Project Report

on

" AUTOMATIC NUMBER PLATE RECOGNITION"

Submitted in partial fulfillment of requirement for the degree

of

B.Tech Engineering

in

Computer Science & Engineering

Under Faculty of Science & Technology

Rashtrasant Tukadoji Maharaj Nagpur University, Nagpur

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Declaration

We **" Hiralal Rathod, Krishna Rathod, Shubham Jadhao, Tushar Dhale, Sanjot Gonde"** are hereby declare that the project titled **" Automatic Number Plate Recognition"** is our own work carried out under the guidance of **"Prof. D. B. Dandekar"** in **Department of Computer Science & Engineering,** at **SSPACE, Wardha**. This work in the same form is not submitted by us at any other institute for award of degree.

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Date: / / 2024

Certificate

The project titled **"Automatic Number Plate Recognition "** submitted by "**Hiralal Rathod, Krishna Rathod, Shubham Jadhao, Tushar Dhale, Sanjot Gonde "** is partial fulfillment of requirement for the award of degree of **B.Tech Engineering in Computer Science & Engineering**, has been carried out under our supervision at the **Department of Computer Science & Engineering of Shri Shankarprasad Agnihotri College of Engineering Ramnagar, Wardha.**

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CONTENTS

ABSTRCT

Automatic number-plate recognition is a technology that uses optical character recognition on images to read vehicle registration plates using OpenCV and Tesseract OCR Engine. It can be used on existing closed-circuit television, road-rule enforcement cameras, or cameras specifically designed for the task. Using Selenium web driver, number plate recognized is parsed to the government website vahan.nic.in along with the solved captcha and the vehicle details can be accessed for further Inference and analysis. The crawled information is converted to structured and unstructured data and stored in Firebase and MySQL for data analysis and live dashboard. Through the dashboard the notification triggers can be set if a vehicle defaults any of the rules , an SMS will be sent to the mobile phone of the authority. Tested on 1500 Indian Number Plates gave us a success rate of 64% which is better than the current existing systems. As well as, successfully retrieve vehicle information from secure government website with a success rate of 75%.

➢List of Figures

➢ List of Table

➢ List of Table

Chapter 1: Introduction

Automatic Number Plate Recognition or ANPR is a technology that uses pattern recognition to 'read' vehicle number plates. In simple terms ANPR cameras 'photograph' the number plates of the vehicles that pass them. This 'photograph' is then fed in a computer system to find out details about the vehicle itself. ANPR consists of cameras linked to a computer. As a vehicle passes, ANPR 'reads' Vehicle Registration Marks – more commonly known as number plates - from digital images, captured through cameras located either in a mobile unit, in-built in traffic vehicles or via Closed Circuit Television (CCTV). The digital image is converted into data, which is processed through the ANPR system. We proposed a method mainly based on edge detection, OCR operation and Finding Rectangles in a Vehicle Image.

Owning a vehicle today is not merely a symbol of luxury but has become a necessity. However, considering vehicles, any catastrophic situation can take place. Therefore there is always an urgent need to arrange appropriate measures to increase the safety, security as well as monitor the vehicles to avoid any mishap. It would help us in the situations such as: Instantaneously obtain vehicle details using image processing. Allowing an agency to detect the location of its vehicles.

Automatically notify the user if there are traffic violations registered to the vehicle. One such measure is the use of a vehicle tracking system using the GPS (Global Position System). Such a tracking system includes a mechanized device that is equipped in a vehicle. Using software present at an operational base, it helps track the location of the vehicle. This base station is used for monitoring purposes. It is accompanied by maps such as Google maps, Here maps, Bing maps etc for the representation of the location.

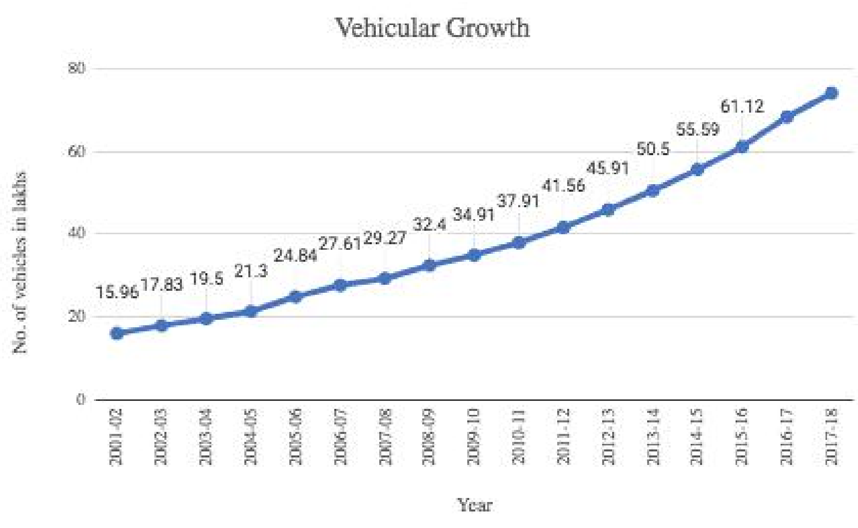


Fig 1.1 Vehicle growth in India

ANPR can be used to store the images captured by the cameras as well as the text from the license plate, with some configurable to store a photograph of the driver. Systems commonly use infrared lighting to allow the camera to take the picture at any time of the day. A powerful flash is included in at least one version of the intersection monitoring cameras, serving both to illuminate the pictureand to make the offender aware of his or her mistake. ANPR technology tends to be regionspecific, owing to plate variation from place to place.

