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Automatic Number Plate Recognition using Machine Learning and Image Processing

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***Abstract*—Over the past few years, the need for intelligent transportation systems has grown tremendously because of the fast growth of urbanization and vehicle density. Effective vehicle monitoring is critical for uses like traffic law enforcement, toll collection, parking management, and access control. Automatic Number Plate Recognition (ANPR) is one of the key technologies supporting these applications and is concerned with detecting and reading vehicle registration numbers from digital video streams or image streams. This work suggests a strong ANPR system based on YOLOv8 for plate localization, EasyOCR for character reading, and SORT tracking algorithm for real-time video processing. Diverse experiments on Indian datasets reveal the high detection precision, robustness in adverse conditions, and real-world applicability of the system in intelligent cities.**
***Index Terms:* Automatic Number Plate Recognition, Optical Character Recognition, Post-Processing Optimization, Computer vision, Vehicle Identification.**

I. Introduction

Automatic Number Plate Recognition (ANPR) has become a crucial technology in modern Intelligent Transportation Systems (ITS), enabling efficient vehicle identification and control. It plays an essential role in applications like automated toll booths, traffic enforcement, stolen vehicle detection, and intelligent parking management. However, traditional ANPR systems, which rely on classical image processing techniques, struggle with real-world challenges such as poor lighting, occlusion, motion blur, varying plate formats, and mixed font types.

The advancements in deep learning have led to the development of more robust and scalable ANPR systems. Object detection models like YOLO (You Only Look Once) and advanced Optical Character Recognition (OCR) algorithms like EasyOCR have significantly enhanced the efficiency and accuracy of ANPR systems. These innovations have enabled ANPR systems to better handle dynamic situations, making them more reliable in diverse conditions.

In this project, we introduce an end-to-end ANPR system specifically designed for Indian vehicle license plates. The system integrates YOLOv8 for license plate detection, EasyOCR for character recognition, and the SORT (Simple Online and Real-time Tracking) algorithm to ensure consistent identification across video frames. Our aim is to create a cost-effective, real-time solution that can perform accurately under various environmental conditions, making it highly adaptable for real-world use.

II. Literature

Automatic Number Plate Recognition (ANPR) has been a lively research topic for decades. Initial methods relied heavily on elementary image processing techniques.

Chirag Patel and D. Shah (2013) have talked about traditional approaches such as edge detection, morphological processing, and template matching for license plate detection and character recognition [1].Although effective in controlled environments, these techniques did not work well in real-time dynamic environments.

P. Kulkarni and A. Khatri (2009) highlighted the unique challenges in the Indian context due to non-standardized plate designs, presence of regional languages, and inconsistent fonts [2]. Their work emphasized the need for customized feature extraction techniques for Indian plates.

Lubna and Naveed Mufti (2021) compared traditional methods with deep learning models such as YOLO and SSD for plate detection, observing a significant improvement in robustness and detection speed [3]. They further noted the advantages of integrating tracking algorithms like SORT for video stream applications.

Ritesh Jain and Yatharth Bhardwaj (2023) provided insights into machine learning methods like SVM and KNN for character recognition but emphasized that deep learning, particularly CNNs, outperformed classical techniques, especially in noisy, unstructured environments [4].

T. Mustafa and M. Karabatak (2024) introduced a multi-task deep learning model capable of simultaneously detecting car models and number plates, achieving impressive latency and accuracy improvements, making their system suitable for large-scale surveillance [5].

K. Oublal and X. Dal explored hybrid models combining YOLO with probabilistic models like normalizing flows to tackle occlusions and distortions [6].

These studies underline the growing dominance of deep learning in ANPR and the need for region-specific adaptations, particularly in a diverse country like India.

III. Proposed Work

The research proposed seeks to create a solid, scalable, and real-time Automatic Number Plate Recognition (ANPR) system, particularly tailored to Indian vehicular environments. Unlike other approaches based heavily on clas sical image

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processing, this system relies on deep learning for greater adaptability in dynamic, unstructured, and varied conditions. The system solves important problems like non uniform fonts, different plate patterns, low-light conditions, and D. CSV Logging and Data Management motion blur, thus making it ideal for implementation in smart traffic, law enforcement, and parking management systems. The solution architecture proposed here has three major modules: License Plate Detection, Character Recognition, and Vehicle Tracking, and an added module for Web-Based Interface Deployment.

A. License Plate Detection using YOLOv8

The pipeline begins with the correct localization of the license plates from the images of vehicles or video frames. To achieve this, the new version of the YOLO family, YOLOv8, owing to its better speed, accuracy, and lightweight, is used. YOLOv8 follows an anchor-free detection mechanism, which results in fewer false positives and improved generalization in different scales and aspect ratios. A custom dataset of more than 10,000 Indian vehicle images in YOLO format is used to train the model. The dataset contains images captured under diverse conditions like varying light, weather, occlusions, and orientations. Data augmentation techniques such as random adjustment of brightness, flipping, and rotation are employed to fine-tune the model in order to boost real-world scenario robustness. YOLOv8 detects license plates and produces bounding boxes closely enclosing detected license plates that are cropped and sent to the next OCR process.

