Efficient Automated Number Plate Recognition System using YOLOv8 and Paddle OCR

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ABSTRACT

Automatic Number Plate Recognition (ANPR) is an essential technology widely used for traffic monitoring, toll collection, parking management, and law enforcement. Traditional ANPR systems employ Optical Character Recognition (OCR) frameworks like Easy OCR. However, they face challenges due to varying lighting conditions, skewed plates, and diverse language scripts, which impact their accuracy. The proposed research addresses these limitations by integrating YOLOv8 with Paddle OCR, enhancing the robustness, accuracy, and multilingual capabilities of ANPR systems. This survey explores various methodologies in ANPR, literature reviews, problem identification, and the impact of advanced AI models in improving license plate recognition

Keywords: ANPR, YOLOv8, Paddle OCR, license plate recognition, OCR, AI models.

I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) is an essential technology used in traffic monitoring, toll collection, parking management, and law enforcement, automating vehicle identification to improve efficiency and security. Traditional ANPR systems use Optical Character Recognition (OCR) frameworks like Easy OCR to extract text from license plates. However, challenges such as poor lighting conditions, skewed plates, and diverse language scripts reduce their accuracy.[1],[3] To address these limitations, this research integrates YOLOv8, a deep learning-based object detection model, with Paddle OCR, a robust text recognition framework, enhancing detection accuracy, robustness, and multilingual support. This survey explores different ANPR methodologies, including deep learning-based approaches, OCR-based techniques, and hybrid models, reviewing existing literature to identify gaps in current systems and highlighting how advanced AI models improve license plate recognition. By leveraging AI advancements, ANPR systems can achieve higher accuracy and efficiency, making them ideal for real-world applications in smart cities, automated toll collection, and intelligent traffic management. [1],[3] The integration of YOLOv8 and Paddle OCR ensures better performance under challenging conditions, improving law enforcement capabilities and streamlining transportation systems. This research aims to enhance ANPR's effectiveness, addressing key limitations faced by traditional OCR-based methods.

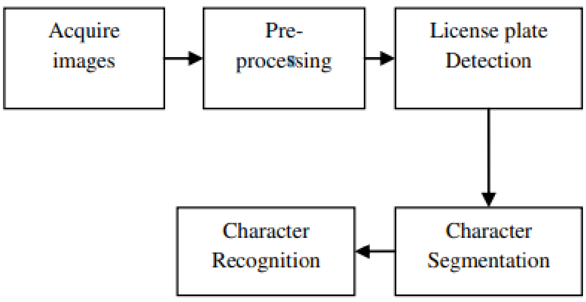

Fig 1. Block diagram of License Plate Recognition System

II. Literature Review

Several research studies have contributed to the development of ANPR systems. The following literature highlights the evolution of detection and recognition models.

- **Sankhe P.et al., (2023):** Improved robustness in license plate detection using YOLOv7 and optical character recognition techniques.

- **Aqaileh T.et al., (2023):** Implemented a deep learning model trained on extensive datasets for Jordanian license plates, enhancing detection and recognition.
- **Al-Batat R. et al., (2022):** Showcased an end-to-end YOLOv4-based ANPR system capable of recognizing vehicle types and plates with high accuracy.
- **Salma & Saeed et al., (2021):** Introduced an ANPR framework combining YOLOv4 and OCR Tesseract for Pakistani plates, demonstrating significant improvements.
- **Putri S.A. et al., (2020):** A comparative study of YOLO and RCNN models for vehicle license plate detection found YOLOv3 to be more effective for Indian license plates.

These studies emphasize the growing importance of deep learning models in ANPR, highlighting the effectiveness of YOLO-based architectures for plate detection.

III. Problem Identification

Despite advancements in ANPR technology, existing solutions still face major challenges:

Lighting Conditions: OCR frameworks struggle with poor illumination (e.g., nighttime, shadows, and reflections).

Skewed or Angled Plates: OCR performance degrades when license plates are not perfectly aligned.

Diverse Language Scripts: ANPR systems should be adaptable to different regional plate formats and scripts.

Accuracy & Reliability: Easy OCR fails to deliver consistent results across diverse datasets, requiring a more robust OCR framework.

IV. Proposed Solution

The proposed research enhances ANPR by integrating YOLOv8 with Paddle OCR, replacing Easy OCR for better performance. Paddle OCR provides:

High Accuracy: Advanced deep learning models enhance script recognition.
Multilingual Support: Recognizes diverse plate formats across different regions.
Robustness: Handles image distortions, low-resolution inputs, and various lighting conditions.
Open-Source & Customizable: Facilitates fine-tuning and adaptation for different applications.

V. Methodology

The proposed **Automated Number Plate Recognition** (ANPR) system follows a structured, multi-step process to ensure high accuracy and efficiency in vehicle identification.

The first step, **Image Acquisition**, involves capturing vehicle images using high-resolution surveillance cameras strategically placed to handle various lighting and environmental conditions. These cameras ensure clear and detailed image capture, forming the foundation of the recognition process.

Next, [1],[3] **License Plate Detection** is performed using YOLOv8, a deep-learning-based object detection model known for its speed and precision. YOLOv8 effectively localizes the license plate region within the captured image, even in challenging conditions such as varying angles, lighting, and plate styles.

The **Preprocessing** stage enhances image clarity through noise reduction, contrast adjustment, geometric correction, and grayscale conversion, preparing the image for optimal character recognition.

Following this, [1] **Character Recognition** is executed using Paddle OCR, an advanced deep-learning-powered optical character recognition engine. It extracts and accurately identifies alphanumeric characters across different fonts and languages.

