size: 16
- Learning Rate: 0.001
- Optimizer: SGD with momentum

5.3. Performance Metrics

- **Detection Accuracy:** 89.29%
- **Precision:** 91.1%
- **Recall:** 86.4%
- **F1 Score:** 0.87

6. Results and Discussion

Strengths: The system performed well under varied lighting, plate angles, and distances. Detection latency was under 40 ms per frame.

Weaknesses: OCR struggled on heavily stylized or obscured plates. Reflection from glossy plates degraded recognition accuracy.

Example: A vehicle plate partially hidden by a bike rack was detected by YOLOv8, but OCR returned "MH12XXX..." with missing digits.

7. Applications

- Automated Toll Collection
- Smart Parking Systems
- Traffic Law Enforcement
- Entry Management for Secure Premises

8. Limitations

- Limited dataset size restricts generalization.
- Poor OCR on non-standard or tampered plates.
- Not optimized for mobile/edge deployment.

9. Future Enhancements

- Integration of deep OCR models like TrOCR or CRNN.
- Fine-tuning on global datasets including international plates.
- Deploying lightweight versions using TensorRT or ONNX.

10. Conclusion

The proposed YOLOv8-based ANPR system shows high promise for real-time vehicle identification. It overcomes many drawbacks of traditional systems and offers scalability for urban infrastructure. With further enhancement, this system can support large-scale deployment in smart cities and traffic governance.

References

1. Ultralytics: YOLOv8 Documentation. `https://docs.ultralytics.com`
2. Sharma et al., "Automatic Vehicle License Plate Recognition Using YOLO and KNN", IEEE, 2022.
3. Rahman et al., "YOLO and Mask R-CNN for ANPR", Springer, 2021.
4. EasyOCR Documentation. `https://github.com/JaidedAI/EasyOCR`