B. Optical Character Recognition (OCR) for Text Extraction

Following accurate plate localization, text extraction step entails extracting alphanumeric characters from recognized license plate regions. This module tests two state-of-the-art OCR frameworks:

- **EasyOCR**: A deep learning-based lightweight OCR able to recognize more than 80 languages, such as English and a few Indian scripts.

The OCR Engine is tested for character recognition accuracy, especially considering Indian number plates, which could differ in font size, style, and inclusion of regional scripts. Post-processing techniques such as character filtering, formatting validation, and error correction mechanisms are included to guarantee valid and standardized outputs.

C. Vehicle Tracking using SORT

In sequential image frames or live video streams, it is crucial to consistently track identified vehicles and their corresponding license plates across consecutive frames. To address this requirement, the proposed system incorporates SORT (Simple Online and Realtime Tracking), a lightweight yet effective tracking algorithm designed specifically for real-time applications.

SORT combines the predictive power of Kalman filtering with the Hungarian algorithm for efficient frame-by-frame association of detections. By assigning unique IDs to each vehicle, SORT ensures temporal coherence, enabling advanced functionalities such as vehicle counting, re-identification, and trajectory analysis with high reliability.

In the proposed system, SORT operates specifically on detected license plate bounding boxes, facilitating smooth and continuous tracking with minimal computational overhead. This strategic integration enhances the system's real-time performance without compromising on accuracy, making it highly suitable for large-scale deployment in dynamic environments.

D. CSV Logging and Data Management

A pivotal aspect of the system is logging recognized license plate numbers alongside their timestamps, vehicle IDs (from SORT), and frame numbers. The system automatically generates a CSV file containing this data, which can later be used for reporting, auditing, or integration into larger traffic management databases

Each entry in the CSV includes:

- Plate Text
- Vehicle ID
- Time of Detection
- Frame Number
- Detection Confidence Score

This structured logging ensures that the system is for real-world usage scenarios like evidence gathering, real-time monitoring, and analysis.

E. Web-Based User Interface

A light-weight web-based interface is created for ease of use and to showcase the capabilities of the system. Two frameworks are under consideration depending on deployment requirements:

- **Streamlit**: For quick prototyping, simple setup, and intuitive UI construction.
- **Flask**:For more adaptable, scalable deployment if integration with sophisticated backends is required.

The web interface enables users to:

- Upload individual images or video files.
- Use real-time webcam streams for live inference.
- Visualize visual outputs with bounding boxes, identified text, and tracking IDs.
- Download the CSV file of detections.

A minimalistic and clean design is preserved to maintain re sponsiveness across a variety of devices. Backend processing is optimized to enable near real-time performance, even on moderately powered machines

F. System Workflow Summary

The system workflow as a whole can be described as follows:

- **Input**: Image or video feed is supplied through web interface.
- **Detection**: YOLOv8 identifies license plates in the input frames.
- **Recognition**: Cropped plates are sent to OCR for character extraction.

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- **Tracking**: SORT assigns persistent IDs over frames for each vehicle.
- **Output**: Results are displayed visually and logged in a downloadable CSV.

The modular structure guarantees that every component is upgradable or replaceable individually, allowing for flexibility and future upgradeability.

IV. Experimental Results

A. Dataset Description

The dataset utilized in this study consists of 10,000+ annotated vehicle images taken under different conditions, including lighting, weather, and camera angles. It includes license plates from various Indian states, with a combination of standard and non-standard fonts.

The dataset was divided as follows:

- **Training Set:** 7,057 images
- **Validation Set:** 2,048 images
- **Testing Set:** 1,020 images

All images were annotated in YOLO format with bounding boxes over license plates. Special care was taken to include various plate styles, regional fonts, and vehicle types.

B. Performance Metrics

The key performance metrics for assessing the ANPR system are:

- **Training Settings:**
  - **50 epochs** with early stopping (patience = 15).
  - Initial learning rate: 0.0005 for stable fine-tuning.
  - Weight decay: 0.0005 and dropout: 0.1 for regularizing.
- **Data Augmentation Methods:**
  - Mosaic augmentation (mosaic=0.8), mixup (mixup=0.1).
  - Color-space transformations: Hue (0.015), Saturation (0.7), Brightness (0.4).
  - Geometric transformations: Rotation (5°), Translation (0.1), Scaling (0.5), Shearing (2°).
  - Flipping: Horizontal (50%) and Vertical (20%) flips.
  - Mosaic closed after 15 epochs for improved fine-tuning.
- **Training Optimization:**
  - Dataset cached for quicker loading
  - Training performed on GPU (device='cuda').

