MANIPAL UNIVERSITY JAIPUR

A Synopsis on

Automatic Number Plate Detection

carried out as part of the course,

Project Based Learning –

Submitted by

Anika Mathur

Reg. No. 229310128

Supervised by:

Ms. Jyoti Rani

V-AIML

in partial fulfilment for the award of

the degree of

BACHELOR OF TECHNOLOGY

In

Computer Science and Engineering (AIML)

Department of Artificial Intelligence and Machine Learning

School of Computer Science & Engineering

Manipal University Jaipur,

November 2024

Automatic Number Plate Recognition

Team Members -

Anika Mathur - 229310128

Problem Definition -

The problem this project addresses is the challenge of effectively recognizing vehicle license plates in diverse real-world environments using Automatic Number Plate Recognition (ANPR) systems. ANPR systems are crucial in applications like traffic surveillance, law enforcement, toll collection, and parking management, where the accurate and efficient recognition of license plates is required.

There are several approaches to ANPR, each with unique strengths and limitations. Traditional methods such as **Edge Detection** focus on detecting the edges of the license plate in an image, but they can struggle in noisy environments or with complex backgrounds. On the other hand, advanced deep learning techniques like **YOLO (You Only Look Once)** offer high accuracy and speed in plate detection, but they require substantial computational power and large datasets for training. Another promising approach is **Model Fusion**, which aims to combine the benefits of multiple techniques to create a more robust and reliable system.

This project seeks to answer the following questions:

- Which method offers the best performance in terms of accuracy, speed, and adaptability to different conditions?
- How do traditional image processing methods (like edge detection) compare to modern deep learning approaches (like YOLO)?
- Can model fusion improve performance by combining multiple approaches?

Introduction -

Automatic Number Plate Recognition (ANPR) is a pivotal technology used for automating the process of identifying and recording vehicle license plates. ANPR systems have been widely adopted in applications such as traffic management, security, toll collection, and parking enforcement, where quick and accurate vehicle identification is required.

The goal of an ANPR system is to reliably detect and recognize license plates despite challenges such as variations in lighting, image resolution, plate design, and environmental conditions like motion blur or complex backgrounds. As such, selecting the appropriate technique for ANPR is essential for achieving high performance and reliability.

There are several techniques used for ANPR, including traditional image processing approaches and more modern deep learning-based methods. In this project, three methods are explored:

1. **Edge Detection**: This approach uses traditional computer vision techniques to detect the edges of license plates. It is computationally less expensive and faster but can be less reliable in noisy or cluttered environments.
2. **YOLO Object Detection**: YOLO is a real-time deep learning model that detects license plates by identifying objects in images. It is efficient and accurate but requires large training datasets and high computational resources, making it more suited for real-time applications where performance is critical.
3. **Model Fusion**: This method combines multiple models or techniques to enhance the overall ANPR performance. For example, edge detection could be used to preprocess the image before applying YOLO for plate detection. The goal of fusion is to leverage the strengths of each model to improve accuracy and robustness across different conditions.

Scope/Objective -

This project evaluates three ANPR methods—**Edge Detection**, **YOLO**, and **Model Fusion**—to determine the best approach for license plate recognition.

Objectives:

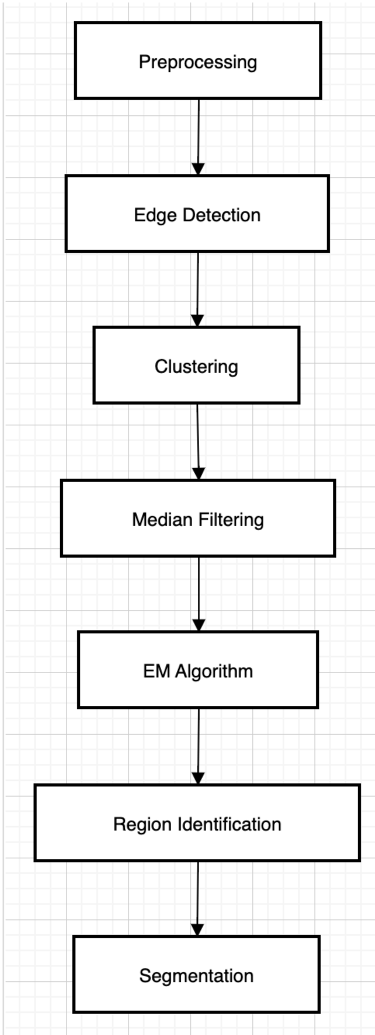
1. **Implement and Analyze**:
   - **Edge Detection**: Use traditional methods like Canny Edge Detection to detect license plates by edges.
   - **YOLO**: Apply a deep learning object detection model for real-time plate detection.
   - **Model Fusion**: Combine methods to improve accuracy and performance.
2. **Evaluate**:
   - **Accuracy**: How well each method detects plates in varying conditions.
   - **Efficiency**: Measure processing speed.
   - **Limitations**: Identify challenges, such as noise or occlusion.
3. **Comparative Analysis**: Compare all methods based on performance to identify the optimal solution for ANPR.

