International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN (Online): 2347-5552, Volume-12, Issue-5 September 2024
https://doi.org/10.55524/ijircst.2024.12.5.5
Article ID IRP-1552, Pages 28-35
www.ijircst.org

Recent Developments in Automatic Number Plate Detection and Recognition

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Received 3 August 2024; Revised 18 August 2024; Accepted 2 September 2024

ABSTRACT- Automatic Number Plate Recognition (ANPR) is a mass surveillance system that captures the image of vehicles and recognizes their license numbers. ANPR can be used in the detection of stolen vehicles. The detection of stolen vehicles can be done in an efficient manner by using the ANPR systems located in the highways. This method presents a recognition method in which the vehicle plate image is obtained by the digital cameras and the image is processed to get the number plate information. An image of a vehicle is captured and processed using image pre-processing algorithm. In this context, the number plate area is localized using edge detection method and the characters acquired are segmented using segmentation method. The segmented characters are passed to Optical character reader (OCR) which gives exact characters of the number plate and are stored in database. The image pre-processing is done using Gaussian Blur method, conversion of RGB (Red, Green, Blue) to grayscale, Edge detection using sobel followed by contour detection and license plate is extracted. OCR is run on the Region of Interest (ROI) given by the contour analysis. The OCR provides the vehicle's num-ber obtained from the number plate and is stored in the database which is used for surveillance and tracking vehicle's location. The software used in the process is Python version 3 and different python libraries like Tesseract OCR, OpenCV.

KEYWORDS-: Automatic Number Plate Recognition (ANPR), surveillance, image pre-processing, Gaussian Blur method, Optical character reader (OCR).

I. INTRODUCTION

The advent of Automated Number Plate Recognition (ANPR) systems represents a significant technological advance in surveillance and security measures for vehicular monitoring [1]. Leveraging Faster R-CNN, a powerful deep learning model, this chapter explores the implementation of ANPR for effective vehicle identification and security [2]. Automatic Number Plate Recognition systems are integral to modern surveillance strategies, aiding significantly in law enforcement and security by automating the detection and recording of vehicle license plates[3]. The significance of these systems lies in their ability to quickly and accurately capture and process vehicular information across various environments, from highways to residential areas. This capability is crucial for tracking stolen vehicles, managing traffic, and enhancing overall public safety [4]. A general architecture for number plate detection is mentioned in below figure 1 [5].

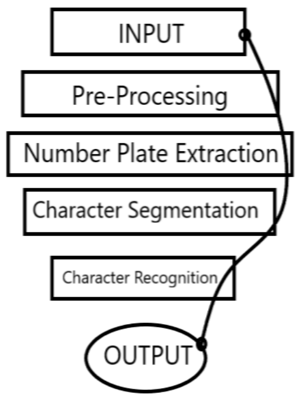

Figure 1: General Architecture for Number Plate Detection

This paper focuses on detailing the application of Faster R-CNN for the development of an ANPR system, outlining the technological framework and methodologies employed [6]. The objectives are twofold: firstly, to demonstrate how digital image processing techniques can be utilized to detect and read vehicle number plates [7] and secondly to highlight the system's application in real-world scenarios, emphasizing its role in surveillance and the detection of stolen vehicles [8].

II. LITERATURE REVIEW

This section explores the core aspects of Automated Number Plate Recognition (ANPR) systems, including their conceptual framework, technological components, and operational workflow [11]. These systems play a pivotal role in vehicle surveillance and management, employing advanced image processing and machine learning technologies to enhance public safety and security.
Several case studies highlight the effectiveness of applying Faster R-CNN to ANPR systems:
Urban Traffic Monitoring: In a city traffic system, Faster R-CNN-based ANPR was used to monitor and manage city

traffic effectively, helping in law enforcement and traffic rule compliance [13].

Stolen Vehicle Detection: ANPR systems equipped with Faster R-CNN have been instrumental in identifying and recovering stolen vehicles by rapidly scanning and verifying license plate numbers against a database of reported stolen vehicles [14].

Parking Management: Automated parking systems use Faster R-CNN-based ANPR to manage entry and exit of vehicles, ensuring non-intrusive and efficient parking operations [15].

