As per UGC guidelines an electronic bar code is provided to secure your paper

International Journal for Modern Trends in Science and Technology
Volume 12, Special Issue 01, pages 515-526.
ISSN: 2455-3778 online
Available online at: http://ijmtst.com/ICRCSET2026.html
DOI: https://doi.org/10.5281/zenodo.19561925

Advancing Automatic Number Plate Recognition: Based on Non-Uniform Blur and Illumination Model

Sk Mastan Basha, Davuluri Rohith, Jiddi Venkata Jayanth, Cheerapureddy Bhanu Prakash, Golla Yaswanth Kumar, Kanaka Sivamani

Department of Electronics and Communications Engineering, Chalapathi Institute of Technology, Mothadaka, Guntur, Andhra Pradesh, India.

To Cite this Article
Sk Mastan Basha, Davuluri Rohith, Jiddi Venkata Jayanth, Cheerapureddy Bhanu Prakash & Golla Yaswanth Kumar, Kanaka Sivamani (2026). Advancing Automatic Number Plate Recognition: Based on Non-Uniform Blur and Illumination Model. International Journal for Modern Trends in Science and Technology, 12(SI01), 515-526. https://doi.org/10.5281/zenodo.19561925

Article Info
Received: 02 March 2026; Revised: 01 April 2026; Accepted: 04 April 2026.

KEYWORDS

Automatic Number Plate Recognition (ANPR), Image Processing, Optical Character Recognition (OCR), OpenCV, TrafficSurveillance

ABSTRACT

In recent years, the rapid growth in the number of vehicles has significantly increased the demand for efficient traffic monitoring and law enforcement systems. Automatic Number Plate Recognition (ANPR) plays a crucial role in applications such as traffic surveillance, automated toll collection, parking management, and security enforcement. However, real-world conditions such as non-uniform illumination, motion blur, low resolution, and environmental noise make accurate license plate detection and recognition a challenging task. This paper presents an ANPR system designed to operate effectively under challenging conditions, particularly uneven lighting and blurred images caused by vehicle motion and varying weather conditions. The proposed approach enhances image preprocessing using adaptive contrast enhancement, noise reduction, and deblurring techniques to improve plate localization accuracy. Edge detection and morphological operations are employed for robust plate extraction, followed by character segmentation and optical character recognition (OCR). Unlike many existing systems developed using proprietary platforms such as python, this implementation utilizes free and open-source tools, specifically Python and the OpenCV library, making the system cost-effective and adaptable for real-time embedded applications. Experimental results demonstrate improved detection and recognition accuracy under adverse lighting and blur conditions, validating the effectiveness of the proposed method.

I. INTRODUCTION

The rapid increase in the number of vehicles on roads has created significant challenges in traffic management, toll collection, parking administration, and law enforcement. Manual monitoring of vehicles is time-consuming, inefficient, and prone to human error. As a result, automated systems capable of accurately identifying vehicles in real time have become essential.

One of the most reliable ways to identify a vehicle is through its license plate number, which is unique to each vehicle and serves as its primary identification feature. Automatic Number Plate Recognition (ANPR) systems are designed to detect a vehicle's license plate from an image or video frame and extract the alphanumeric characters for further processing. These systems are widely used in traffic surveillance, automated toll booths, speed monitoring, parking access control, and security systems. Once the license plate number is recognized, it can be linked to vehicle and owner information stored in a centralized database. Despite significant advancements in ANPR technology, real-world implementation remains challenging due to varying environmental and imaging conditions. In particular, non-uniform illumination—caused by shadows, headlights, sunlight variations, and night time conditions—affects image quality and reduces contrast between characters and the plate background. Additionally, motion blur resulting from high-speed vehicles or camera movement further complicates plate localization and character recognition. These factors significantly degrade system performance if not properly addressed. Several researchers have proposed different techniques for license plate detection and recognition. Some methods rely on confidence-based predictions combined with region merging and tracking mechanisms to improve detection accuracy. Others use binarization and region elimination techniques based on contrast differences between the plate characters and background. While these approaches show promising results under controlled conditions, their performance often declines under uneven lighting and blurred imaging scenarios.