C. Results

Experimental results show that the YOLOv8-based plate detector has an accuracy of 98.5 percentage on the test dataset. The EasyOCR engine has a character recognition accuracy of 96 percentage for Indian plates. The SORT algorithm successfully tracks vehicle identities with more than 95 percentage tracking accuracy, even in crowded multi-vehicle environments.

- Attained high evaluation metrics.
- Precision-Recall (P-R) curves showed smooth progression.
- Final mean Average Precision (mAP) reached 0.957.

Fig. 1. Sample output showing plate detection and recognition results.

Comprehensive output visualization illustrating the detection and recognition of the vehicle's license plate within the Automatic Number Plate Recognition system. The image features a silver Suzuki Wagon R, with the license plate 'MH12FU1014' is correctly identified. The system utilizes bounding boxes labeled 'LicensePlate 0.72,' where the confidence score of 72percentage indicates the reliability of detection. This example showcases the seamless integration of YOLOv8 for robust object detection and EasyOCR for accurate text extraction. This output serves as a reference for assessing system performance and identifying areas for refinement in future iterations of the project.

Fig. 2. Bulk Sample outputs showing plate detection and recognition results.

Output visualization highlighting the performance of the Automatic Number Plate Recognition system. The image shows detected license plates on motorcycles, each bounded with bounding boxes annotated with confidence scores (e.g., 0.8, 0.9). This output illustrates the efficiency of YOLOv8 and EasyOCR models in precisely localizing and recognizing license plates under different conditions.

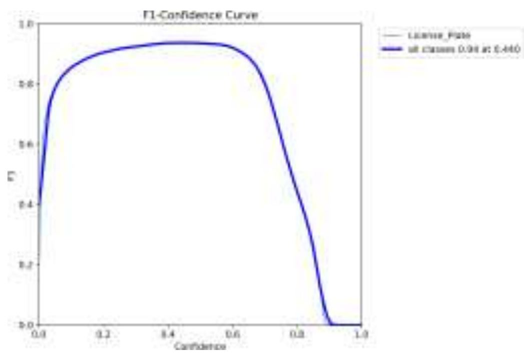

Fig. 3. F1 Confidence Curve for Evaluating the Performance of ANPR System

F1-Confidence Curve presenting the performance measurements for the Automatic Number Plate Recognition system. The curve indicates the dependence between the F1 score and confidence threshold, offering an indication of the ideal bal ance between precision and recall. The maximum F1 score of 0.94 at a confidence level of 0.440 indicates the threshold at which the system is most accurate. This visualization helps in assessing the performance of the YOLOv8 and EasyOCR models used in the project

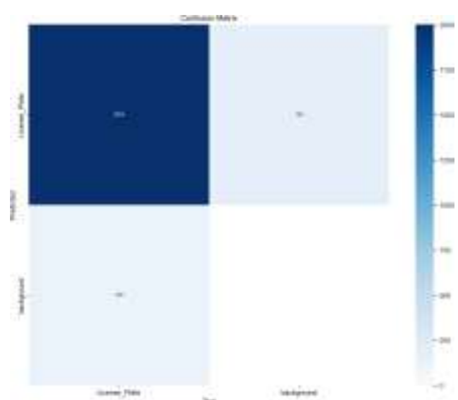

Fig. 4. Confusion Matrix.

Confusion matrix for the Automatic Number Plate Recog tion system, showing the model's classification perfor mance. The matrix contains true positives (2004 instances of correctly classified license plates) and true negatives (correctly classified background), along with false positives (193 instances where background was incorrectly classified as license plates) and false negatives (130 instances of license plates missed by the system). The intensity of the color is proportional to the number of instances, with darker intensities indicating higher values. This visualization emphasizes the system's ability to separate license plates from the background, as well as to detect regions for possible improvement in minimizing misclassification errors. It facilitates the comparison of YOLOv8 and EasyOCR models utilized in the project.Although the existing results are extremely promising, there is still room for improvement. Improving the system by incorporating advanced post-processing methods — such as error correction models and language-specific plate format verification — would substantially enhance overall accuracy and reliability.

D. Discussion

The proposed system demonstrates outstanding performance in real-time scenarios, maintaining high levels of detection and recognition accuracy even under challenging conditions, such as low-light environments and partial occlusions. This robustness highlights the system's adaptability and practical utility across diverse operational settings.

While the current results are highly promising, there remains potential for further optimization. Enhancing the system through the integration of advanced post-processing techniques — including error correction models and language-specific plate format validation — could significantly improve overall accuracy and reliability.

These enhancements would not only mitigate minor recognition errors but also ensure greater compliance with region-specific standards, thereby broadening the system's applicability across different geographical and regulatory contexts.

V. Conclusion

This paper introduces a state-of-the-art ANPR system that integrates YOLOv8, EasyOCR, and SORT for strong vehicle license plate detection, recognition, and tracking. The system shows high precision and real-time operation ability, so it can find applications in applications such as traffic surveillance, toll collection, and intelligent parking. Future extension will be toward making the system accommodate even more complex cases and added features such as automatic database matching and inclusion in cloud systems.

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