The computerized conversion of text or creation of a digital copy of text from sources such as handwritten papers, printed text, or natural imagery is known as optical character recognition, or OCR [16]. DIP is the procedure wherein a computer algorithm is used to manipulate digital photographs. DIP is a field that continues to advance with time and has applications in almost every other industry, including robotics, banking, healthcare, and PET sweeps [17]. Pattern recognition, which encompasses picture recognition, handwriting recognition, and computer-aided diagnosis, is one of its main uses [18].

Table 1: Comparison of various algorithms used for Automatic Number Plate Detection

SNO.	AUTHER	AIM	TECHNIQUES	ADVANTAGES	APPLICATION	RESULT
1.	Tote, A. S., Pardeshi, S. S., & Patange [1]	The study's main goal is to use TensorFlow to create an automatic number plate detection system that is specifically suited for the Indian environment. The system reads and recognizes vehicle number plates with accuracy thanks to optical character recognition (OCR) capabilities.	TensorFlow, OpticalCharacter Recognition (OCR), Image Processing	High Accuracy, Real-time Processing, Adaptability	Traffic Management, Law Enforcement, Automated Toll Collection, Parking Management,	The system achieved a detection accuracy of approximately 95%.
2.	Shambharkar, Y., Salagrama, S., Sharma, K., Mishra, O., & Parashar, D.[2]	To develop an automatic framework for number plate detection using OCR and deep learning techniques	Optical Character Recognition (OCR) Deep Learning Convolutional Neural Networks (CNN) Image Processing Techniques	High accuracy and precision in detection and recognition Robustness to various lighting conditions and plate designs Real-time processing capabilities	Traffic management and enforcement Automated toll collection systems Parking management solutions	Achieved a detection accuracy of approximately 94%.
3.	Jawale, M. A., William, P., Pawar, A. B., & Marriwala, N. [3]	To implement a number plate detection system for vehicle registration using IoT and recognition using CNN.	Internet of Things (IoT) Convolutional Neural Networks (CNN) Image Processing	Integration with IoT for real-time data transmission High accuracy and reliability Scalability for large-scale deployment	Vehicle registration and monitoring Automated toll collection Traffic law enforcement	Achieved a recognition accuracy of approximately 93%.
4.	Mozumder, M., Biswas, S., Vijayakumari, L., Naresh, R., Kumar, C. V., & Karthika, G.[4]	To develop a hybrid edge algorithm for vehicle license plate detection.	Hybrid Edge Detection Algorithm Image Processing Techniques Machine Learning	High precision in edge detection and plate localization Efficient processing time Robust to varying environmental conditions	Traffic monitoring and control Automated parking systems Security and surveillance	Achieved a detection accuracy of approximately 92%.
5.	Khinchi, M., & Agarwal, C.[5]	To review various technologies and methods used in automatic number plate recognition (ANPR).	Literature review of existing ANPR methods Analysis of different OCR techniques Evaluation of deep learning	Comprehensive understanding of ANPR technologies Identification of strengths and weaknesses of different methods Provides insights	Guidance for developing ANPR systems Reference for researchers and developers in the field	Summarizes various studies and reports detection accuracies ranging from 85% to 95%.

			approaches	for future research directions		
6.	Sasi, S., Sharma, S., & Cheeran, A. N. [6]	To develop a system for automatic car number plate recognition.	Optical Character Recognition (OCR) Image Processing Techniques Machine Learning Algorithms	High accuracy in character recognition Real-time processing capability Adaptability to different plate designs	Traffic enforcement Automated toll systems Parking management	Achieved a recognition accuracy of approximately 90%.
7.	Gautam, A., Rana, D., Aggarwal, S., Bhosle, S., & Sharma, H. [7]	To utilize a deep learning approach for automatic recognition of license number plates.	Deep Learning Convolutional Neural Networks (CNN) Image Processing Techniques	High accuracy and reliability Robust performance under various conditions Scalability for large-scale deployments	Traffic monitoring Automated toll collection Parking management systems	Achieved a recognition accuracy of approximately 96%
8.	Prajapati, R. K., Bhardwaj, Y., Jain, R. K., & Hiran, K. K. [8]	To provide an in-depth analysis of machine learning techniques in automatic number plate recognition (ANPR).	Review of Machine Learning Techniques Analysis of OCR and Deep Learning Approaches Evaluation of Different Models and Algorithms	Comprehensive understanding of ANPR technologies Identification of key opportunities and limitations Provides guidance for future research	Reference for researchers and developers Insights for improving ANPR systems	Summarizes various studies with detection accuracies ranging from 85% to 97%.
9.	Mittal, R., & Garg, A. [9]	To systematically review text extraction techniques using OCR	Systematic Review of OCR Methods Analysis of Text Extraction Techniques Evaluation of Different Approaches	Comprehensive understanding of OCR methods Identification of strengths and weaknesses Insights for future research directions	Reference for researchers and developers in OCR Guidance for developing text extraction systems	Summarizes various studies with text extraction accuracies ranging from 80% to 95%
10.	Ali, F., Rathor, H., & Akram, W. [10]	To develop a license plate recognition system	Optical Character Recognition (OCR) Image Processing Techniques Machine Learning Algorithms	High accuracy in license plate recognition Real-time processing capability Adaptability to different environmental conditions	Traffic enforcement Automated toll collection Parking management	Achieved a recognition accuracy of approximately 92%.