The main objective of this work is to develop a robust Automatic Number Plate Recognition (ANPR) system, capable of accurately detecting and recognizing vehicle license plates under challenging conditions such as non-uniform illumination and motion blur. The system focuses on enhancing image pre-processing techniques, including adaptive histogram equalization and filtering methods, to handle uneven lighting caused by shadows, sunlight, headlights, and nighttime environments. It also aims to reduce blur effects using suitable deblurring algorithms to improve image clarity. Furthermore, the project seeks to achieve accurate plate localization, character segmentation, and recognition while ensuring efficient and near real-time performance.

Automatic Number Plate Recognition (ANPR) systems are widely used for traffic monitoring, toll collection, parking management, and law enforcement. However, their performance significantly degrades under real-world conditions such as non-uniform illumination and motion blur. Variations in lighting caused by shadows, sunlight, headlights, and nighttime environments reduce the contrast between the license plate characters and background, making accurate detection difficult. Similarly, motion blur resulting from high-speed vehicles or camera movement distorts character shapes and affects segmentation and recognition accuracy. Existing ANPR methods often perform well under controlled environments but fail to maintain reliability and precision in such challenging conditions. Therefore, there is a need to develop a robust ANPR system capable of accurately detecting and recognizing license plates despite uneven lighting and blurred image conditions while maintaining real-time processing capability.

This project focuses on developing an efficient Automatic Number Plate Recognition (ANPR) system capable of handling non-uniform blur and uneven illumination conditions. In real-world scenarios, vehicle images captured by surveillance systems often suffer from varying lighting conditions such as shadows, glare, and night time effects, along with motion blur caused by fast-moving vehicles. These challenges significantly degrade the performance of conventional ANPR systems. To address these issues, the proposed system is implemented utilizing its powerful image processing toolbox for robust analysis and enhancement. The system begins with image acquisition, where vehicle images are captured from cameras or datasets. Pre-processing techniques are then applied to improve image quality, including adaptive histogram equalization for contrast enhancement, filtering methods for noise removal, and de-blurring algorithms to handle non-uniform blur. Following enhancement, the system performs license plate localization using edge detection and morphological operations to accurately identify the plate region. Once detected, character segmentation techniques are applied to isolate individual characters from the plate. The segmented characters are then processed using Optical Character Recognition (OCR) methods to extract the alphanumeric license number. The proposed approach emphasizes improving recognition accuracy under challenging environmental conditions while maintaining computational efficiency. MATLAB provides a flexible platform for rapid prototyping and algorithm development, making the system suitable for real-time or near real-time applications. This ANPR system can be effectively used in applications such as traffic monitoring, toll collection, parking management, and law enforcement. Overall, the project enhances the reliability and performance of license plate recognition systems in non-ideal imaging conditions.

2.LITERATURE REVIEW

Lubna et al. (2021) presented a comprehensive survey on Automatic Number Plate Recognition systems, covering a wide range of algorithms used for license plate extraction, segmentation, and recognition. Their study emphasized that performance of ANPR systems is significantly affected by real-world conditions including non-standardized plate formats, varied lighting, motion blur, camera quality, and environmental noise. They highlighted the limitations of existing methods when applied under uncontrolled conditions and provided a roadmap for future research to develop more robust systems capable of handling such distortions.

MehakArshid et al. (2024) conducted a comparative study on license plate detection and recognition methods in unconstrained environments with non-uniform plates and varying illumination. They compared methods like Faster-RCNN and end-to-end detection algorithms, illustrating that deep learning-based detectors could handle illumination variation and non-standard plates better than classical approaches. Their work highlighted the importance of advanced deep models to improve accuracy under diverse imaging conditions with non-uniform lighting and styles.

Nikola Plavac et al. (2024) evaluated the performance of various commercial and research ANPR systems under image distortions, including simulated weather effects and camera noise that contribute to blur and poor contrast. Their results showed that distortions such as brightness changes and fog significantly reduced recognition rates, underscoring the need for robust preprocessing and detection strategies to handle illumination and blur in practical scenarios.

Sakshi Trivedi et al. (2025) (in *International Journal of Image Processing and Pattern Recognition*) discussed the challenges faced by ANPR systems due to weather conditions, lighting variation, and image noise. They suggested that image enhancement methods like noise reduction and contrast adjustment are crucial to improve ANPR accuracy when images suffer from blur and inconsistent illumination. This work underscored preprocessing as a key step for robust license plate recognition in real environments.