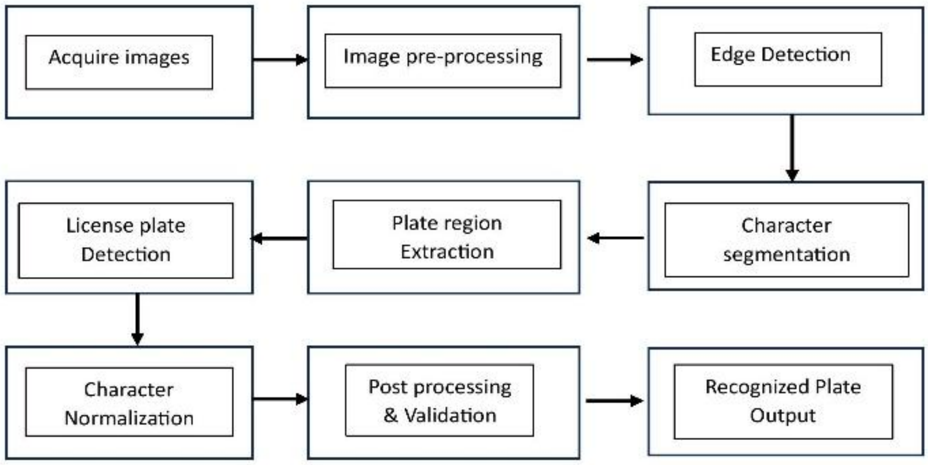

Fig 2. Work Flow

Finally, [2] the **Post-Processing & Validation** stage refines the recognition results by applying syntax validation, database cross-referencing, and error correction algorithms. This ensures reliable and standardized output, enabling seamless integration with traffic monitoring, law enforcement, parking management, toll collection, and other security applications.

VI. Comparative Analysis

[3],[4] A comparison of **YOLOv8 + Paddle OCR** with other traditional OCR systems like **Tesseract OCR** and **Easy OCR** highlights the advantages of using Paddle OCR.

Accuracy: [7] Tesseract OCR has low accuracy and requires significant pre-processing. Easy OCR provides moderate accuracy, performing better than Tesseract. Paddle OCR achieves high accuracy and effectively handles noisy and complex images.

Multilingual Support: Tesseract OCR supports multiple languages but requires additional training for new scripts. Easy OCR supports multiple languages but has some limitations. Paddle OCR provides extensive support for multiple languages, making it highly adaptable.

Processing Speed: [5] Tesseract OCR is slow due to its rule-based character recognition approach. Easy OCR offers moderate processing speed, utilizing deep learning techniques. Paddle OCR is optimized for fast processing with deep learning models.

Robustness: [6] Tesseract OCR struggles with skewed, low-light, and blurry conditions, making it less reliable. Easy OCR has moderate robustness but struggles with rotated text. Paddle OCR is highly robust, handling image distortions and low-quality inputs effectively.

Adaptability: Tesseract OCR requires tuning for different plate formats, limiting its flexibility. Easy OCR supports various plate styles but needs additional training for optimal performance. Paddle OCR is highly customizable and can be fine-tuned for different applications.

Training Capability: Tesseract OCR has limited customization options and lacks modern deep learning features. Easy OCR can be fine-tuned but lacks extensive customization tools. Paddle OCR offers better fine-tuning capabilities, making it suitable for custom datasets.

VII. Justification for Choosing Paddle OCR

Paddle OCR is chosen over **Tesseract OCR** and **Easy OCR** for the following reasons:

Higher Accuracy: [5] Paddle OCR uses advanced deep learning models that outperform traditional rule-based OCRs like Tesseract. Compared to Easy OCR, Paddle OCR provides better recognition under poor lighting and distorted text conditions.

Multilingual Capabilities: [5] Unlike Tesseract OCR, which requires extensive retraining for new languages, Paddle OCR supports multiple languages natively. Easy OCR has multilingual support, but Paddle OCR handles a wider variety of scripts efficiently.

Robustness to Real-World Conditions: Paddle OCR can recognize license plates even under extreme conditions like **motion blur, low resolution, and tilted angles**. Tesseract OCR struggles with skewed and noisy text, while Easy OCR has moderate performance.

Speed and Efficiency: Paddle OCR is optimized for speed, making it suitable for real-time **Automatic Number Plate Recognition (ANPR)** applications. Tesseract OCR is slow and computationally heavy, making it inefficient for real-time systems.

Customization & Open-Source Benefits: Paddle OCR is open-source, allowing further **fine-tuning and training on specific datasets**. Easy OCR provides some level of customization but lacks the extensive tools that Paddle OCR offers.

VIII. Applications

The proposed ANPR system benefits multiple domains:

- **Traffic Law Enforcement:** Detecting traffic violations and identifying vehicles.
- **Toll Collection:** Automating payment processes for highways.
- **Parking Management:** Monitoring vehicle entry/exit.
- **Security & Surveillance:** Enhancing security in restricted areas.

IX. Conclusion

The integration of **YOLOv8 with Paddle OCR** significantly improves **license plate recognition accuracy, robustness, and adaptability** compared to traditional OCR frameworks like **Tesseract OCR and Easy OCR**. The research justifies choosing Paddle OCR as it provides superior recognition capabilities, multilingual support, and better handling of real-world conditions. Future work can focus on further optimizing Paddle OCR models, implementing cloud-based ANPR solutions, and exploring hybrid deep learning approaches for even higher accuracy.

X. References

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