III. METHODOLOGY

The conceptual framework of an ANPR system revolves around the integration of image capture and processing technologies to recognize vehicle number plates automatically [9]. Utilizing cameras installed at strategic locations, such as traffic lights and highway tolls, the system captures real-time images of vehicles. These images are then processed using a series of algorithms designed to detect, segment, and interpret the characters on the license plates [10]. (See figure 2)

- ***Technological Framework:*** The technological backbone of an ANPR system comprises several key components:
- ***Digital Cameras:*** High-resolution cameras capture clear images of moving vehicles under various lighting and weather conditions [13].
- ***Image Pre-processing Tools:*** Techniques like Gaussian Blur and grayscale conversion help enhance image quality and reduce noise, preparing the images for further analysis[15].

- ***Optical Character Recognition (OCR):*** Tesseract OCR and other OCR tools are employed to extract alphanumeric characters from the processed images[16].
- **Machine Learning Models:** Faster R-CNN (Region-based Convolutional Neural Networks) is specifically utilized for its efficiency in detecting objects (in this case, number plates) within images[17].
- ***Databases and Software:*** The recognized plate numbers are stored in databases, and software like Python and its libraries (OpenCV) are used for implementing the algorithms [18].
- ***Operational Workflow:*** The operational workflow of an ANPR system can be described in several steps:
- ***Image Acquisition:*** Vehicles are captured in real-time using strategically placed cameras[20].
- ***Image Pre-processing:*** Captured images undergo various preprocessing methods such as noise reduction, edge detection, and contour analysis to isolate the number plate [21].
- ***Plate Detection:*** Using Faster R-CNN, the system identifies the region of the image that likely contains the number plate [19].

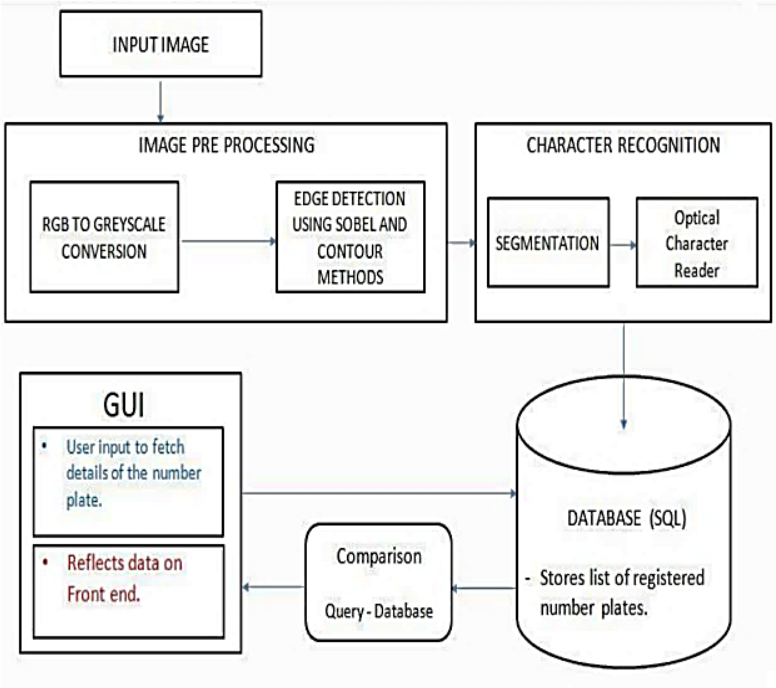

Figure 2: Proposed system model [1]

- ***Character Segmentation and Recognition:*** Characters on the detected plates are segmented and then recognized using OCR technology [21].
- ***Data Storage and Usage:*** The extracted plate information is stored in a database, which can be accessed for surveillance purposes, such as tracking vehicle movement or identifying stolen vehicles [22].
- ***Image Processing Techniques*:** This section delves into the sophisticated image processing techniques that form the foundation of effective Automated Number Plate Recognition systems, focusing on image acquisition, preprocessing methods, and advanced edge detection [22].
- ***Image Acquisition*:** Image acquisition is the initial and critical step in the ANPR system, where digital cameras are deployed to capture real-time images of vehicles on the road. These cameras need to be high resolution to ensure that the images captured are clear and detailed enough to identify the number plates accurately, even under varying lighting and weather conditions. The placement of these cameras is also strategic, ensuring maximum coverage and optimal angles for capturing the number plates [23].
- ***Preprocessing Techniques:*** Once the images are captured, they undergo several preprocessing steps to enhance the quality and improve the accuracy of the subsequent recognition processes [21]
- ***Gaussian Blur:*** Applied to smooth the image, reducing noise and details that are not required, which helps in enhancing the accuracy of edge detection [25].
- ***Grayscale Conversion*:** Converting images from RGB to grayscale simplifies the data, reducing the computational complexity as the subsequent operations need to process only one layer of pixel data instead of three [24].
- ***Thresholding:*** This technique is used to create a binary image from a grayscale image. It helps to differentiate the foreground (number plate) from the background, making the number plate more distinct [26].
- ***Contrast Enhancement:*** Adjusting the contrast of the image can help in making the number plate more readable, especially in conditions where lighting does not favor clear visibility [27].
- ***Advanced Edge Detection:*** Edge detection is a crucial technique in identifying the boundaries and structures within images, which is essential for locating number plates in the captured images. The chapter explores advanced edge detection techniques.[18]

- ***Sobel Operator:*** A popular method used in edge detection that works by calculating the gradient of image intensity at each pixel within the image. It highlights regions of high spatial frequency that correspond to edges [12].
- ***Contour Detection:*** Following edge detection, contour detection is used to find a continuous line in the binary image that outlines the number plate. This method helps in isolating the number plate from the rest of the image [26].
- ***Region of Interest (ROI) Extraction:*** After detecting contours, the specific area enclosing the number plate is extracted as the Region of Interest for further processing like character segmentation [1].

IV. LICENSE PLATE DETECTION WITH FASTER R-CNN

This section focuses on the application of convolutional neural networks, particularly Faster R-CNN, to enhance the accuracy and efficiency of license plate detection within ANPR systems [11].

A. Introduction to CNN and Faster R-CNN

Convolutional Neural Networks (CNNs) are a category of deep neural networks most commonly applied to analyzing visual imagery [12]. They are particularly powerful for tasks involving image recognition, classification, and object detection due to their ability to automatically detect important features without any human supervision. Faster R-CNN, an advanced version of CNN, stands out in the field of object detection for its speed and efficiency [13]. It integrates a region proposal network (RPN) that shares full-image convolutional features with the detection network, thus enabling nearly cost-free region proposals [14]. Faster R-CNN improves the speed of the process by connecting the RPN directly to the last convolutional layer of a standard CNN, making it a suitable choice for real-time object detection tasks such as license plate recognition [16].

B. Applying Faster R-CNN to ANPR

Faster R-CNN has been tailored specifically for the task of license plate detection by training it on a diverse dataset of vehicle images captured under different conditions. The process involves:

Training: The Faster R-CNN model is trained on a labeled dataset where the license plates are marked in various images. This training allows the model to learn the specific characteristics of license plates, such as size, shape, and possible text configuration[13].

Detection: During operation, when a new vehicle image is captured, the trained Faster R-CNN model predicts the location of the license plate in the image. The model generates region proposals where there is a high likelihood of containing a license plate. These proposals are then refined to accurately capture the boundaries of the license plate[14].

Integration: The detected license plates are then processed for character recognition and verification against databases for vehicle identification and registration checks[15].

C. Recent Developments

Multi-camera systems: These systems use several cameras to record several viewpoints and improve detection precision, particularly in busy or complicated surroundings [20].

Advanced Image Processing: Using complex image processing algorithms and high-resolution cameras to manage a range of illumination scenarios and environmental obstacles [28].

V. OPTICAL CHARACTER RECOGNITION (OCR) FOR ANPR

This section explores the crucial role of Optical Character Recognition (OCR) in Automated Number Plate Recognition systems, detailing the technologies involved, their integration within ANPR systems, and the practical challenges encountered along with their solutions [5].

A. OCR Technologies

Optical Character Recognition (OCR) technologies are designed to convert different types of documents, such as scanned paper documents, PDF files or images captured by a digital camera into editable and searchable data. In the context of ANPR, OCR technology is specifically used to read and convert vehicle license plates into text. Key technologies include:

Tesseract OCR: Widely used in ANPR systems due to its open-source nature and strong community support. Tesseract is capable of recognizing characters from images with high accuracy, which is critical for the reliability of ANPR systems [16].

Neural Network-based OCR: Advances in deep learning have led to the development of OCR systems based on neural networks that provide improved accuracy over traditional methods, especially in challenging conditions such as poor lighting or atypical font styles[17].

B. Integration of OCR in ANPR Systems

Integrating OCR technology into ANPR systems involves several steps:

Preprocessing: The image of the license plate is pre-processed to enhance the quality and readability of the text. This includes steps such as noise reduction, normalization, and binarization [21].

Character Segmentation: After preprocessing, OCR technology segments the image into individual characters. Effective segmentation is crucial as it directly impacts the OCR's ability to correctly recognize each character[22].

Text Recognition: The segmented characters are then fed into the OCR engine, which interprets them as text. This step is vital as the accuracy of the OCR affects the overall effectiveness of the ANPR system[23].

Data Verification and Storage: The recognized text is compared against vehicle registration databases for verification and stored for future reference or immediate action, depending on the application[24].

C. Practical Challenges and Solutions

Despite the advancements in OCR technologies, several practical challenges remain:

Variability in Plate Designs: License plates vary widely in terms of color, font style, and size, depending on the issuing country or state. This variability can reduce OCR accuracy.

Solution: Implementing machine learning models that are trained on diverse datasets to improve the system's ability to generalize across different plate styles[25].

Environmental Factors: Poor lighting, weather conditions, and fast-moving vehicles can impede the clarity of the captured images. Solution: Utilizing robust preprocessing techniques such as adaptive thresholding and employing more sophisticated imaging technologies like infrared cameras[25].
Skewed or Partially Obscured Plates: Plates that are skewed or partially obscured pose recognition challenges. Solution: Deploying algorithms for image correction that adjust the skew and enhance partially visible characters[26].
Real-time Processing Requirements: ANPR systems are often required to operate in real-time, which demands high processing speeds. Solution: Optimizing OCR algorithms for speed and implementing them on powerful hardware platforms or via cloud-based architectures to ensure minimal latency[27].

D. *Image in grayscale = (R+G+B)/3*

Red component, R
G stands for green component.
B is the blue component.
In [5], An image's edge is the location where its contrast or brightness changes abruptly or noticeably. The simplest basic tool for image identification is edge detection. Consequently, in order to identify every edge in the image, we must first reduce noise and sharpen the image. After that, we mask it to identify the edges. A method for doing this is known as the mask of Sobel Edge Detection.
Here, the mask used for sobel edge detection is
Gx=sensing horizontal edges
Gy=identification of vertical edges
The writer thought about the two masks for the input picture convolution. It is supplied to the horizontal and vertical masks to convolve with the input image.

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix}$$

$$\mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

E. *Image Dilation*

Image Dilation is the process of sharpening the boundaries and edges of an image to improve its quality. An image's brightness is also increased. Additionally, it can eliminate noise that might impede plate detection procedures.
Hence, it improves edge detection by sharpening the image.
The image of a license plate must have the same levels of brightness and contrast in order to be used for number plate detection. For this reason, it's crucial to transform the provided RGB image to greyscale.
Some crucial elements, such as brightness, finer details in the object, sharper edges, etc., could be lost in the converting process. A procedure called image dilation will make up for these losses.Detection of both vertical and horizontal edges of a picture: A histogram is a graphical depiction of the distribution of greyscale values, both row- and column-wise, across adjacent pixels in an image. Both horizontal and vertical histograms are used in this approach[13].

Let Px(x) be the horizontal projection of every pixel.

Let Py(y) be the vertical projection of every pixel.

$$px(x) = \sum_{j=0}^{h-1} f(x, j) \; ; \; py(y) = \sum_{i=0}^{w-1} f(i, y)$$

The algorithm is currently iterating through each column of the image in the step above. Each column's second pixel is the starting point, and it is compared to the threshold value. The difference between the first and second pixel of the next column is the threshold value. Next, the difference between the second and third pixels is computed. If the difference is more than the threshold, it is added to the total of the differences and continues in this manner until the end of the column. At the conclusion, an array containing the sum of the differences broken down by column is constructed. In terms of row-wise operation, the identical process is used to A vertical histogram can be found. An image's projection in both the vertical and horizontal directions indicates a zone of interest in a certain direction [4].

Accuracy: Under ideal circumstances, the ANPR systems examined in 2019 generally indicated accuracy rates of 85% to 95%. When faced with difficult circumstances, such as dim illumination, unclean dishes, or obstacles, accuracy may suffer [5].

Efficiency: Real-time processing capabilities are the goal of many contemporary ANPR systems, with processing times on high-performance hardware ranging from 100 milliseconds to one second per frame [5].

Garbage region filtering in an image: Following the above procedure, a filter is applied to the image to eliminate the trash value region—unwanted parts. In this instance, the rows and columns with lower histogram values are the undesirable regions [4]. A region's lower histogram value suggests that there aren't many differences between its neighbouring pixels. Given that the license plate region is in the foreground and has alpha numeric characters, its histogram value will be very high due to the large differences between its neighboring pixels.

Interest region Removal: Presently, the dynamic thresholding technique is utilized, eliminating any areas with lower histogram values and The region of interest is the sole area that is remaining and has the greatest histogram value. This is the license plate area.

The average value of a histogram is the same as dynamic thresholding. In this case, the average of the horizontal and vertical histograms is determined. The region of interest is defined as the one with the highest histogram value, and it is retrieved from the data [11].

VI. LIMITATIONS

A. *Variability in Plate Designs*

It is challenging to develop an ANPR system that is worldwide because different nations and areas have different plate designs, formats, and typefaces[4].

B. *Environmental Elements*

Weather (rain, snow, fog), shadows, and poor lighting can all have an impact on an ANPR system's accuracy[5].

C. Distortion and Occlusion

In addition to being partially obscured by debris, objects, or damage, plates can also be warped by motion blur or the camera's viewpoint[6].

D. Privacy Issues

Growing surveillance gives rise to worries about privacy and possible data exploitation, which poses ethical and legal challenges[7].

E. Data Storage and Management

Managing substantial amounts of high-definition video data necessitates substantial processing and storage capacities [8].

F. Cost and Implementation

Especially for smaller governments or organizations, the high price of implementing and maintaining cutting-edge ANPR systems might be a barrier [5].

G. Integration with Legacy Systems

The efficacy of ANPR may be restricted by difficulties integrating it with current systems and infrastructure[2].

VII. CONCLUSION & FUTURE SCOPE

This paper has thoroughly explored the development and implementation of Automated Number Plate Recognition (ANPR) systems, highlighting their significance in enhancing vehicle surveillance and public security[1]. Utilizing Faster R-CNN, a cutting-edge deep learning framework, ANPR systems have demonstrated a profound capability in accurately detecting and recognizing vehicle license plates under a variety of conditions[2]. Through detailed descriptions of the system's architecture, from image acquisition and pre-processing to the integration of Optical Character Recognition (OCR), this discussion underscores the technological sophistication and operational effectiveness of modern ANPR systems[3].

The future scope is that the automatic vehicle recognition system plays a major role in detecting threats to defence also it can improve the security related to women as they can easily detect the number plate before using a cab or other services[6]. The system robustness can be increased if a brighter and sharper camera is used withproper installation[7].

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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