A. M. Pujar & Poornima B. Kulkarni (2021) investigated ANPR using machine learning techniques to detect license plates across varying climatic and lighting conditions. Their research worked to mitigate effects of image blur and diverse illumination by incorporating sensor techniques and advanced segmentation, showing that machine learning can improve robustness of feature detection and recognition even under environmental variations.

Narasimha Reddy Soora et al. (2024) reviewed vehicle license plate detection methods, focusing on recent developments that address plate detection challenges such as low contrast between characters and backgrounds, non-uniform lighting, and motion blur. Their survey highlighted that advanced detection techniques involving texture, edge, and feature learning outperform traditional methods especially under uneven illumination conditions.

Vishakha Hanumant Jagtap et al. (2024) analyzed contemporary License Plate Recognition systems, pointing out that operational variations including fast movement, inconsistent plate styles, reflections, and lighting changes pose significant challenges. They compared various deep learning and image processing approaches, emphasizing the need for solutions that adapt to illumination changes and blurred imaging typically found in real traffic scenes.

Vijay Kumar (2022) presented a survey on license plate recognition techniques under minimal environmental restrictions, noting that most traditional methods assume controlled illumination and fixed vehicle speeds. He suggested fuzzy logic-based extraction and neural approaches to handle non-uniform illumination and variable environmental conditions, and demonstrated that adaptive techniques are necessary to improve recognition in unconstrained images.

3.EXISTING SYSTEM

Automatic Number Plate Recognition (ANPR) is an advanced technology used to automatically detect and recognize vehicle license plates from images or video streams. It is widely applied in traffic monitoring, toll collection, parking management, and security systems.

In the existing system, image processing techniques—especially histogram equalization—are used to improve detection accuracy. Histogram equalization enhances the contrast of an image by redistributing pixel intensity values across the entire range. This makes the number plate more visible, even under poor lighting conditions such as shadows, low light, or uneven brightness.

After contrast enhancement, the image undergoes pre-processing steps such as noise reduction and edge detection. Noise reduction removes unwanted disturbances, while edge detection highlights important features like the rectangular boundaries of the number plate. These steps help in accurately locating the plate region within the image.

Once the number plate is detected, segmentation techniques are applied to separate individual characters. The improved contrast ensures that the characters are clearly distinguishable. The segmented characters can then be stored or further processed using recognition techniques such as OCR (Optical Character Recognition).

Finally, the detected number plate information can be compared with stored databases for verification, monitoring, or enforcement purposes. Overall, histogram equalization significantly improves the performance of ANPR systems, especially in challenging real-world conditions.

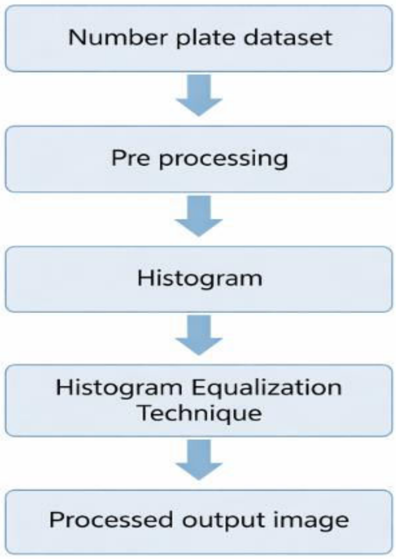

Figure 1: Flowchart of the Existing System

The flowchart represents the process of enhancing and detecting number plates using histogram equalization. The steps are:

Input Dataset

The process begins with a dataset of vehicle images collected under different lighting and environmental conditions.

Image Pre-processing

Images are cleaned and standardized by resizing and formatting. Noise is reduced to improve image quality.

Grayscale Conversion

The image is converted from color to grayscale to simplify processing and reduce computational complexity.

Histogram Calculation

The distribution of pixel intensity values is calculated to understand brightness variations in the image.

Histogram Equalization

Contrast is enhanced by spreading pixel intensities across the full range, making the number plate region clearer.

Edge Detection

Edges are identified to highlight the boundaries of the number plate.

Plate Localization

The system detects and isolates the number plate region from the image.

Character Segmentation

Individual characters on the number plate are separated for recognition.