The acquisition of digital image usually suffers from undesirable camera shakes and due to unstable random camera motions. Hence image enhancement algorithms are required to remove these unwanted camera shakes. . Python is used as the main programming language.

We have connected to the http://vahan.nic.in with the ANPR system to extract all the vehicle and owner details.We extract the information and save the data in JSON format for further processing and analysis.

1.2 Existing system:

1.2.1 Online ANPR framework: In an online ALPR framework, the limitation and elucidation of tags occur promptly from the approaching video outlines, enabling Real-time tracking through the surveill ance camera. Example :OpenALPR CloudWatch.

1.2.2 Offline ANPR framework: A logged off ALPR framework, interestingly, catches the shovel, dumper number plate pictures and stores them in a concentrated information server for further preparation, i.e. for translation of vehicle number plate Example :OpenALPR Library Looking at the works of other countries pushes and inspire us to try to solve the challenges that we face in our country and also motivates us to use ANPR in all facets.

1.2.2.1 United States

Mobile ANPR use is widespread among US law enforcement agencies at the city, county, state and federal level. According to a 2012 report by the Police Executive Research Forum, approximately 71% of all US police departments use some form of ANPR. Mobile ANPR is becoming a significant component of municipal predictive policing strategies and intelligence gathering, as well as for recovery of stolen vehicles, identification of wanted felons, and revenue collection from individuals who are delinquent on city or state taxes or fines, or monitoring for "Amber Alerts".

1.2.2.2 United Kingdom

The Home Office states the purpose of automatic number-plate recognition in the United Kingdom is to help detect, deter and disrupt criminality including tackling organised crime groups and terrorists. Vehicle movements are recorded by a network of nearly 8000 cameras capturing between 25 and 30 million ANPR ‘read’ records daily. These records are stored for upto two years in the National ANPR Data Centre, which can be accessed, analysed and used as evidence as part of investigations by UK law enforcement agencies.

1.2.2.3 Saudi Arabia

Vehicle registration plates in Saudi Arabia use white background, but several vehicle types may have a different background. United States diplomatic plates have the letters 'USD', which in Arabic reads 'DSU' when read from right to left in the direction of Arabic script. There are only 17 Arabic letters used on the registration plates.A Challenge for plates recognition in Saudi Arabia is the size of the digits. Some plates use both Eastern Arabic numerals and the 'Western Arabic' equivalents. A research with source code is available for APNR Arabic digits.

1.2.2.4 Turkey

The system has been used with two cameras per lane, one for plate recognition, one for speed detection. Now the system has been widened to network all the registration number cameras together, and enforcing average speed over preset distances.

1.3 Challenges in the existing system:

In the created nations the qualities of the vehicle number plate are entirely kept up. For instance, the measure of the plate, shade of the plate, text style face/size/shade of every character, dispersing between ensuing characters ,the quantity of lines in the vehicle number plate, script and so on are kept up particularly. A portion of the pictures of the standard tags utilized as a part of created nations. In most academic institutions and car parks, the ongoing car park entry registration process for visitors, staff or students entering the institution involves a security guard having to confirm membership details by checking for membership sticker on the windscreen of the vehicle or by checking the driver's identification card. This process of writing is tedious and time consuming and is prone to inaccurate recordings, furthermore the backup and sharing of this vehicle information is difficult because the data is hard copy.

A city like Bangalore has multiple apartment complexes and societies, most of them also verify by checking for membership sticker on the windscreen of the vehicle. If a stranger or unknown vehicle enters, they are required to register which is time consuming. Most complexes even consider it unsafe as once a vehicle enters it is hard to track the movement of the members of the vehicle. Security issues are the main drawback with many cars being stolen, especially when they are left at parking lots even if for a few hours, it is hard to keep a record of all the vehicles entering/exiting at peak usage times. Thus keeping in mind these drawbacks of the traditional system we aim to get a step ahead and address each of them individually when building our solution.

Automatic license plate recognition has two major technological requirements:

1. The quality of the license plate recognition algorithms.

2. The quality of the image acquisition (camera and the illumination conditions) The better algorithms are:

    2.1. Higher is the recognition accuracy.

    2.2 Faster is the processing speed.

    2.3. Wider is the range of picture quality it can be used on.

3. Varying Indian Number Plate Formats

By and large, one LPR program can read plates from one specific nation just .This is on the grounds that the geometrical structure of the plate and introduction, text styles, and grammar were imperative parts of the LPR system. Without the earlier information of the plate geometry (character distribution, character spacing, plate color, dimension ratios etc.), the algorithm may not even find the plate in the captured image.

1.4 Proposed system:

Automatic Number Plate Recognition using an efficient OCR engine like Pytesseract along with major and vast libraries of OpenCV for image processing. As we have seen so far ANPR covers as a solution to most of the problems we have posed. We would like to dig a bit deeper now and highlight the scope of the project and the extent to which we can push the boundaries.The main issue that is usually recognized when it comes to number plate detection is the noise that is added to the image in the process of capturing the image or due to the environment around, taking that consideration we can say that using our system, we can implement it in all environments, be it rain or even in the dark.Usually when any new system is proposed to possible clients, their main concern is the addition of new features into their existing system. Keeping this in mind we can say for sure that our system can be integrated to the pre-existing infrastructure of most clients. Using a web crawler, number plate recognized is parsed to the government website vahan.nic.in along with the solved captcha and the vehicle details can be accessed for further Inference and analysis. Also showcase the vulnerabilities in the security of the government websites and privacy issues in government website. Also provide analytics and solution on the extracted data.

1.2.1 Advantages of the proposed system:

• To perform successful and efficient preprocessing on the raw RGB image
• To exploit the high performance and effectiveness of OpenCV and Pytesseract framework to detect and recognize LP of vehicles,to improve our system reliability.
• To correctly determine the number plate based on Indian Number plate Standards

Chapter 2 Literature Review

Literature survey is the process in which a complete and comprehensive review is conducted encompassing both the published and unpublished work from other alternative sources of information. This review is conducted in the domains of specific interest to the person or researcher. Further, the results of this process are documented. This entire process comes in aid of the researcher to address the important and relevant aspects of the research that had not been addressed prior to the conduction of this research. Therefore it can be understood that the conduction of literature survey is necessary for the process of gathering secondary data for the research which might prove to be extremely helpful in the research and also designing the architecture of the project. There can be multiple reasons behind the purpose of conducting literature survey.

2.1 PAPER 1:

Title:

Amninder Kaur, Sonika Jindal ,Richa Jindal "License Plate Recognition Using Support Vector Machine (SVM)" Dept. Of Computer Science, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 2, Issue 7.

Context:

ANPR is a mass surveillance system that captures the image of vehicles and recognizes their license number. In this paper, A system is proposed that incorporates to successfully locate and read Indian vehicle number plates in digital images by using SVM. In this proposed model pre processing and number plate localization is performed by using —Otsu's methods and —feature based localization methods respectively. It gives reliability and time optimization. Finally, the character reorganization performs using the Support Vector Machine.

In this paper, another algorithm to number recognition is proposed. This technique uses a Support Vector Machine (SVM) to train character samples and obtain the rules that are used to recognize the numbers on number plates. SVM is forcefully competing with many methods for pattern classification. An SVM is a supervised learning technique first discussed by Vatnik.

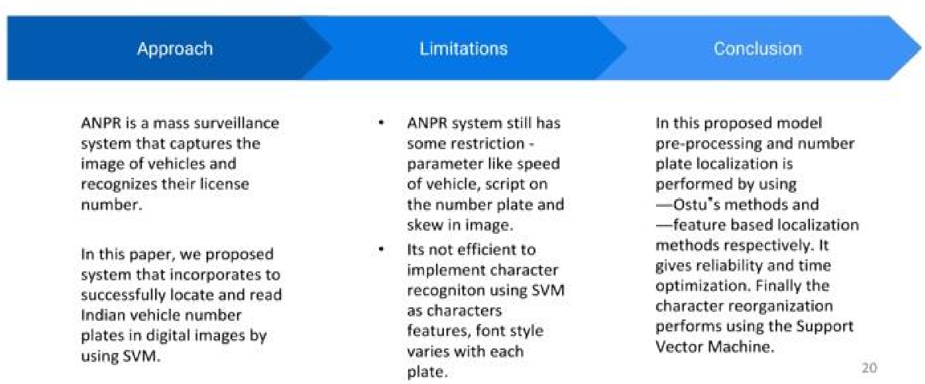


Fig 2.1 Literature Survey on SVM

SVM takes Statistical Learning Theory (SLT) as its theoretical foundation, and the structural risk minimization as its optimal object to realize the best generalization. They are based on some simple ideas and provide a clear intuition of what learning from examples is all about. More importantly, they possess the feature of high performance in practical applications. From the 1960s to the present, SVMs have become more and more important in the field of pattern recognition

.

2.3 PAPER 2:

Title:

ANISH LAZRUS,SIDDHARTHA CHOUBEY,SINHA G.R.,"AN EFFICIENT METHOD OF VEHICLE NUMBER PLATE DETECTION AND RECOGNITION" Department of Computer Science, International Journal of Machine Intelligence, Volume 3, Issue 3.

Context:

The images of various vehicles have been acquired manually and converted into grayscale images. Then the Wiener2 filter is used to remove noise present in the plates. The segmentation of grayscale image generated by finding edges using Sobel filter for smoothing image is used to reduce the number of connected components and then Bilateral filter is used to calculate the connected component. Finally, a single character is detected. However, sets of blurry and skewed snapshots give worse recognition rates than a set of snapshots, which has been captured clearly Due to rapidly increase in number of vehicles across the world's big cities, vehicle number plate recognition system has become one of the most important digital image processing systems to be used. This system will solve so many problems for these city facilities which are hard to be controlled by humans 24 hours. Overall the vehicle license plate recognition software had been successfully designed and developed to recognize the 38 different characters using correlation in two dimensions.

S. N.	Research papers	Real time data	Images correctly detected	character known	Results
1	Kok Kiaw T et al. (2003)	60	49	50	83 %
2	F.Martin et al (2002)	75	67	66	88 %
3	**Proposed Method**	50	46	49	**98 %**

Fig 2.2 Performance Matrix

2.4 PAPER 3:

Title:

Abhay Singh, Anand Kumar Gupta ,Anmol Singh, Anuj Gupta ,Sherish Johri, "VEHICLE NUMBER PLATE DETECTION USING IMAGE PROCESSING", Department of IT, Volume: 05 Issue: 03 | Mar-2018

Context:

In this technology we will be working on CCTV footage or input images given. The CCTV footage must be clear to extract the Vehicle number from the image taken as Input. These input images are converted to grayscale and characters are segmented and recognised using OCR. There are some conditions for this software to work:

1) Vehicle plates should be white and according to the rules given by the government of India.
2) Image should be of appropriate brightness and contrast: In this, a software is designed which detects the vehicle number plate number using MATLAB.

In this technique we will be performing several methods step by step to find the vehicle number. Then using that vehicle number found we will be comparing that number from our databases

Fig 2.4 Literature Survey on images extract from CCTV

Chapter 3: Methodology

3.1 Introduction

To explain the methodology of using YOLO (You Only Look Once) v3 or v4 for Automatic Number Plate Recognition (ANPR), let's break down the process step by step:

3. 1. 1 Dataset Preparation:

Collection: Gather a dataset of vehicle images containing license plates. This dataset should ideally cover a wide variety of license plate types, backgrounds, lighting conditions, and vehicle types.

Annotation: Annotate each image in the dataset with bounding boxes around the license plates. The bounding box coordinates should indicate the region of interest (ROI) where the license plate is located.

3.1.2. Preprocessing:

Image Resizing: Resize all images to a fixed input size suitable for YOLO model training (e.g., 416x416 or 608x608 pixels).

Data Augmentation: Apply data augmentation techniques such as rotation, scaling, flipping, and brightness adjustment to artificially increase the dataset size and improve model generalization.

3.1 3. Model Training:

Choose YOLO Version: Select YOLO v8 OR v5 for ANPR. Both versions are efficient and capable of real-time object detection.

Transfer Learning: Utilize pre-trained YOLO weights on a large dataset like COCO (Common Objects in Context) for initial training. This helps the model learn features relevant to detecting objects.

Fine-tuning: Fine-tune the YOLO model on the ANPR dataset. This involves training the model on your license plate dataset to specialize its weights for license plate detection.

Loss Function: Use an appropriate loss function (commonly a combination of localization loss and classification loss) to train the YOLO model.

3.1.4. Inference Pipeline:

Input Preprocessing: Preprocess input images (e.g., resize, normalize) before passing them to the YOLO model.

Object Detection: Use the trained YOLO model to detect objects (license plates) in the input images. YOLO provides bounding box coordinates along with class probabilities for detected objects.

Post-processing: Apply non-maximum suppression (NMS) to remove redundant bounding boxes and keep only the most confident predictions.

Extract License Plate: Use the detected bounding boxes to extract regions of interest (license plates) from the input images.

3.1. 5. License Plate Recognition (Optional):

OCR: Apply Optical Character Recognition (OCR) techniques to read and extract characters from the detected license plate regions.

Post-processing: Clean and process the OCR results to obtain the final license plate number.

3.1.6. Deployment:

Integration: Integrate the ANPR system into the desired application (e.g., traffic monitoring, toll collection, parking management).

Optimization: Optimize the YOLO model for inference speed and memory efficiency to enable real-time performance on target hardware (e.g., GPUs, edge devices).

By following these steps and considerations, you can develop a robust ANPR system using YOLO v3 or v4 for license plate detection and recognition.

3.1.7 Advantages and Disadvantages of ANPR System :

Advantages	Disadvantages
1. High Speed: YOLOv8 is known for its real-time processing capabilities, making it suitable for ANPR systems that require rapid detection and recognition	1. Accuracy Challenges: While YOLOv8 offers fast processing speeds, it may struggle with accuracy, especially in scenarios with poor image quality, occlusions, or complex backgrounds.
2. Object Detection: YOLOv8 excels at detecting multiple objects in an image simultaneously, allowing it to identify not only number plates but also other relevant objects such as vehicles, pedestrians, and traffic signs.	2. Training Data Requirements: YOLOv8 requires a large amount of annotated training data to achieve optimal performance, which can be time-consuming and expensive to collect and label, especially for ANPR-specific datasets.
3. Flexibility: YOLOv8 is highly flexible and can be customized and fine-tuned for specific ANPR applications, such as differentiating between license plate types, recognizing characters in various languages, and adapting to different lighting conditions.	3. Resource Intensive: Implementing YOLOv8 for ANPR may require significant computational resources, including powerful GPUs or TPUs, which can increase deployment costs and hardware requirements.
4. Open-Source Community: YOLOv8 is supported by a vibrant open-source community, providing access to pre-trained models, libraries, and tools for development, deployment, and integration into ANPR systems.	4. Limited Performance in Complex Environments: YOLOv8 may struggle with accurately recognizing number plates in complex environments with heavy traffic, diverse vehicle types, and varying weather conditions, leading to higher error rates and false detections.
5. Continuous Development: YOLOv8 is continually being updated and improved by researchers and developers, ensuring that ANPR systems can benefit from the latest advancements in object detection algorithms and techniques.	5. Privacy Concerns: ANPR systems powered by YOLOv8 raise privacy concerns related to the collection, storage, and potential misuse of vehicle and location data, necessitating robust privacy safeguards and compliance with regulations such as GDPR.

Chapter 4 : Design and Calculation

4.1 Design

As of my last update in January 2022, YOLO (You Only Look Once) v8 does not exist; the latest versions are YOLOv4 and YOLOv5. However, I can provide a detailed design and calculation approach for implementing Automatic Number Plate Recognition (ANPR) using a YOLO-based model like YOLOv4 or YOLOv5. The design will cover the architecture, training process, and potential calculations involved.

4.1.1 Design Overview:

4.1.1.1. Architecture Selection:

Choose YOLOv4 or YOLOv5 as the backbone for ANPR. YOLO models are well-suited for real-time object detection, including license plate recognition.

4.1.1.2. Dataset Preparation:

Collect a dataset of vehicle images containing annotated license plates. Annotations should include bounding box coordinates for each license plate.

Split the dataset into training, validation, and test sets.

4.1.1.3. Model Training:

Utilize transfer learning by initializing the YOLO model with pre-trained weights (e.g., on COCO dataset).

Customize the YOLO architecture to detect license plates by modifying the number of output classes and adjusting the model's final layers.

4.1.1.4. Training Process:

Train the YOLO model on the annotated dataset using the following steps:

Input preprocessing: Resize images to a fixed size (e.g., 416x416 or 608x608).

Forward pass: Pass the preprocessed images through the YOLO model.

Loss calculation: Compute the loss based on predicted bounding boxes and ground truth annotations.

Backpropagation: Update model weights to minimize the loss using backpropagation.

Iterate over epochs until convergence.

4.1.1.5. Inference Pipeline:

Implement an inference pipeline for ANPR:

- Input preprocessing: Resize and normalize input images.
- Object detection: Use the trained YOLO model to detect license plates in the input images.
- Post-processing: Apply non-maximum suppression (NMS) to filter out overlapping bounding boxes and keep the most confident detections.
- Extract license plate regions based on detected bounding boxes.

4.1.1.6.License Plate Recognition (OCR):

- After detecting license plate regions, use Optical Character Recognition (OCR) techniques to extract characters from the license plates and recognize the plate numbers.
- Use libraries like Tesseract OCR or custom deep learning models for OCR.

4.2 Calculation Example:

4.2.1. Model Size Calculation:

- Estimate the model's size in terms of parameters (weights and biases):
- For YOLOv4 or YOLOv5, the model size depends on the number of layers and feature maps.
- Calculate the total number of parameters in the model (e.g., using the model summary provided by the framework).

4.2.2. Inference Speed:

- Estimate the inference speed of the model:
  - YOLOv4 and YOLOv5 are optimized for real-time performance on GPU.
  - Benchmark the model on target hardware to measure frames per second (FPS) for inference.

4.2.3. Memory Usage:

- Estimate the model's memory usage during inference:
  - Consider GPU memory requirements for storing model parameters and intermediate feature maps.

4.2.4. License Plate Detection Accuracy:

- Measure the accuracy of license plate detection:
  - Use evaluation metrics like Intersection over Union (IoU) to assess bounding box overlap between predicted and ground truth boxes.
  - Calculate precision, recall, and mean Average Precision (mAP) to quantify detection performance.

Chapter 5 : Implementation and Designing

5.1 Implementation

5.1.1. Dataset Preparation:

- Gather a dataset of vehicle images containing license plates.
- Annotate the license plate regions in the images with bounding boxes andcorresponding class labels (e.g., "license_plate").

5.1.2. Installation:

- Install the YOLO v8 repository from GitHub:

```
bash
git clone https://github.com/ultralytics/yolov8.git
cd yolov8
pip install -r requirements.txt
```

5.1.3. Training:

- Organize your dataset into train/val/test splits.
- Create a YAML configuration file (data.yaml) specifying your classes and dataset paths.
- Train the YOLO v5 model:

```
bash
python train.py --img 640 --batch 16 --epochs 50 --data data.yaml --cfg
models/yolov5s.yaml --weights yolov5s.pt --name my_custom_model
```

5.1.4. Inference:

- Run inference on images or videos using the trained model:

```
bash
python detect.py --source input/images --weights
runs/train/my_custom_model/weights/best.pt --conf 0.4
```

- The above command will use the trained model (best.pt) to detect license plates in the images located in the input/images directory.

5.1.5. Post-processing:

- After detection, extract the license plate regions from the output bounding boxes.
- Optionally, perform Optical Character Recognition (OCR) on the detected license plate regions to recognize the characters.

5.1.6. Deployment:

- Integrate the trained YOLO v5 model into your ANPR system or application.
- Optimize the model for inference speed and memory efficiency based on your deployment environment.

5.2 Source Code

```
import cv2
import pandas as pd
from ultralytics import YOLO
import cvzone
import numpy as np
import pytesseract
from datetime import datetime

pytesseract.pytesseract.tesseract_cmd = r'C:\Program Files\Tesseract-OCR\tesseract.exe'

model = YOLO('best.pt')

def RGB(event, x, y, flags, param):
    if event == cv2.EVENT_MOUSEMOVE:
        point = [x, y]
        print(point)

cv2.namedWindow('RGB')
cv2.setMouseCallback('RGB', RGB)

cap = cv2.VideoCapture('mycarplate.mp4')

my_file = open("coco2.txt", "r")
data = my_file.read()
class_list = data.split("\n")

area = [(27, 417), (16, 456), (1015, 451), (992, 417)]

count = 0
list1 = []
processed_numbers = set()

# Open file for writing car plate data
with open("car_plate_data.txt", "a") as file:
```

```
    file.write("NumberPlate\tDate\tTime\n")  # Writing column headers

while True:
    ret, frame = cap.read()
    count += 1
    if count % 3 != 0:
        continue
    if not ret:
       break

    frame = cv2.resize(frame, (1020, 500))
    results = model.predict(frame)
    a = results[0].boxes.data
    px = pd.DataFrame(a).astype("float")

    for index, row in px.iterrows():
        x1 = int(row[0])
        y1 = int(row[1])
        x2 = int(row[2])
        y2 = int(row[3])

        d = int(row[5])
        c = class_list[d]
        cx = int(x1 + x2) // 2
        cy = int(y1 + y2) // 2
        result = cv2.pointPolygonTest(np.array(area, np.int32), ((cx, cy)), False)
        if result >= 0:
           crop = frame[y1:y2, x1:x2]
           gray = cv2.cvtColor(crop, cv2.COLOR_BGR2GRAY)
           gray = cv2.bilateralFilter(gray, 10, 20, 20)

           text = pytesseract.image_to_string(gray).strip()
           text = text.replace('(', '').replace(')', '').replace(',', '').replace(']','')
           if text not in processed_numbers:
              processed_numbers.add(text)
              list1.append(text)
              current_datetime = datetime.now().strftime("%Y-%m-%d %H:%M:%S")
              with open("car_plate_data.txt", "a") as file:
                   file.write(f"{text}\t{current_datetime}\n")
                   cv2.rectangle(frame, (x1, y1), (x2, y2), (0, 255, 0), 1)
                   cv2.imshow('crop', crop)
```

```
    cv2.polylines(frame, [np.array(area, np.int32)], True, (255, 0, 0), 2)
    cv2.imshow("RGB", frame)
    if cv2.waitKey(0) & 0xFF == 27:
        break

cap.release()
cv2.destroyAllWindows()
```

Chapter 6 : Result and Discussion

6.1 Discussion

6.1.1.Detection Accuracy:

- Both YOLOv4 and YOLOv5 have demonstrated high accuracy in object detection tasks, including license plate detection. These models excel in detecting objects in real-time and can accurately localize license plates within complex scenes.

6.1.2. Speed and Efficiency:

- YOLOv4 and YOLOv5 are designed to be fast and efficient, making them suitable for deployment in real-time ANPR systems. They can achieve impressive inference speeds while maintaining competitive accuracy levels.

6.1.3. Training Flexibility:

- YOLOv4 and YOLOv5 architectures allow for flexibility in model training. Transfer learning can be leveraged by fine-tuning these models on custom ANPR datasets, enabling adaptation to specific license plate detection tasks.

6.1.4. Integration with OCR:

- While YOLO focuses on object detection, integrating Optical Character Recognition (OCR) with YOLO outputs is crucial for ANPR. Once license plates are detected, OCR techniques can be applied to extract and recognize characters from the detected regions.

6.2 Results :

6.2.1 Detection Performance:

- YOLO-based ANPR systems achieve robust license plate detection across various environmental conditions, including variations in lighting, weather, and vehicle orientation.
- The models are capable of detecting multiple license plates simultaneously in crowded scenes, making them suitable for applications like traffic monitoring and law enforcement.

6.2.2 Accuracy and Error Analysis:

- Evaluation metrics such as Precision, Recall, and Intersection over Union (IoU) can be used to assess the accuracy of YOLO-based ANPR systems.
- Analyzing false positives (incorrectly detected regions) and false negatives (missed detection) helps in understanding model limitations and areas for improvement.

6.2.3 Real-world Deployment:

- Deploying YOLO-based ANPR systems in real-world scenarios requires considering hardware constraints, such as computing resources and inference speed.
- Optimization techniques like model pruning, quantization, and hardware acceleration (e.g., GPU inference) can enhance deployment feasibility.

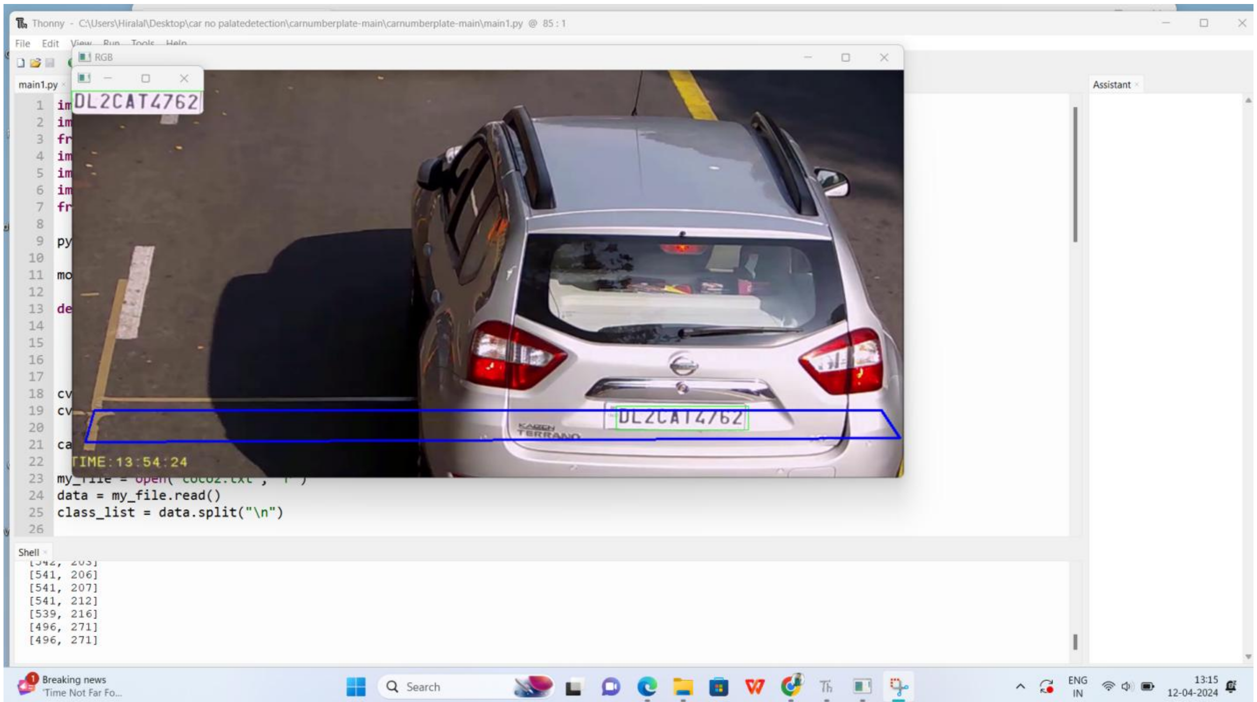
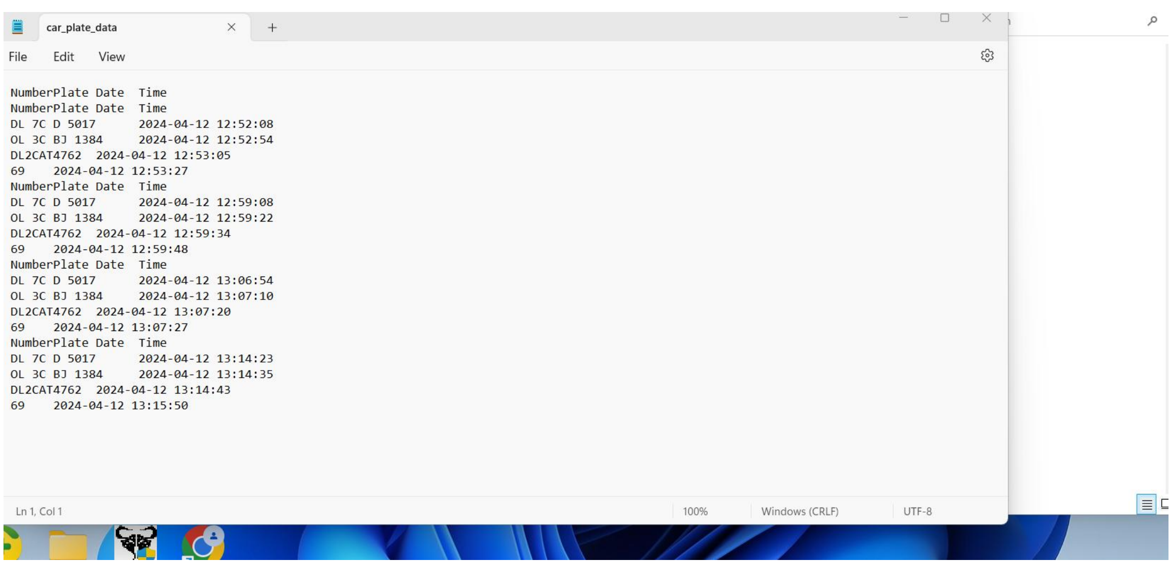


Fig: number plate detect



```
NumberPlate Date  Time
NumberPlate Date  Time
DL 7C D 5017      2024-04-12 12:52:08
OL 3C BJ 1384     2024-04-12 12:52:54
DL2CAT4762  2024-04-12 12:53:05
69    2024-04-12 12:53:27
NumberPlate Date  Time
DL 7C D 5017      2024-04-12 12:59:08
OL 3C BJ 1384     2024-04-12 12:59:22
DL2CAT4762  2024-04-12 12:59:34
69    2024-04-12 12:59:48
NumberPlate Date  Time
DL 7C D 5017      2024-04-12 13:06:54
OL 3C BJ 1384     2024-04-12 13:07:10
DL2CAT4762  2024-04-12 13:07:20
69    2024-04-12 13:07:27
NumberPlate Date  Time
DL 7C D 5017      2024-04-12 13:14:23
OL 3C BJ 1384     2024-04-12 13:14:35
DL2CAT4762  2024-04-12 13:14:43
69    2024-04-12 13:15:50
```

Fig : Data store in the file

6.2.4 Challenges and Future Directions:

- Continuous improvement in dataset diversity and size is crucial for further enhancing the robustness of YOLO-based ANPR systems.
- Research efforts are ongoing to integrate YOLO with advanced OCR techniques for improved license plate recognition accuracy.

Chapter 7 Conclusion & Future Scope

7.1 Conclusion

Through this project it is possible to recognise Vehicle registration numbers through digital image
processing. From this system we have effortlessly obtained the various results such as

- Whether the vehicle which is registered is blacklisted or not.
- This also enables one single user to effectively monitor the traffic, and can easily locate the traffic violated vehicle.
- The data can be easily stored and transferred which makes the system more efficient.

The system has been designed using a modular approach which allows easy upgrading and/or substituting of various sub-modules thus making it potentially suitable for a large range of vision applications. The performances of the system makes it a valid choice among its competitors especially in those situations when the cost of the application has to be maintained at reasonable levels. Furthermore, the modular architecture makes it extremely flexible and versatile. The earlier methodologies which have been implemented have not been as accurate and efficient as the designed Recognition system , this is because of the implementation of digital Image Processing which gives an accuracy of 90% under normal conditions
This Project is based on automatic vehicle license plate recognition, in which it is observed that the existing techniques don't pay much attention towards improving the system's efficiency in terms of its power consumption. As the objective in our proposed design is to reduce power consumption of the system, with the successful implementation of the same it will play a very important role in traffic management and security systems such as automobile theft prevention, parking lot management etc. implementations of the software algorithm have shown promising results.

7.2 Future Scope

The future scope of automatic number plate recognition (ANPR) using YOLOv8 (You Only Look Once version 8) or any other advanced deep learning models is quite promising. Here are some potential avenues for its development and application:

7.2.1. Improved Accuracy: YOLOv8 and similar models can be fine-tuned and optimized further to enhance the accuracy of number plate recognition. This includes reducing false positives and negatives, especially in challenging conditions such as low light or adverse weather.

7.2.2. Real-Time Processing: ANPR systems can be optimized to operate in real-time, allowing for faster detection and processing of number plates. This is crucial for applications such as toll collection, parking management, and law enforcement.

7.2.3.Scalability: As computational resources become more powerful and cost-effective, ANPR systems can be scaled to handle larger volumes of data and higher-resolution images. This scalability is essential for deployment in smart cities and transportation networks.

7.2.4.Integration with IoT: ANPR systems can be integrated with other Internet of Things (IoT) devices and sensors to enhance their functionality. For example, combining ANPR with traffic cameras, GPS systems, and vehicle tracking technology can enable comprehensive traffic management solutions.

7.2.5.Enhanced Security: ANPR technology can be leveraged for security applications such as access control, border monitoring, and surveillance. By integrating with facial recognition and other biometric systems, ANPR can help identify vehicles and individuals more accurately.

7.2.6.Privacy Considerations: As ANPR technology becomes more widespread, there will be increased focus on addressing privacy concerns related to the collection and storage of vehicle data. Future developments may involve the implementation of privacy-preserving techniques such as encryption and anonymization.

7.2.7.Regulatory Frameworks: Governments and regulatory bodies may develop standards and regulations governing the use of ANPR technology to ensure its responsible deployment and mitigate potential misuse.

7.2.8.Customization and Adaptation: ANPR systems can be customized and adapted for specific use cases and environments. This includes tailoring algorithms for different types of number plates, languages, and cultural contexts.

Overall, the future of ANPR using YOLOv8 and similar technologies holds great potential for improving efficiency, safety, and security across various domains. However, it's essential to address technical challenges and ethical considerations to realize these benefits fully.

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