This project aims to provide insights into the most effective ANPR methods for practical applications.

Methodology and Proposed Diagram -

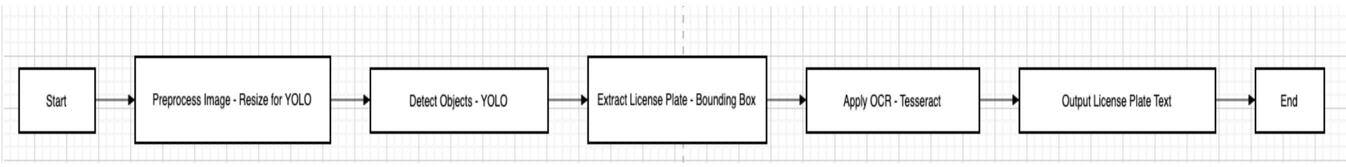
<u>Edge Detection:</u>

Preprocessing: Convert the image to grayscale to simplify analysis.
Edge Detection: Apply Canny Edge Detection to highlight the edges of the license plate.
Segmentation: Extract the region of interest (ROI) where the license plate is located using contour detection.
OCR (Tesseract): Use Tesseract OCR to recognize the text from the segmented plate.



YOLO Method:

- **Preprocessing**: Resize the image for YOLO input.
- **YOLO Detection**: Use the YOLO model to detect objects (license plates).
- **Bounding Box Extraction**: Get the bounding box coordinates of the detected plate.
- **OCR (Tesseract)**: Extract text from the detected license plate using Tesseract.



Model Fusion:

- **Preprocessing**: Convert the image to grayscale.
- **Edge Detection**: Apply Canny Edge Detection to find edges.
- **Segmentation**: Extract the region of interest where the license plate is located.
- **YOLO Detection**: Use YOLO to detect the license plate.
- **Model Fusion**: Combine edge detection and YOLO results to improve detection accuracy.
- **OCR (Tesseract)**: Apply Tesseract OCR to recognize the license plate text from the fused model outputs.

Expected Outcomes:

1. **ANPR System Development**:
   - **Edge Detection with Tesseract**: Works well in clear, simple conditions but struggles with noise and occlusion.
   - **YOLO**: Expected to perform better, especially in real-time and complex scenarios.
   - **Model Fusion**: Aims to combine both methods for improved accuracy and robustness, but may slow processing.
2. **Performance Metrics**:
   - **Accuracy**: YOLO likely to be more accurate than edge detection in complex conditions.
   - **Processing Time**: YOLO may be slower; model fusion could be even slower.
   - **Robustness & Adaptability**: YOLO should handle varied environments better than edge detection.
3. **Biases**:
   - Literature may bias towards YOLO due to its success in object detection, potentially overlooking simpler methods like edge detection.
4. **Unforeseen Results**:
   - Edge detection may outperform expectations in controlled settings.
   - Model fusion might not provide expected improvements and could introduce unnecessary complexity.

Timeline -

Phase	Duration
Research & Literature Review	Week 1-2
Edge Detection Implementation	Week 3-4
YOLO Model Implementation	Week 5-6
Model Fusion Implementation	Week 7-8
Testing & Evaluation	Week 9
Comparative Analysis & Documentation	Week 10

Conclusion:

This project will provide a comprehensive comparison of three methods for ANPR, highlighting each technique's unique benefits and limitations. Through this study, we aim to guide future implementations of ANPR systems by recommending the optimal approach for specific contexts. Edge Detection provides a simple yet effective method, while YOLO offers a robust deep-learning alternative, and Model Fusion combines the strengths of multiple models. The insights from this comparative analysis will assist in designing efficient and reliable ANPR solutions.

References:

1. "Leveraging Model Fusion for Improved License Plate Recognition" by Rayson Laroca, Luiz A. Zanlorensi, Valter Estevam, Rodrigo Minetto, and David Menotti
2. “An Overview of the Tesseract OCR Engine” by Ray Smith
3. "Contour-Based Number Plate Recognition System Using EM Segmentation Method" by V. R. Viju and Dr. R. Radha
4. "Comparison of Various Edge Detection Filters for ANPR" by Lubna, M. F. Khan, and N. Mufti
5. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks" by Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun
6. "You Only Look Once: Unified, Real-Time Object Detection" by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi