A

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Automatic Licence Plate Detection

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May, 2023

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that Project Report entitled "Automatic Licence Plate Detection" which is submitted by Khushi Gupta and Sarah Handu in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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ABSTRACT

Automatic License Plate Recognition (ALPR), is a comput- erized system that uses optical character recognition (OCR) to auto- matically read license plate information. ANPR systems can be used in a variety of applications such as traffic management, toll collection, and law enforcement.

This report explores the advancements in Automatic License Plate Recognition (ALPR) systems, which utilize optical character recog- nition (OCR) technology to automatically extract license plate informa- tion. ALPR finds applications in various domains including traffic man- agement, toll collection, and law enforcement.

The paper highlights the primary advantage of ALPR systems, emphasizing their exceptional speed and accuracy. Notably, the proposed method demonstrates an increase in accuracy from 82.73 percent (in the YOLO system) to 86.53 percent, showcasing the continual improvement in ALPR technology. ALPR systems excel in efficiently reading license plates at high speeds, enabling the processing of large vehicle volumes. The enhanced accuracy greatly reduces errors, which commonly occur with manual systems or under unfavorable weather conditions.

We have outlined a comprehensive five-step procedure for ALPR: vehicle image capture, preprocessing, number plate extraction, character segmentation, and character recognition. To accomplish this, we have introduced the utilization of advanced techniques such as Gen- erative Adversarial Networks (GANs), OpenCV, and Optical Character Recognition. The inspection camera placement in strategic locations on the vehicle enables efficient identification of the number plate.

Moreover, the study highlights the potential for integrating ANPR systems with complementary technologies like cameras, sensors, and databases. This integration enhances the tracking and identification of vehicles, further expanding the capabilities of ANPR systems.

In conclusion, we have underscored the significant advantages of ANPR technology, including its remarkable speed, accuracy, and seam- less integration with other technologies. The findings presented contribute to the ongoing development of ALPR systems, fostering their broader adoption in various domains where rapid and reliable license plate recognition is crucial.

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LIST OF ABBREVIATIONS

ANPR – Automatic Number Plate Recognition System

OCR – Optical Character Recognition

GAN – Generative Adversarial Networks

CHAPTER 1

INTRODUCTION

Automatic Number Plate Recognition, sometimes known as ANPR, is a technology that "reads" vehicle number plates using pattern recognition. In plain English, ANPR cameras 'photograph' the licence plates of the cars that pass them. In order to learn more about the car itself, this "photograph" is subsequently transmitted into a computer system. Cameras connected to a computer make up ANPR. As a vehicle passes, ANPR uses digital images acquired by cameras mounted on mobile units, built-in to traffic vehicles, or via closed-circuit television (CCTV) to "read" the vehicle registration marks, or number plates as they are more generally known. A digital image is transformed into data and then processed by the ANPR system. We presented a technique that is mostly focused on edge detection, OCR, and finding rectangles. Therefore, it is always vital to put in place the necessary arrangements to boost safety and security as well as to monitor the vehicles to prevent any accidents. We could use it in the following circumstances: Get car information right away using picture processing. enabling a company to find where its vehicles are. Any traffic infractions associated with the car should be automatically reported to the user. Utilising a GPS (Global Positioning System)-based vehicle tracking system is one such measure. A vehicle-mounted mechanical gadget is a part of this tracking system. It assists in tracking the location of the vehicle using software found at an operational base. This base station is employed for surveillance. For the purpose of illustrating the location, it is supplemented by maps such as Google maps, Here maps, Bing maps, etc. Some ANPR systems can be configured to keep a picture of the driver in addition to the text from the licence plate and the photos taken by the cameras. Infrared lighting is frequently used in systems to enable the camera to snap the photo at any time of day. At least one variant of the junction monitoring cameras has a strong flash that both illuminates the scene and alerts the violator to their error. Because licence plate variations exist from location to location, ANPR technology is typically region-specific.

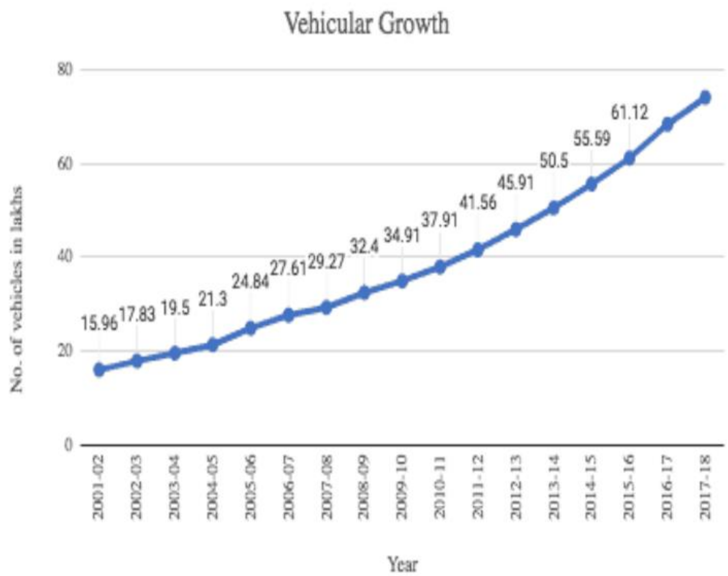

Fig 1.1 Vehicle Growth in India [Source: http://203.201.63.46:8080/jspui/bitstream]

Digital picture acquisition frequently experiences unfavourable camera shaking and unpredictable, erratic camera motions. For this reason, picture improvement algorithms are needed to eliminate these undesirable camera tremors. The primary programming language is Python.

1.1 Existing system:

1.1.1 Online ANPR framework:

A real-time tracking system using the security camera is made possible by the prompt limiting and clarification of tags in an online ALPR framework.

For instance, OpenALPR CloudWatch

1.1.2 Offline ANPR framework:

Interestingly, a logged-off ALPR framework captures the shovel and dumper number plate images and stores them in a concentrated information server for later processing, i.e. for vehicle number plate translation.

Consider the OpenALPR Library.

Our efforts to deploy ANPR in all areas are pushed and inspired by the works of other nations, as well as by the issues that we confront in our own nation.

United States

US law enforcement agencies at the city, county, state, and federal levels frequently deploy mobile ANPR. 71% of US police agencies employ ANPR in some capacity, according to a 2012 research by the Police Executive Research Forum. The recovery of stolen vehicles, the identification of wanted felons, the revenue collection from people who are behind on city or state taxes or fines, or the monitoring for "Amber Alerts" are all uses for mobile ANPR that are increasingly important in municipal predictive policing strategies and intelligence gathering.

United Kingdom

According to the Home Office, the goal of automatic number-plate recognition in the United Kingdom is to help identify, discourage, and disrupt illegal activity, particularly taking on terrorists and organised crime organisations. A network of about 8000 cameras records vehicle movements, capturing between 25 and 30 million ANPR'read' records daily. These records can be accessed, studied, and used as evidence in investigations by UK law enforcement agencies because they are held for up to two years in the National ANPR Data Centre.

Saudi Arabia

While many different vehicle types may have a varied backdrop, Saudi Arabian automobile registration plates generally have a white background. The letters 'USD' on diplomatic plates from the United States spell out 'DSU' when read from right to left in the Arabic alphabet. The registration plates only employ 17 Arabic characters.The size of the digits presents a problem for Saudi Arabian licence plate recognition. Some plates combine the 'Western Arabic' equivalents with the Eastern Arabic numerals. For APNR Arabic digits, a research with source code is available.

Turkey

Two cameras have been utilised in the system, one for speed detection and the other for licence plate identification. The system has now been expanded to connect every registration number camera and enforce average speed across certain distances. Some arteries have speed limits of 70 km/h (43 mph), while others are 50 km/h (31 mph). If a speeding infraction is discovered, photo evidence with date-and-time details is posted to the registration address. The penalty for violating the speed limit by more than 30% as of 2012 is roughly $175.

Canada

The police service in Ontario uses automatic licence-plate recognition software to nab drivers behind the wheels of vehicles with Ontario number plates.

1.1.3 Challenges in the existing system:

The characteristics of the car licence plate are fully maintained in the developed countries. Examples include the size of the plate, colour of the plate, text style face/size/shade of each character, spacing between subsequent characters, number of lines on the vehicle number plate, script, and so forth. a selection of the images from the common tags used in developed countries. In the majority of academic buildings and parking lots, a security guard must verify membership information by looking for a membership sticker on the windscreen of the vehicle or by looking at the driver's identification card as part of the ongoing car park entry registration process for visitors, staff, or students entering the building. In addition to being arduous, time-consuming, and prone to faulty recording, this writing technique makes it challenging to backup and share this car information because it is hard copy.

In a city like Bangalore, there are many different apartment buildings and societies, and the majority of them also conduct membership checks by looking for stickers on the vehicle's windscreen. It takes time for strangers or unknown vehicles to register when they arrive. The majority of complexes even deem it dangerous because it is difficult to follow the movement of the car's occupants once it has entered. Security concerns are the biggest disadvantage because many automobiles are stolen, especially when they are left in parking lots even for a short while, making it difficult to maintain track of every vehicle entering and leaving during peak usage periods.

Therefore, when developing our solution, we attempt to advance and overcome each of these shortcomings of the existing system individually.

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

Generally speaking, one LPR programme can only read licence plates from one particular country.This is due to the fact that the plate's geometrical layout, the introduction's textual style, and grammar were all essential components of the LPR system. The algorithm might not even recognise the plate in the taken image without the preceding knowledge of the plate geometry (character distribution, character spacing, plate colour, dimension ratios, etc.).

1.2 Project Description

A system known as automated number plate recognition (ANPR) permits the automatic recognition and reading of vehicle number plates. The usage of ANPR technology is widespread in a number of industries, including toll collecting, parking management, and law enforcement. OCR (optical character recognition) algorithms are used in the technology to extract and recognise the characters from photos of licence plates taken by cameras. The device then converts the characters into text, enabling precise vehicle identification and tracking. The system's capacity to identify licence plates in a variety of environmental settings is one of the main issues with ANPR technology. ANPR systems must be capable of recognising licence plates in a variety of lighting, weather, and time-of-day situations. For instance, in poor light or at night, it may be difficult to see licence plates.

The desire for intelligent transport systems and smart city solutions has increased usage of ANPR technology in recent years. Automating vehicle monitoring and identification with ANPR technology has the potential to dramatically improve traffic management, increase public safety, and make it easier to implement sustainable transportation policy. The image capture system, image processing system, OCR algorithm, and database management system are the four primary parts of an ANPR systemThe image acquisition system uses cameras to take pictures of licence plates. The collected photographs are processed by the image processing system, which also gets rid of noise and other blemishes. The database administration system stores and manages the extracted data once the OCR algorithm extracts the characters from the image of the licence plate.

The OCR algorithm is a crucial part of ANPR technology, and its precision is necessary to prevent incorrectly detecting licence plates and guarantee the proper identification of vehicles. The quality of the image that is collected, the lighting, the camera angle, and the typeface used on the licence plate are some of the variables that can determine how accurate OCR algorithms are. To obtain the best level of accuracy, these elements must be taken into account when designing the OCR algorithm. From 82.73 percent accuracy performance across various data sets for YOLO and 84.83 percent accuracy performance for Faster R-CNN algorithms, to 86.53 percent accuracy performance for our model's Generative Adversarial Network.

The development of automatic ANPR systems, which greatly increased the accuracy and effectiveness of licence plate recognition, was sparked by the arrival of OCR technology in the 1990s. OCR algorithms enabled automatic licence plate character recognition, doing away with the requirement for manual character recognition. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in particular, have made significant advancements in deep learning techniques, which have had a significant impact on the development of automatic number plate recognition (ANPR) technology. The current advancements in ANPR technology have been greatly influenced by these cutting-edge approaches. Because they make it possible for reliable feature extraction and efficient sequence modelling, respectively, CNNs and RNNs have proved crucial in improving the accuracy and effectiveness of ANPR systems. Utilising these deep learning approaches has revolutionised the ANPR industry and opened the door for licence plate recognition technology that is more precise and dependable [4]. These methods have demonstrated promising improvements in ANPR system accuracy and a decrease in errors brought on by various environmental factors. Parking management and toll collection are two areas where ANPR technology is used in real-world situations. For instance, ANPR systems can be used to automate the issuing and payment of parking tickets, doing away with the need for paper tickets and lightening the strain on parking attendants. The adoption of ANPR technology to automate toll collection systems has increased the use of ANPR technology in toll collecting as well.

We were inspired to produce this article because, despite being a widely utilised technology in a variety of contexts, it has privacy and technical issues. In addition to resolving privacy concerns and advancing practical applications like tracking down stolen automobiles, research in this field can assist to increase the accuracy, speed, and reliability of ANPR systems and enforcing traffic laws.

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

• To Successfully extract the information from Government vehicle information database

• To Show the security vulnerabilities

1.3 Market Value of the ANPR System:

Automatic number plate recognition (ANPR) system market was valued at USD 1.78 billion in 2016 and is anticipated to reach USD 3.57 billion by 2023, according to the new market research report, "Automatic Number Plate Recognition (ANPR) System Market by Type (Fixed, Mobile, Portable), Component (ANPR Cameras, Software, Frame Grabbers, Triggers), Application (Traffic Management, Law Enforcement, Electronic Toll Collection, Parking Management), and Geography - Global Forecast to 2023".

Infrastructure development in developing nations, increased governmental funding for intelligent transportation systems (ITS), the use of camera technologies for security and surveillance, traffic enforcement, and growing video analytics adoption are some of the factors driving this market for intelligent monitoring of vehicles.

The biggest market for ANPR systems in 2016 was Europe. Due to the widespread use of intelligent transportation systems for traffic control, toll management, law/police enforcement, and other applications, this region has a sizable market. Germany, the UK, France, and the rest of Europe make up the segments of the European market. ARH Inc. (Hungary), Digital Recognition Systems Ltd. (UK), NDI Recognition Systems Ltd. (UK), and Q-Free ASA (Norway) are some significant businesses that provide ANPR systems in Europe [2].

The key players in the market include Kapsch TrafficCom AG (Austria), Conduent, Inc. (US), QFree ASA (Norway), Siemens AG (Germany), Genetec Inc. (Canada) Neology, Inc. (US), Bosch Security Systems GmbH (Germany), Tattile srl (Italy), TagMaster North America, Inc. (US), NDI Recognition Systems Ltd. (UK), Euro Car Parks Limited (UK), Quercus Technologies, S.L. (Spain) Vigilant Solutions, Inc. (US), Elsag North America, LLC (US), ARH Inc. (Hungary), Digital Recognition System Ltd. (UK), Beltech BV (Netherlands), ANPR International Ltd. (UK), HTS (New York), FF Group (Cyprus), and so on.

This report categorizes the global ANPR system market on the basis of type, component, application, and geography. The report describes the drivers, restraints, opportunities, and challenges for the growth of this market.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction:

OCR (Optical Character Recognition) technology has been widely used to rec- ognize text and numbers from scanned documents, images, and videos. In license plate recognition, OCR technology plays a crucial role in extracting vehicle reg- istration numbers. The significance of OCR-based number recognition in various applications such as traffic control, security, and surveillance has led to substan- tial research efforts in recent years [14]. In this literature survey, we provide a review of some noteworthy research papers in this domain, highlighting their contributions and approaches.

One significant study titled ”Automatic License Plate Recognition using Deep Convolutional Neural Networks” by R. Tawari, P. Krishna, and S. Chan- dra (2016) focuses on employing deep learning techniques to tackle license plate recognition challenges. The authors propose a deep learning approach utilizing Convolutional Neural Networks (CNNs) for accurate and efficient license plate recognition. They introduce a CNN architecture that can be trained on large datasets of license plate images, demonstrating promising results [14].

Another notable contribution is the research paper by Kakani et al. (year). They present an innovative methodology to enhance OCR-based license plate recognition, particularly in challenging scenarios where the license plate may be partially obstructed or the image is captured at an angle. The authors propose novel techniques to address these difficulties and achieve more accurate and reliable license plate recognition results. Their work offers valuable insights into improving the performance of OCR-based license plate recognition systems in real-world scenarios [5].

Additionally, a study by Gondhalekar et al. provides a comprehensive com- parison of several state-of-the-art license plate recognition algorithms, including traditional OCR-based methods and deep learning-based methods. The authors evaluate the performance of these algorithms on benchmark datasets and discuss the advantages and disadvantages of each approach. This comparative analysis aids in understanding the strengths and limitations of various techniques in li- cense plate recognition [7].

Another research paper by H. Jain, A. Singh, and P. Jain (2020) titled ”Li- cense Plate Recognition using Deep Learning and Image Processing Techniques” presents a license plate recognition system that combines deep learning and im- age processing techniques. The authors propose a pipeline consisting of image segmentation, character segmentation, and character recognition modules. They evaluate the performance of their system on real datasets, providing insights into the effectiveness of their approach [10].

The literature review demonstrates the sustained interest in developing OCR- based license plate recognition systems with a specific focus on enhancing ac- curacy and reliability in real-world scenarios. These research contributions con- tribute valuable insights, proposing innovative techniques, and comparing dif- ferent approaches. Future work in this field can build upon these studies to further advance the capabilities of OCR-based license plate recognition systems, enabling their wide application in diverse domains.

CHAPTER 3

PROPOSED METHODOLOGY

To ensure effective and precise performance, the suggested solution presents a well-structured architecture made up of multiple different components. These modules contain Character Segmentation and Character Recognition, Number Plate Extraction, Image Capture, and Preprocessing. The first stage is the Image Capture module, which is in charge of taking pictures to be processed later. The duty of preparing the collected images by adding the appropriate filters and enhancements to improve their quality and lower noise is subsequently handled by the preprocessing module. Next, the Number Plate Extraction module uses cutting-edge methods and algorithms to precisely extract the number plate regions from the preprocessed images. Last but not least, the Character Segmentation and Character Recognition module is essential for accurately segmenting and interpreting the retrieved number plate's individual characters using strong recognition algorithms. The strategy tries to streamline licence plate identification and produce better results by segmenting the suggested architecture into three parts. Below, a quick analysis of each of these is presented.

3.1 Image Capture:

The primary step in ANPR is the image capturing of the license plate. Images that are ideal for ANPR use should be able to be captured by the camera. This is essential to the system's overall effectiveness. It might be challenging to get a clear picture of a license plate because of poor lighting, a lot of other plates, and the area that the plate takes up in the picture. The type of integrated camera has an impact on how well the ANPR system performs while controlling hundreds of parking spaces, reducing traffic jams, or quickly recognizing traffic infractions. Due to the need to account for ambient light, choosing the appropriate camera for this application requires careful consideration of crucial elements including shutter artifacts, exposure periods, and dynamic range [5]. Mostly HDR camera is recommended. The difference between a normal camera and an HDR camera can be seen in figure 1 and figure 2. Next, the discussion shifts towards the place- ment of the gadgets. In comparison to software triggers that can be configured remotely from a control center, adjusting traffic cameras to capture vehicles ac- curately requires physical intervention at the location. This involves tilting the cameras on-site to ensure optimal positioning. Apart from the ball joint situated on the camera console, the ANPR imaging process necessitates securely bolt-ing the camera console base onto the gantry. These physical adjustments are crucial for achieving precise and reliable Automatic Number Plate Recognition (ANPR) results [17]. This ensures that the gadget will remain in place even in difficult circumstances. When fixing the equipment to its permanent places, in- stallation workers must additionally tilt the camera at the ideal 20° to 30° angle.

Fig 1. Image captured by normal camera

Fig 2. Image captured by HDR camera

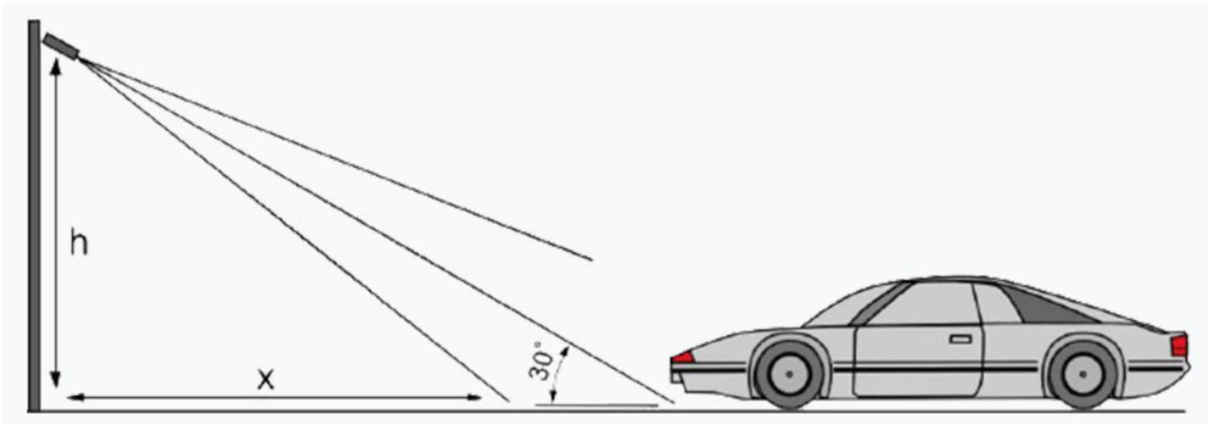

Fig 3. Calculated angle for accurate Image Capture

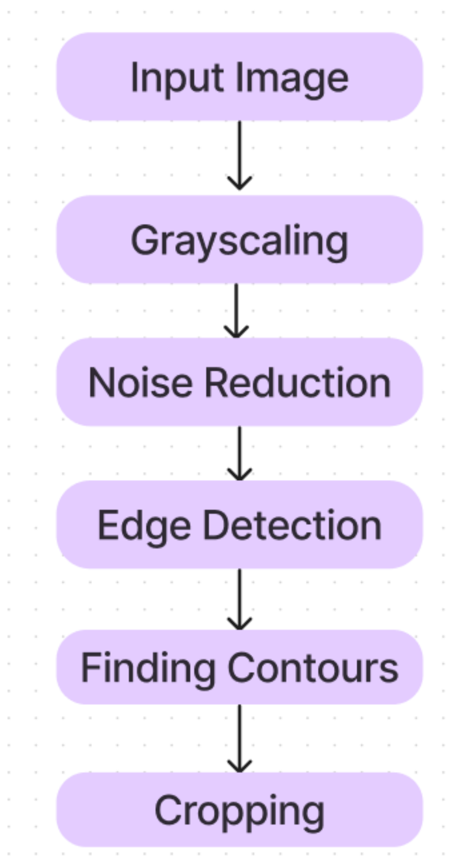

Fig 4. Flow Chart for preprocessing of image

3.1.1 Digital Image Processing

Analysing and processing analogue and digital signals, as well as storing, filtering, and other operations on signals, are the focus of the mathematical and electrical engineering field of signal processing. These signals range from transmission signals to speech, sound, and image signals, among others. Out of all these signals, image processing is the field that works with the kind of signals where the input is an image and the output is also an image. It deals with the processing of photographs, as its name would imply.The development of a digital system that manipulates a digital image is the focus of digital image processing.

Considering that taking a photo with a camera is a physical process. A source of energy is utilised, the sun. For the purpose of picture acquisition, a sensor array is utilised. As a result, when sunlight strikes an object, the sensors detect the quantity of light that object reflects, and the amount of detected data is used to generate a continuous voltage signal. We must convert this data into a digital form in order to build a digital image. As a result, a digital image—actually a two-dimensional array or matrix of numbers—is produced.

• Image Preprocessing:

Prior to processing, remote sensing data must typically be preprocessed since faults in the picture data captured by the sensors reduce the image's quality and make it appear noisy, blurry, and distorted. Errors start to appear during the data collecting procedure. Geometric and radiometric mistakes are the two most typical types of errors. During preprocessing, all of these flaws are rectified using the appropriate mathematical models.

• Image Enhancement:

To make particular visual aspects more visible and aid in human interpretation and analysis, image enhancement is practised. Remember that image enhancement is distinct from the image preparation phase. The image enhancement stage draws attention to image characteristics for the interpretation, whereas the image preparation step creates a comparably better image from an initially subpar or degraded image.

• Image Transformations:

Operations for transforming images are conceptually analogous to those for enhancing images. However, picture transformations typically entail algebraic operations on multiple-layer images, unlike image enhancement operations, which are typically done to a single channel of data at a time. With the use of algebraic operations like subtraction, addition, multiplication, division, alogarithms, exponentials, and trigonometric functions, the original images are changed into new ones that either display certain elements of the original images more clearly or emphasise other features. In the following block, Block 4 of MGY-002, we will go over all four stages of digital image processing. 71 Ground Truth Data Collection.

• Thematic Information :

Extraction It contains every technique used to get thematic information from photographs. One such method is image classification, which uses spectral signatures to group pixels in an image into thematic classifications like land cover classes. Depending on the degree of human involvement in the classification process, image classification techniques are further divided into supervised, unsupervised, and hybrid categories.

3.1.2 Advantages of Digital Image Processing:

1. Digital images can be processed by digital computers.

2. Important features such as edges can be extracted from images which can be used in industry.

3. Images can be given more sharpness and better visual appearance.

4. Minor errors can be rectified.

5. Image sizes can be increased or decreased.

6. Images can be compressed and decompressed for faster image transfer over the network.

7. Images can be automatically sorted depending on the contents they have.

8. unrecognizable features can be made prominent.

9. Images can be smoothened.

10. It allows robots to have vision.

11. It allows industries to remove defective products from the production line.

12. It allows weather forecasting.

13. It is used to analyse cells and their composition.

14. It is used to analyse medical images.

3.1.3 Problems associated with Digital Image Processing:

1. It is very costly depending on the system used, the number of detectors purchased.

2. Time consuming

3. Lack of qualified professional

3.2 Preprocessing:

After the successful capturing of the image, the next step is of pre-processing the image. The main aim of preprocessing is to enhance the processing speed of the algorithm. It is helpful in improving the contrast of the captured im- age and reducing noise. For preprocessing, the algorithm used is the OpenCV library. OpenCV is an extensive open-source library that encompasses a wide range of functionalities related to computer vision, machine learning, and image processing. With its vast collection of tools and algorithms, OpenCV has be- come a pivotal component in various applications requiring real-time operation, which holds paramount significance in today's systems. Its ability to handle tasks efficiently in real-time, such as object detection, facial recognition, and video processing, has made it indispensable in numerous fields like surveillance, robotics, augmented reality, and autonomous vehicles. By providing an accessible and comprehensive set of tools, OpenCV empowers developers and researchers to implement advanced computer vision techniques and build robust and high- performance systems that cater to the demands of modern technology. It provides all the facilities from reading an image to contouring. The original image cap- tured is in RGB format. The first step is to convert it to Greyscale. Greyscaling is done to detect edges easily and reduce model complexity.Many algorithms are customized to work only on grayscale images [16]. OpenCV provides various methods for greyscaling. Here the method used is cv2.COLOR BGR2GRAY. After the greyscaling is done, noise removal needs to be performed. Denoising an image refers to the process of reconstruction of a signal from noisy images. Denoising is done to remove unwanted noise from the image to analyze it in a better form. It refers to one of the major pre-processing steps. In our algorithm noise detection can be performed using a bilateral filter. Then in the next step detection of edges on the smoothed image is performed using a canny edge detec- tion algorithm which uses Gaussian smoothing to remove edges. The next step is to find contours from the processed image in the previous step. Contours are defined as the line joining all the points along the boundary of an image that are having the same intensity. We have used findContour() function that helps in extracting the contours from the image. Now comes the process of sorting the identified contours which are done using the sorted function in OpenCV.

Fig 5. Grayed Image

Fig 6. Smoothed Image

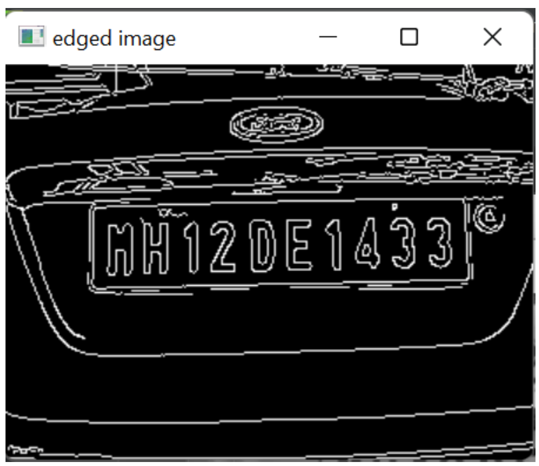

Fig 7. Edged Image

Fig 8. Image after finding contours

3.2.1 OpenCV

A computer vision and machine learning software library called OpenCV is available for free use. A standard infrastructure for computer vision applications was created with OpenCV in order to speed up the incorporation of artificial intelligence into products. OpenCV makes it simple for businesses to utilise and alter the code because it is a BSD-licensed product.

More than 2500 optimised algorithms are available in the collection, including a wide range of both traditional and cutting-edge computer vision and machine learning techniques. These algorithms can be used to find similar images from an image database, remove red eyes from flash-taken photos, follow eye movements, recognise scenery, and establish markers to overlay. They can also be used to detect and recognise faces, identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects, produce 3D point clouds from stereo cameras, stitch images together to produce high-resolution images of entire scenes, extract 3D models of objects from stereo cameras, and extract 3D models of objects More than 47 thousand people use OpenCV, and it has been downloaded more than 18 million times, according to estimates. The library is heavily utilised by businesses, research teams, and governmental organisations.

Along with well-known firms like Google, Yahoo, Microsoft, Intel, IBM, Sony, Honda, and Toyota that use the library, several startups also heavily rely on OpenCV, including Applied Minds, VideoSurf, and Zeitera. OpenCV has been used for a variety of purposes, including stitching together streetview images, detecting intrusions in surveillance video in Israel, monitoring mine equipment in China, assisting robots in navigating and picking up objects at Willow Garage, detecting swimming pool drowning accidents in Europe, operating interactive art in Spain and New York, checking runways for debris in Turkey, inspecting product labels in factories all over the world, and performing rapid face detection in Japan.

It supports Windows, Linux, Android, and Mac OS and offers C++, Python, Java, and MATLAB interfaces. When available, OpenCV makes use of MMX and SSE instructions and leans heavily towards real-time vision applications. A fully functional

CUDA and OpenCL interface is currently being developed. Over 500 algorithms exist, and roughly ten times as many functions make up or support each algorithm. The templated interface of OpenCV, which is designed exclusively in C++, integrates perfectly with STL containers.

3.2.2 Advantages of OpenCV:

1. OpenCV is a Python library that allows you to perform image processing and computer vision tasks.

2. It provides a wide range of features, including object detection, face recognition, and tracking.

3.2.3 Problems associated with OpenCV:

The movement of head or different camera positions can cause changes of facial texture and it will generate the wrong result.

3.3 Number Plate Extraction:

In this section, we propose in our novel generative framework the use of Genera- tive Adversarial Networks (GANs) to generate features that provide robustness for license plate detection on preprocessed images. [1] GANs are unsupervised deep learning techniques. Usually, it is implemented using two neural networks: Generator and Discriminator [3]. The main goal of the generator is to maximize the loss of the discriminator. Figure 13

The Discriminator loss is

$$L_D = -E_{xr} [\log (D (x_r, x_f))] - E_{xf} [\log (1 - D (x_f , x_r))] \quad (1)$$

The Adversarial loss for the generator is as follows

$$L_G = -E_{xr} [\log (1 - D (x_r, x_f))] - E_{xf} [\log (D (x_f , x_r))] \quad (2)$$

x_r and x_f denotes real image and fake image, respectively, while E_{xr} and E_{xf} represent the operation of taking an average of all real and fake images, respectively.

Fig 9. Top 30 contours

Fig 10. Image with detected licence plate

Summing up, we have

$$min_G max_D V(D, G) = E_{x\ p} data(x)\ [\log (D(x))] + E_{z\ px} z\ (z)\ [\log (1 - D(G(z)))]$$

The LR image undergoes a series of convolutional and ReLU layers. It is then passed through the RRDB block to incorporate residual learning for training our adversarial loss function. The discriminator function contributes to generating authentic textures. In the process of the RRDB model, we start with the Low- Resolution image (x) as input. The feature extraction takes place through the convolutional layer, and the resulting features are utilized as input for the RRDB mode.

$$F_0 = K_{CNN}(x) \tag{3}$$

F_0 Let's consider the process involving feature extraction and residual dense blocks in relation to the LR image (x). The feature extracted by the convolutional layer, denoted as F and obtained using the kernel Kcnn, serves as an input. When utilizing n residual dense blocks, the output of the nth RRDB model can be represented as follows.

$$F\mathrm{N} = K\mathrm{RRDB}n\,(F\mathrm{rrdb}-1) \qquad (4)$$

In our model, we incorporated 26 RRDB blocks, each representing the nth RRDB operation, which encompasses the operations of both Convolutional Neu- ral Networks (CNN) and Rectified Linear Units (ReLU) layers. Furthermore, we

Fig 11. Cropped Image

employed ReLU as the activation function throughout the model. The dense function of the CNN and RRDB blocks is precisely formulated to ensure opti- mal performance and effective feature extraction.

$$F_{\mathrm{n,c}} = \sigma\,(W_{\mathrm{n,c}}\,[F - n - 1, F_{\mathrm{n-2}}, \ldots.., F_{\mathrm{n,c-1}}]) \qquad (5)$$

where σ denotes the activation function. The Global Residual Learning is

$$F_{\mathrm{GRL}} = 6F_{\mathrm{n,c}} \qquad (6)$$

In this context, the output of the first convolutional layer plays a crucial role in capturing essential features and patterns from the input data. By incorporating the global residual learning approach, the network can effectively learn and refine these features throughout the subsequent layers, ultimately leading to improved performance and better representation of the data.

$$F\mathrm{total} = F\mathrm{GRL} + F0 \qquad (7)$$

3.3.1 Generative Adversarial Network(GAN)

In a generative adversarial network (GAN), two neural networks fight with one another by employing deep learning techniques to improve the accuracy of their predictions. GANs often operate unsupervised and learn through cooperative zero-sum games where one person's gain is the same as another's loss.

The generator and the discriminator are the two neural networks that make up a GAN. A deconvolutional neural network serves as the discriminator, and a convolutional neural network serves as the generator. The generator's objective is to provide outputs that could be mistaken for actual data by users. The discriminator's objective is to determine whether of the outputs it receives were produced intentionally.

Generative models essentially generate their own training data. The discriminator network is taught to discriminate between the generator's created data and real examples while the generator is educated to produce fake data. The generator incurs a penalty if the discriminator quickly detects the phoney data it produces, such as an image that isn't a real face. The discriminator will get better at identifying data that has been intentionally manufactured as the feedback loop between the adversarial networks continues, and the generator will start to provide output that is higher-quality and more credible. For example, a generative adversarial network can be trained to produce human faces that look realistic but don't actually belong to any real people.

3.4 Character Segmentation and Character Recognition:

Characters are further recognized after the identification of license plates. Segmentation that is based on recognition is often referred to as implicit segmentation. Segmentation and character recognition are accomplished simultaneously in this process. The system breaks down the image into its component parts. Words that should be characters are divided into segments by the implicit segmentation program, which then sends each segment to a classifier. When segmentation is called again with the feedback that the previous sequence was rejected, the clas- sification results should be appropriate. The system can detect and transform the image into text by using character recognition. Here for character segmentation and Recognition, we use Optical

Character Recognition(OCR). Once, the license plate is detected and pre-processed for segmentation and then passed forward through the Character Recognition process to detect alphanumeric characters.

Optical character recognition (OCR) refers to the process of converting text from various sources, including handwritten, printed, or typed text, into machine- readable format. This conversion takes place by analyzing images captured from different mediums, such as photographs of documents, scanned documents, or even scene photos. OCR technology plays a crucial role in automating data entry tasks, digitizing physical documents, and enabling text searchability. By leverag- ing sophisticated algorithms and image processing techniques, OCR systems can accurately extract textual information from images, enabling efficient text analysis and manipulation in various applications. OCR is mainly used in Artificial Intelligence, computer vision, and most important pattern recognition.

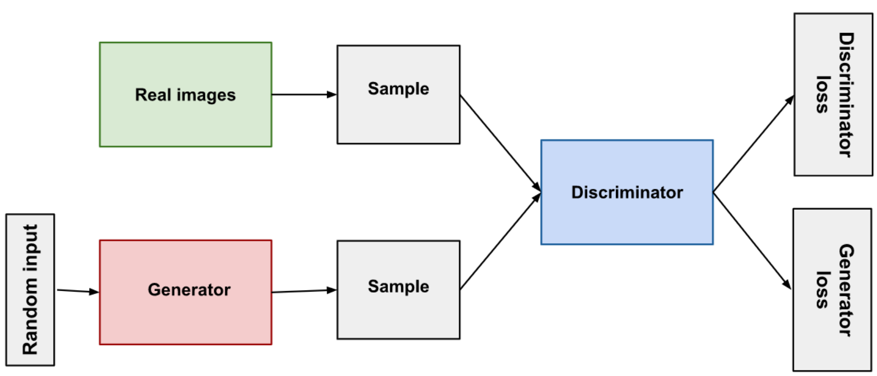

Fig 13. Image Detection through OCR

3.4.1 Optical Character Recognition

The electronic or mechanical process of turning images of typed, handwritten, or printed text into machine-encoded text, whether from a scanned document, a photo of a document, or a scene-photo (for instance, the text on signs and billboards in a landscape photo), is known as optical character recognition, also known as optical character reader (OCR).

It is a common practise to digitise printed texts so they can be electronically edited, searched, stored more compactly, displayed online, and used in machine processes like cognitive computing, machine translation, (extracted) text-to-speech. This method of digitising printed texts is used to enter data from printed paper data records such as passports, invoices, bank statements, computerised receipts, business cards, mail, printouts of static-data, or any suitable documentation. OCR is a field of research in pattern recognition, artificial intelligence and computer vision.

Early iterations worked on one font at a time and required training with photos of each character. Today, sophisticated systems with support for a range of digital image file formats inputs and a high degree of recognition accuracy for the majority of fonts are the norm. Some systems have the ability to reproduce structured output including elements like columns, graphics, and other non-textual content that closely resembles the original page.

3.4.2 Techniques of OCR

• **Pre-processing**

OCR software frequently "pre-processes" images in order to increase the likelihood of accurate recognition. techniques consist of:

• De-skew - If the document's alignment was off while scanning, it might be necessary to tilt it a few degrees in either direction to make text lines completely horizontal or vertical.

• Despeckle - eliminate positive and negative blemishes, rounded edges • Cleans up non-glyph boxes and lines using line removal

• "Zoning" or layout analysis identifies columns, paragraphs, captions, etc. as separate blocks. Particularly crucial in tables and multi-column layouts.

• Text Recognition

Matrix matching, also known as "pattern matching," "pattern recognition," or "image correlation," involves comparing an image to a recorded graphic pixel-by-pixel. This depends on the stored glyph having the same scale and font as the input glyph, as well as being correctly separated from the rest of the image. This method does not perform well when using unfamiliar fonts and is most effective when used with typewritten material. The early physical photocell-based OCR employed this method rather directly.

• **Post-processing**

If the output is limited by a lexicon—a list of words that are allowed to appear in a document—OCR accuracy can be improved. [15] For instance, this may be the entire English language or a more technical vocabulary for a particular industry. If the text uses proper nouns or other words that are not part of the vocabulary, using this strategy can be challenging. Tesseract influences the character segmentation process using its vocabulary to increase accuracy. Although increasingly advanced OCR systems can preserve the original page layout and produce products like annotated PDFs that have both the original image of the page and a searchable textual representation, the output stream may still be a plain text stream or file of characters.

3.4.3 Uses of OCR

• Data entry for business documents, e.g. check, passport, invoice, bank statement and receipt

• Automatic number plate recognition

• In airports, for passport recognition and information extraction

• Automatic insurance documents key information extraction

• Traffic sign recognition

• Extracting business card information into a contact list

• More quickly make textual versions of printed documents, e.g. book scanning for Project Gutenberg

• Make electronic images of printed documents searchable, e.g. Google Books

• Converting handwriting in real time to control a computer (pen computing)

• Defeating CAPTCHA anti-bot systems, though these are specifically designed to prevent OCR. The purpose can also be to test the robustness of CAPTCHA anti-bot systems.

• Assistive technology for blind and visually impaired users

• Writing the instructions for vehicles by identifying CAD images in a database that are appropriate to the vehicle design as it changes in real time.

• Making scanned documents searchable by converting them to searchable PDFs.

3.4.4 Database:

A database is a collection of data that has been set up to be readily managed, updated, and accessed. Aggregations of data records or files from sales transactions or interactions with certain clients are frequently seen in computer databases.

Digital data on a particular client is arranged in a relational database into rows, columns, and tables that are then indexed to make it simpler to retrieve relevant data using SQL or NoSQL queries. A graph database, in contrast, uses nodes and edges to specify the connections between data items, and queries call for a unique semantic search syntax. As of this writing, the World Wide Web Consortium (W3C) has only approved SPARQL as a semantic query language.

Users often have control over read/write access, specify report generation, and analyse usage through the database manager. To ensure that data is consistent and transactions are completed, some databases offer ACID (atomicity, consistency, isolation, and durability) compliance.

Relational database

A relational database is a tabular database that E.F. Codd created at IBM in 1970. Data is defined in a relational database so that it can be reorganised and retrieved in a variety of ways.A series of tables with data that falls into a specific category make up relational databases. Each row in a table contains a specific data instance for each of the categories that are defined in the columns, and each table includes at least one data category per column.The default user and application programme interface for a relational database is the Structured Query Language (SQL). Relational databases are simple to expand, and after the initial database development, a new data category can be introduced without necessitating the modification of all the current applications.

MySQL database

Programmers use the domain-specific language SQL to manage data stored in relational databases or for stream processing in relational data stream management systems. A database can be communicated with using SQL.

It is the accepted language for relational database management systems, claims ANSI (American National Standards Institute). To change data on a database or to obtain data from a database, SQL statements are employed.

CHAPTER 4

SYSTEM DESIGN

The architecture of an information extractor and a number plate recognition system is thoroughly described in this section. The suggested approach recognises the vehicle's licence plate and extracts it in characters. The input image is preprocessed and the characters in the image are segmented in this module of vehicle number plate recognition. The segmented characters are recognised and trimmed. The string of recognised characters is then given back.

The following module uses a web crawler to gather the vehicle's data. The information is fetched, translated to JSON format, and then stored in a database or shown on a dashboard to be processed further.

4.1 Use Case Diagram

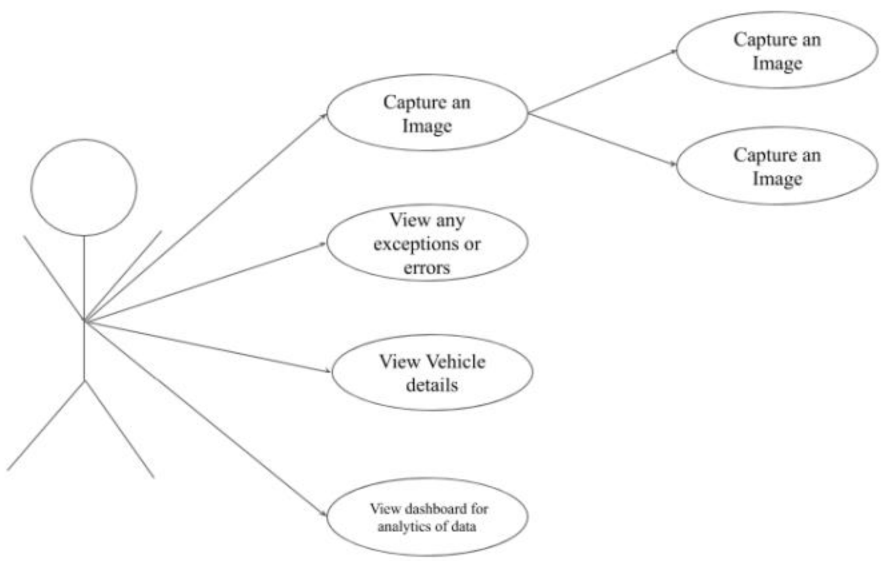

Fig 14. Use Case Diagram

CHAPTER 5

IMPLEMENTATION

This section contains the algorithms that are used by the system. The system makes use of these algorithms in order to satisfy the various functional and non functional requirements of the proposed scheme.

5.1 ALGORTIHMS:

5.1.1 Algorithm to Recognize the Number Plates

The sequence of processes associated with Number plate recognition is given below. The file upload process is initiated by the data owner entity.

Input: Uploading the image file from camera

Output: Vehicle number plate in characters

1) Read the original image or Capture the image

2) Resize the image

3) Convert it to grayscale.

4) Apply Bilateral Filter.

What is a bilateral filter ? A bilateral filter is a non-linear, edge preserving, and noise-reducing smoothing filter for images. It replaces the intensity of each pixel with a weighted average of intensity values from nearby pixels.

5) Identify and store the Canny edges.

What are Canny edges ? The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images.

6) Find the contours in from the edges detected and sort the top 30 contours.

7) Get the perimeter of each contour and select those with 4 corners.

8) Mask all other parts of the image and show the final image.

9) Read the text using Tesseract OCR

10) Standardize the text to Indian vehicle number plate format

11). Stop On upload of the image file to the system, the number plate recognition system performs its functions to provide the output.

5.2 CODE:

5.2.1 Code to capture the image of the vehicle number plate

```
#importing the libraries we need

def read():

    #Specifying the path to which tesseract is installed

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

    #Taking in our image input and resizing its width to 300 pixels

    image = cv2.imread("test.jpg")

    image = imutils.resize(image, width=300 )

    cv2.imshow("original image", image)

    cv2.waitKey(0)


    #Converting the input image to greyscale

    gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

    cv2.imshow("greyed image", gray_image)

    cv2.waitKey(0)

    #Reducing the noise in the greyscale image
```

```
gray_image = cv2.bilateralFilter(gray_image, 11, 17, 17)

cv2.imshow("smoothened image", gray_image)

cv2.waitKey(0)

#Detecting the edges of the smoothened image

edged = cv2.Canny(gray_image, 30, 200)

cv2.imshow("edged image", edged)

cv2.waitKey(0)

#Finding the contours from the edged image

cnts,new = cv2.findContours(edged.copy(), cv2.RETR_LIST, cv2.CHAIN_APPROX_SIMPLE)

image1=image.copy()

cv2.drawContours(image1,cnts,-1,(0,255,0),3)

cv2.imshow("contours",image1)

cv2.waitKey(0)

#Sorting the identified contours

cnts = sorted(cnts, key = cv2.contourArea, reverse = True) [:30]

screenCnt = None

image2 = image.copy()

cv2.drawContours(image2,cnts,-1,(0,255,0),3)

cv2.imshow("Top 30 contours",image2)

cv2.waitKey(0)

#Finding the contour with four sides
```

```
i=7
for c in cnts:
    perimeter = cv2.arcLength(c, True)
    approx = cv2.approxPolyDP(c, 0.018 * perimeter, True)
    if len(approx) == 4:
        screenCnt = approx
        #Cropping the rectangular part identified as license plate
        x,y,w,h = cv2.boundingRect(c)
        new_img=image[y:y+h,x:x+w]
        cv2.imwrite('./'+str(i)+'.png',new_img)
        i+=1
        break
    #Drawing the selected contour on the original image
cv2.drawContours(image, [screenCnt], -1, (0, 255, 0), 3)
cv2.imshow("image with detected license plate", image)
cv2.waitKey(0)
#Extracting text from the image of the cropped license plate
Cropped_loc = './7.png'
cv2.imshow("cropped", cv2.imread(Cropped_loc))
plate = pytesseract.image_to_string(Cropped_loc, lang='eng')
print("Number plate is:", plate)
```

```
    cv2.waitKey(0)

    cv2.destroyAllWindows()

# Press the green button in the gutter to run the script.

if __name__ == '__main__':

    read()
```

CHAPTER 6

RESULT AND DISCUSSION

ANPR by OCR is a technology that uses optical character recognition (OCR) to automatically identify and read license plates on vehicles. The process involves capturing an image of the license plate with a camera, processing the image to extract the characters on the plate, and then using OCR algorithms to recognize and translate the characters into the text. The technology has many applications, including law enforcement, parking management, and toll collection.

Research in ANPR by OCR typically focuses on improving the accuracy and efficiency of the technology. Common results and discussion topics in this field include:

Accuracy: Researchers often evaluate the accuracy of ANPR systems by comparing the recognized license plate numbers to ground truth data. This can involve analyzing the frequency and types of errors made by the OCR algo- rithms, such as misread characters or incorrect formatting. Researchers may also compare the accuracy of different OCR algorithms or processing techniques to determine which methods are most effective [11].

1. Speed: Another important factor in ANPR research is the speed of the technology. Researchers may evaluate the processing time required to recognize license plate numbers, as well as the speed at which the system can capture and process images of moving vehicles. This can help determine whether the technology is suitable for real-time applications such as toll collection or parking management.

2. Robustness: ANPR systems must be able to accurately recognize license plates in a variety of conditions, including different lighting, weather, and camera angles. Researchers may evaluate the robustness of the technology by testing it under different environmental conditions and analyzing the frequency and types of errors made [12].

3. Dataset creation and augmentation: Researchers also work on creating datasets for the training and evaluation of ANPR systems. This includes cap- turing images of license plates under different conditions and annotating them with ground truth data. In addition, researchers may work on techniques for data augmentation, such as generating synthetic images with different backgrounds or distortions, to improve the robustness of the OCR algorithms [13].

4. Deep learning methods: Recently, deep learning techniques have shown promise in improving the accuracy of ANPR systems. Researchers may investi- gate the the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) or other deep learning architectures to ANPR. This may in- clude exploring transfer learning approaches that leverage pre-trained models on large datasets such as ImageNet, or developing novel models that can handle the specific challenges of ANPR [14].

Overall, research in ANPR by OCR is a dynamic and active field that involves a range of technical and practical challenges. By improving the accuracy, speed, and robustness of ANPR systems, researchers can help enable a wide range of applications that depend on automatic license plate recognition.

Accuracy performance around different datasets			
Method	Faster R-CNN	YOLO	GAN(Ours)
Small	73.94%	80.88%	79.10%
Small + Inclined	68.64%	78.50%	72.67%
Medium	96.94%	97.62%	97.64%
Medium + Inclined	90.19%	90.89%	91.18%
Large	99.50%	99.30%	99.50%
Total	84.83%	82.73%	86.53%

Table 1. Comparitive Results of Algorithms

Above table shows the mathematical representation of the improved accuracy using Generative Adversarial Network compared with some other algorithms used in previous researchs like Faster R-CNN and YOLO.

CHAPTER 7

CONCLUSION AND FUTURE WORK

In conclusion, the research presented in this paper underscores the significant advancements in Optical Character Recognition (OCR) technology for number plate recognition. The successful implementation of OCR in license plate recog- nition systems has demonstrated its efficacy in various applications. However, there remains ample scope for future work in this field, as OCR technology continues to evolve and improve.

One area of future exploration lies in the improved handling of variations in number plate formats. Different countries and regions have diverse formats for their license plates, posing a challenge for OCR systems. Future research should focus on developing robust algorithms capable of handling these variations with greater ease and accuracy. This could involve the integration of machine learning techniques and sophisticated pattern recognition algorithms to adapt to different plate formats [18].

Integration with other technologies presents another avenue for future work in OCR-based number plate recognition. By combining OCR technology with license plate databases or Vehicle Information Management Systems, additional functionalities can be achieved. This integration would enable real-time retrieval of vehicle-related information, facilitating enhanced law enforcement, traffic man- agement, and security applications.

Furthermore, the rise of special number plates, such as temporary or special- purpose plates, poses new challenges for OCR technology. Future research should focus on adapting OCR algorithms to effectively recognize these unique plate formats. This may involve collecting specialized datasets, refining existing al- gorithms, and exploring novel techniques such as deep learning architectures specifically tailored for handling such challenges.

In summary, the field of OCR number plate recognition offers substantial opportunities for future advancements. Researchers and developers can continue to refine and enhance OCR technology to meet the changing needs of society. By addressing issues such as plate format variations, integration with other tech- nologies, and adaptation to new challenges, OCR-based number plate recogni- tion systems can further solidify their position as a critical component of modern transportation, surveillance, and security systems. [19].

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Appendix

RESEARCH PAPER

A Comprehensive System for Automatic License Plate Detection and Recognition

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Abstract. Automatic License Plate Recognition (ALPR), is a computerized system that uses optical character recognition (OCR) to automatically read license plate information. ANPR systems can be used in a variety of applications such as traffic management, toll collection, and law enforcement.

This research paper explores the advancements in Automatic License Plate Recognition (ALPR) systems, which utilize optical character recognition (OCR) technology to automatically extract license plate information. ALPR finds applications in various domains including traffic management, toll collection, and law enforcement.

The paper highlights the primary advantage of ALPR systems, emphasizing their exceptional speed and accuracy. Notably, the proposed method demonstrates an increase in accuracy from 82.73 percent (in the YOLO system) to 86.53 percent, showcasing the continual improvement in ALPR technology. ALPR systems excel in efficiently reading license plates at high speeds, enabling the processing of large vehicle volumes. The enhanced accuracy greatly reduces errors, which commonly occur with manual systems or under unfavorable weather conditions.

The research paper outlines a comprehensive five-step procedure for ALPR: vehicle image capture, preprocessing, number plate extraction, character segmentation, and character recognition. To accomplish this, the paper introduces the utilization of advanced techniques such as Generative Adversarial Networks (GANs), OpenCV, and Optical Character Recognition. The inspection camera placement in strategic locations on the vehicle enables efficient identification of the number plate.

Moreover, the study highlights the potential for integrating ANPR systems with complementary technologies like cameras, sensors, and databases. This integration enhances the tracking and identification of vehicles, further expanding the capabilities of ANPR systems.

In conclusion, this research underscores the significant advantages of ANPR technology, including its remarkable speed, accuracy, and seamless integration with other technologies. The findings presented in this paper contribute to the ongoing development of ALPR systems, fostering their broader adoption in various domains where rapid and reliable license plate recognition is crucial.

Keywords: License plate, Preprocessing, Generative Adversarial Network, Optical Character Recognition

1 Introduction

Automatic number plate recognition (ANPR) is a technology that enables the automatic identification and reading of vehicle license plates. ANPR technology is widely used in various fields such as law enforcement, parking management, and toll collection. The technology uses cameras to capture images of license plates, and OCR (optical character recognition) algorithms to extract and recognize the characters on the plate. The system then translates the characters into text, making it possible to identify and track vehicles accurately. One of the primary challenges in ANPR technology is the ability of the system to recognize license plates under different environmental conditions. ANPR systems must be robust enough to recognize license plates under different lighting and weather conditions and at different times of the day. For example, it can be challenging to recognize license plates at night or in low-light conditions [2].

The use of ANPR technology has been on the rise in recent years, driven by the growing demand for intelligent transportation systems and smart city solutions. ANPR technology has the ability to automate vehicle tracking and identification, which can significantly improve traffic management, enhance public safety, and facilitate the implementation of sustainable transportation policies. ANPR systems consist of four main components: the image acquisition system, the image processing system, the OCR algorithm, and the database management system. The image acquisition system captures images of license plates using cameras. The image processing system processes the captured images and removes noise and other artifacts. The OCR algorithm then extracts the characters from the license plate image, and the database management system stores and manages the extracted data [1].

The OCR algorithm is a critical component of ANPR technology, and its accuracy is essential to avoid misidentifying license plates and ensure the correct identification of vehicles. Several factors can affect the accuracy of OCR algorithms, including the quality of the image captured, the lighting conditions, the angle of the camera, and the font used on the license plate. Therefore, the design of the OCR algorithm must consider these factors to ensure the highest possible accuracy. Accuracy performance across different data sets has increased from 82.73 percent in YOLO and 84.83 in Faster R-CNN algorithms to becoming 86.53 percent in Generative Adversarial Network used in our model [6].

The introduction of OCR technology in the 1990s led to the developmentof automated ANPR systems, which significantly improved the accuracy and efficiency of license plate recognition. The use of OCR algorithms enabled automated recognition of license plates, eliminating the need for manual character recognition [2]. The advancement of Automatic Number Plate Recognition (ANPR) technology has been greatly influenced by the progress made in deep learning techniques, specifically convolutional neural networks (CNNs) and re current neural networks (RNNs). These cutting-edge methodologies have played a significant role in driving the recent improvements in ANPR technology. CNNs and RNNs have been instrumental in enhancing the accuracy and efficiency of ANPR systems by enabling robust feature extraction and sequence modeling, respectively. The utilization of these deep learning techniques has revolutionized the field of ANPR and paved the way for more accurate and reliable license plate recognition [4]. These techniques have shown promising results in improving the accuracy of ANPR systems and reducing errors caused by different environmental conditions. ANPR technology has practical applications in parking management and toll collection. For example, ANPR systems can be used to automate parking ticket issuance and payment, eliminating the need for physical ticketing and reducing the workload of parking attendants. The use of ANPR technology in toll collection has also been on the rise, with many toll collection systems adopting ANPR technology to automate the system.

Our motivation to write this paper stems from the fact that is an increasingly popular technology used in various settings, but it faces technical and privacy challenges. Research in this area can help to improve the accuracy, speed, and reliability of ANPR systems, while also addressing privacy concerns and improving real-world applications such as identifying stolen vehicles and enforcing traffic laws.

2 Literature Survey

OCR (Optical Character Recognition) technology has been widely used to recognize text and numbers from scanned documents, images, and videos. In license plate recognition, OCR technology plays a crucial role in extracting vehicle registration numbers. The significance of OCR-based number recognition in various applications such as traffic control, security, and surveillance has led to substantial research efforts in recent years [14]. In this literature survey, we provide a review of some noteworthy research papers in this domain, highlighting their contributions and approaches.

One significant study titled ”Automatic License Plate Recognition using Deep Convolutional Neural Networks” by R. Tawari, P. Krishna, and S. Chandra (2016) focuses on employing deep learning techniques to tackle license plate recognition challenges. The authors propose a deep learning approach utilizing Convolutional Neural Networks (CNNs) for accurate and efficient license plate recognition. They introduce a CNN architecture that can be trained on large datasets of license plate images, demonstrating promising results [14].

Another notable contribution is the research paper by Kakani et al. (year). They present an innovative methodology to enhance OCR-based license plate recognition, particularly in challenging scenarios where the license plate may be partially obstructed or the image is captured at an angle. The authors propose novel techniques to address these difficulties and achieve more accurate and reliable license plate recognition results. Their work offers valuable insights into improving the performance of OCR-based license plate recognition systems in real-world scenarios [5].

Additionally, a study by Gondhalekar et al. provides a comprehensive comparison of several state-of-the-art license plate recognition algorithms, including traditional OCR-based methods and deep learning-based methods. The authors evaluate the performance of these algorithms on benchmark datasets and discuss the advantages and disadvantages of each approach. This comparative analysis aids in understanding the strengths and limitations of various techniques in license plate recognition [7].

Another research paper by H. Jain, A. Singh, and P. Jain (2020) titled ”License Plate Recognition using Deep Learning and Image Processing Techniques” presents a license plate recognition system that combines deep learning and image processing techniques. The authors propose a pipeline consisting of image segmentation, character segmentation, and character recognition modules. They evaluate the performance of their system on real datasets, providing insights into the effectiveness of their approach [10].

The literature review demonstrates the sustained interest in developing OCR-based license plate recognition systems with a specific focus on enhancing accuracy and reliability in real-world scenarios. These research contributions contribute valuable insights, proposing innovative techniques, and comparing different approaches. Future work in this field can build upon these studies to further advance the capabilities of OCR-based license plate recognition systems, enabling their wide application in diverse domains.

3 Proposed Method

The proposed method introduces a well-structured architecture that consists of several distinct modules to ensure efficient and accurate performance. These modules include Image Capture, Preprocessing, Number Plate Extraction, and Character Segmentation and Character Recognition. The Image Capture module serves as the initial stage, responsible for capturing images for further processing. The Preprocessing module then handles the task of preparing the captured images by applying necessary filters and enhancements to optimize their quality and reduce noise. Next, the Number Plate Extraction module focuses on precisely extracting the number plate regions from the preprocessed images using advanced techniques and algorithms. Lastly, the Character Segmentation and Character Recognition module plays a crucial role in segmenting individual characters from the extracted number plate and employing powerful recognition algorithms to accurately identify and interpret these characters. By breaking down the proposed architecture into these modules, the method aims to streamline the license plate recognition process and achieve superior results. A brief study of all these is covered below.

3.1 Image Capture

The primary step in ANPR is the image capturing of the license plate. Images that are ideal for ANPR use should be able to be captured by the camera. This is essential to the system's overall effectiveness. It might be challenging to get a clear picture of a license plate because of poor lighting, a lot of other plates, and the area that the plate takes up in the picture. The type of integrated camera has an impact on how well the ANPR system performs while controlling hundreds of parking spaces, reducing traffic jams, or quickly recognizing traffic infractions. Due to the need to account for ambient light, choosing the appropriate camera for this application requires careful consideration of crucial elements including shutter artifacts, exposure periods, and dynamic range [5]. Mostly HDR camera is recommended. The difference between a normal camera and an HDR camera can be seen in figure 1 and figure 2. Next, the discussion shifts towards the placement of the gadgets. In comparison to software triggers that can be configured remotely from a control center, adjusting traffic cameras to capture vehicles accurately requires physical intervention at the location. This involves tilting the cameras on-site to ensure optimal positioning. Apart from the ball joint situated on the camera console, the ANPR imaging process necessitates securely bolting the camera console base onto the gantry. These physical adjustments are crucial for achieving precise and reliable Automatic Number Plate Recognition (ANPR) results [17]. This ensures that the gadget will remain in place even in difficult circumstances. When fixing the equipment to its permanent places, installation workers must additionally tilt the camera at the ideal 20° to 30° angle. An example of which can be seen in figure 3.

Fig. 1. Image captured by normal camera

Fig. 2. Image captured by HDR camera

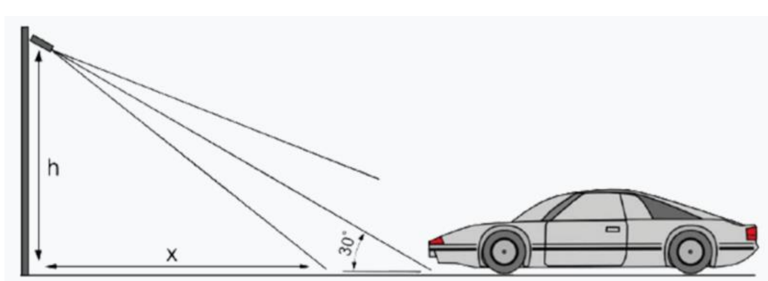

Fig. 3. Calculated angle for acurate image capture

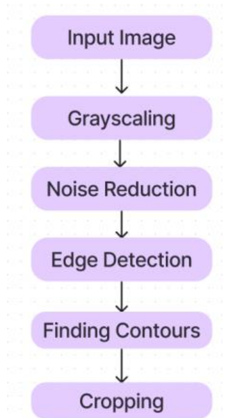

Fig. 4. Flow chart for preprocessing of image

3.2 Preprocessing

After the successful capturing of the image, the next step is of pre-processing the image. The main aim of preprocessing is to enhance the processing speed of the algorithm. It is helpful in improving the contrast of the captured image and reducing noise. For preprocessing, the algorithm used is the OpenCV library. OpenCV is an extensive open-source library that encompasses a wide range of functionalities related to computer vision, machine learning, and image processing. With its vast collection of tools and algorithms, OpenCV has become a pivotal component in various applications requiring real-time operation, which holds paramount significance in today's systems. Its ability to handle tasks efficiently in real-time, such as object detection, facial recognition, and video processing, has made it indispensable in numerous fields like surveillance,

Fig. 5. Greyed Image

Fig. 6. Smoothed Image

robotics, augmented reality, and autonomous vehicles. By providing an accessible and comprehensive set of tools, OpenCV empowers developers and researchers to implement advanced computer vision techniques and build robust and high-performance systems that cater to the demands of modern technology. It provides all the facilities from reading an image to contouring. The original image captured is in RGB format. The first step is to convert it to Greyscale. Greyscaling is done to detect edges easily and reduce model complexity.Many algorithms are customized to work only on grayscale images [16]. OpenCV provides various methods for greyscaling. Here the method used is cv2.COLOR BGR2GRAY. After the greyscaling is done, noise removal needs to be performed. Denoising an image refers to the process of reconstruction of a signal from noisy images. Denoising is done to remove unwanted noise from the image to analyze it in a better form. It refers to one of the major pre-processing steps. In our algorithm noise detection can be performed using a bilateral filter. Then in the next step detection of edges on the smoothed image is performed using a canny edge detection algorithm which uses Gaussian smoothing to remove edges. The next step is to find contours from the processed image in the previous step. Contours are defined as the line joining all the points along the boundary of an image that are having the same intensity. We have used findContour() function that helps in extracting the contours from the image. Now comes the process of sorting the identified contours which are done using the sorted function in OpenCV. A brief representation of the steps involved in preprocessing is: 4. Outputs after

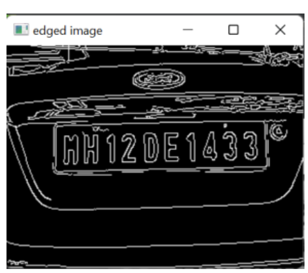

Fig. 7. Edged Image

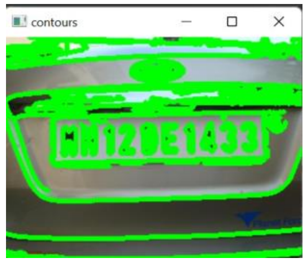

Fig. 8. Image after performing Contours

each process can be seen in figure 12,figure 5, figure 6, figure 7, figure 8, figure 9, figure 10, figure 11

3.3 Number Plate Extraction

In this section, we propose in our novel generative framework the use of Generative Adversarial Networks (GANs) to generate features that provide robustness for license plate detection on preprocessed images. [1] GANs are unsupervised deep learning techniques. Usually, it is implemented using two neural networks: Generator and Discriminator [3]. The main goal of the generator is to maximize the loss of the discriminator. Figure 13

The Discriminator loss is

$$L_D = -E_{xr}\left[\log\left(D\left(x_r, x_f\right)\right)\right] - E_{xf}\left[\log\left(1 - D\left(x_f, x_r\right)\right)\right] \quad (1)$$

The Adversarial loss for the generator is as follows

$$L_G = -E_{xr}\left[\log\left(1 - D\left(x_r, x_f\right)\right)\right] - E_{xf}\left[\log\left(D\left(x_f, x_r\right)\right)\right] \quad (2)$$

x_r and x_f denotes real image and fake image, respectively, while E_{xr} and E_{xf} represent the operation of taking an average of all real and fake images, respectively.

Fig. 9. Top 30 contours on Image

Fig. 10. Image with detected Licence Plate

Summing up, we have

$$min_G max_D V(D, G) = E_{x\ p_{data}(x)}\left[\log\left(D(x)\right)\right] + E_{z\ px_{z}(z)}\left[\log\left(1 - D\left(G(z)\right)\right)\right]$$

The LR image undergoes a series of convolutional and ReLU layers. It is then passed through the RRDB block to incorporate residual learning for training our adversarial loss function. The discriminator function contributes to generating authentic textures. In the process of the RRDB model, we start with the Low-Resolution image (x) as input. The feature extraction takes place through the convolutional layer, and the resulting features are utilized as input for the RRDB mode. [9].

$$F_0 = K_{\mathrm{CNN}}(x) \tag{3}$$

F_0 Let's consider the process involving feature extraction and residual dense blocks in relation to the LR image (x). The feature extracted by the convolutional layer, denoted as F and obtained using the kernel Kcnn, serves as an input. When utilizing n residual dense blocks, the output of the nth RRDB model can be represented as follows.

$$F_{\mathrm{N}} = K_{\mathrm{RRDB}_n}(F_{\mathrm{rrdb}-1}) \tag{4}$$

In our model, we incorporated 26 RRDB blocks, each representing the nth RRDB operation, which encompasses the operations of both Convolutional Neural Networks (CNN) and Rectified Linear Units (ReLU) layers. Furthermore, we

Fig. 11. Cropped Image

Fig. 12. Original Image

employed ReLU as the activation function throughout the model. The dense function of the CNN and RRDB blocks is precisely formulated to ensure optimal performance and effective feature extraction. [15]

$$F_{\mathrm{n,c}} = \sigma\left(W_{\mathrm{n,c}}\left[F - n - 1, F_{\mathrm{n-2}}, \ldots.., F_{\mathrm{n,c-1}}\right]\right) \tag{5}$$

where σ denotes the activation function. The Global Residual Learning is

$$F_{\mathrm{GRL}} = \sum_{1}^{3} 6F_{\mathrm{n,c}} \tag{6}$$

In this context, the output of the first convolutional layer plays a crucial role in capturing essential features and patterns from the input data. By incorporating the global residual learning approach, the network can effectively learn and refine these features throughout the subsequent layers, ultimately leading to improved performance and better representation of the data.

$$F_{\mathrm{total}} = F_{\mathrm{GRL}} + F_0 \tag{7}$$

3.4 Character Segmentation and Character Recognition

Characters are further recognized after the identification of license plates. Seg- mentation that is based on recognition is often referred to as implicit segmenta- tion. Segmentation and character recognition are accomplished simultaneously in this process. The system breaks down the image into its component parts. Words that should be characters are divided into segments by the implicit segmentation program, which then sends each segment to a classifier. When segmentation is called again with the feedback that the previous sequence was rejected, the clas- sification results should be appropriate. The system can detect and transform the

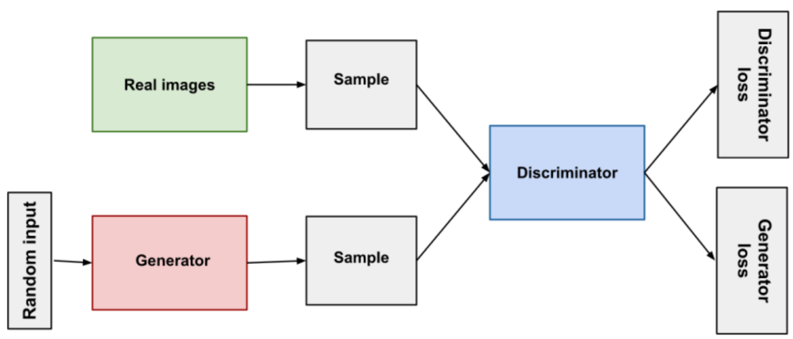

Fig. 13. Image Detection through OCR

image into text by using character recognition. Here for character segmentation and Recognition, we use Optical Character Recognition(OCR). Once, the license plate is detected and pre-processed for segmentation and then passed forward through the Character Recognition process to detect alphanumeric characters [8]. fig16

Optical character recognition (OCR) refers to the process of converting text from various sources, including handwritten, printed, or typed text, into machine-readable format. This conversion takes place by analyzing images captured from different mediums, such as photographs of documents, scanned documents, or even scene photos. OCR technology plays a crucial role in automating data entry tasks, digitizing physical documents, and enabling text searchability. By leveraging sophisticated algorithms and image processing techniques, OCR systems can accurately extract textual information from images, enabling efficient text analysis and manipulation in various applications. OCR is mainly used in Artificial Intelligence, computer vision, and most important pattern recognition.

4 Results and Discussion

ANPR by OCR is a technology that uses optical character recognition (OCR) to automatically identify and read license plates on vehicles. The process involves capturing an image of the license plate with a camera, processing the image to extract the characters on the plate, and then using OCR algorithms to recognize and translate the characters into the text. The technology has many applications, including law enforcement, parking management, and toll collection.

Research in ANPR by OCR typically focuses on improving the accuracy and efficiency of the technology. Common results and discussion topics in this field include:

Accuracy: Researchers often evaluate the accuracy of ANPR systems by comparing the recognized license plate numbers to ground truth data. This can involve analyzing the frequency and types of errors made by the OCR algorithms, such as misread characters or incorrect formatting. Researchers may also compare the accuracy of different OCR algorithms or processing techniques to determine which methods are most effective [11].

1. Speed: Another important factor in ANPR research is the speed of the technology. Researchers may evaluate the processing time required to recognize license plate numbers, as well as the speed at which the system can capture and process images of moving vehicles. This can help determine whether the technology is suitable for real-time applications such as toll collection or parking management.

2. Robustness: ANPR systems must be able to accurately recognize license plates in a variety of conditions, including different lighting, weather, and camera angles. Researchers may evaluate the robustness of the technology by testing it under different environmental conditions and analyzing the frequency and types of errors made [12].

3. Dataset creation and augmentation: Researchers also work on creating datasets for the training and evaluation of ANPR systems. This includes capturing images of license plates under different conditions and annotating them with ground truth data. In addition, researchers may work on techniques for data augmentation, such as generating synthetic images with different backgrounds or distortions, to improve the robustness of the OCR algorithms [13].

4. Deep learning methods: Recently, deep learning techniques have shown promise in improving the accuracy of ANPR systems. Researchers may investigate the the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) or other deep learning architectures to ANPR. This may include exploring transfer learning approaches that leverage pre-trained models on large datasets such as ImageNet, or developing novel models that can handle the specific challenges of ANPR [14].

Overall, research in ANPR by OCR is a dynamic and active field that involves a range of technical and practical challenges. By improving the accuracy, speed, and robustness of ANPR systems, researchers can help enable a wide range of applications that depend on automatic license plate recognition.

Accuracy performance around different datasets			
Method	Faster R-CNN	YOLO	GAN(Ours)
Small	73.94%	80.88%	79.10%
Small + Inclined	68.64%	78.50%	72.67%
Medium	96.94%	97.62%	97.64%
Medium + Inclined	90.19%	90.89%	91.18%
Large	99.50%	99.30%	99.50%
Total	84.83%	82.73%	86.53%

Above table shows the mathematical representation of the improved accuracy using Generative Adversarial Network compared with some other algorithms used in previous researchs like Faster R-CNN and YOLO.

5 Conclusion and Future Work

In conclusion, the research presented in this paper underscores the significant advancements in Optical Character Recognition (OCR) technology for number plate recognition. The successful implementation of OCR in license plate recognition systems has demonstrated its efficacy in various applications. However, there remains ample scope for future work in this field, as OCR technology continues to evolve and improve.

One area of future exploration lies in the improved handling of variations in number plate formats. Different countries and regions have diverse formats for their license plates, posing a challenge for OCR systems. Future research should focus on developing robust algorithms capable of handling these variations with greater ease and accuracy. This could involve the integration of machine learning techniques and sophisticated pattern recognition algorithms to adapt to different plate formats [18].

Integration with other technologies presents another avenue for future work in OCR-based number plate recognition. By combining OCR technology with license plate databases or Vehicle Information Management Systems, additional functionalities can be achieved. This integration would enable real-time retrieval of vehicle-related information, facilitating enhanced law enforcement, traffic management, and security applications.

Furthermore, the rise of special number plates, such as temporary or special-purpose plates, poses new challenges for OCR technology. Future research should focus on adapting OCR algorithms to effectively recognize these unique plate formats. This may involve collecting specialized datasets, refining existing algorithms, and exploring novel techniques such as deep learning architectures specifically tailored for handling such challenges.

In summary, the field of OCR number plate recognition offers substantial opportunities for future advancements. Researchers and developers can continue to refine and enhance OCR technology to meet the changing needs of society. By addressing issues such as plate format variations, integration with other technologies, and adaptation to new challenges, OCR-based number plate recognition systems can further solidify their position as a critical component of modern transportation, surveillance, and security systems. [19].

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Title: **A Comprehensive System for Automatic License Plate Detection and Recognition**

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1. Abstract should be modified highlighting the summary of the manuscript. 2. Figure caption for the fig 3 should be mentioned. 3. All the figure captions should be meaningful. 4. Content of the article is VERY LESS, the author needs to extend the content of the manuscript.

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