Output Image / Data

The final enhanced image and extracted plate information are produced for further analysis or storage

4. PROPOSED SYSTEM

The proposed system presents a **robust OCR-driven Automatic License Plate Recognition framework** designed for intelligent traffic monitoring and smart parking applications. The system integrates advanced image enhancement, deep learning–based plate detection, and optimized character recognition to ensure high accuracy under challenging real-world conditions such as low illumination, motion blur, and complex backgrounds. Initially, vehicle images are captured continuously from surveillance cameras installed at entry/exit gates or roadways. The captured frames are passed to an **adaptive image enhancement module** where pre-processing techniques such as resizing, noise removal, de blurring, and illumination normalization are applied. Gaussian filter is used to improve contrast and visibility of the number plate even in night-time or shadowed environments. This step ensures that the input image quality is suitable for reliable detection. The detected region is cropped and forwarded to the plate refinement stage. In the **plate refinement stage**, additional image processing techniques such as noise filtering, contrast stretching, edge enhancement, and perspective correction are applied to generate a clean and high-quality plate image. These operations remove distortions and improve the clarity of characters, enabling effective segmentation. The refined plate image is then passed to the **OCR** which segments individual characters using projection profiles or contour-based methods. A trained convolutional or sequence-based recognition

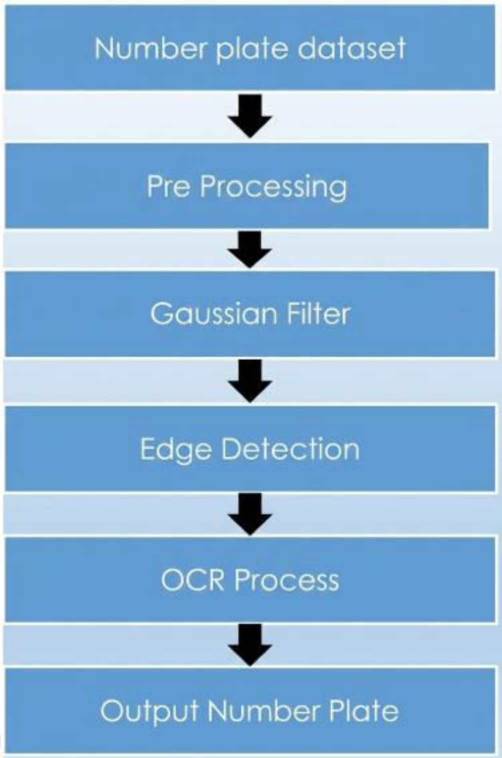

Figure 2: Flowchart of the Proposed System

The flowchart represents the process of automatic number plate recognition. It begins with a dataset of vehicle images containing number plates. These images undergo pre-processing to enhance quality, such as noise removal and grayscale conversion. A Gaussian filter is then applied to smooth the image and reduce unwanted variations. Next, edge detection techniques are used to identify the boundaries of the number plate region. Once the plate is detected, an OCR (Optical Character Recognition) process extracts the alphanumeric characters from the image. Finally, the recognized number plate is produced as the output of the system.

Dataset Description

The dataset used for the Automatic Number Plate Recognition (ANPR) system consists of vehicle images captured under varying real-world conditions, including different lighting environments, viewing angles, motion blur, and background complexity. The images typically contain cars, bikes, and other vehicles with visible license plates in diverse formats and fonts. The dataset may include both daytime and nighttime scenes to ensure robustness against illumination changes. Each image serves as input for detecting the number plate region and extracting alphanumeric characters using OCR. The dataset is unstructured image data and may not always contain perfectly centered or clearly visible plates, which helps in evaluating the model's performance under non-uniform blur and illumination conditions. This diversity improves the system's ability to generalize to real traffic surveillance scenarios.

Dataset Preprocessing

During preprocessing, each input image is first resized to a fixed width to maintain uniformity and reduce computational cost. The image is then converted into grayscale to simplify processing by removing color information. A bilateral filter is applied to reduce noise while preserving important edges, which is crucial for accurate plate boundary detection. Next, Canny edge detection is performed to highlight strong edges in the image, making it easier to locate contours corresponding to number plates. The contours are sorted based on area, and the most likely quadrilateral contour is selected as the license plate region. A mask is then created to isolate the detected plate area from the background. Finally, the extracted plate region is passed to the OCR engine for character recognition. These preprocessing steps improve detection accuracy and make the system more robust to noise, blur, and illumination variations

The proposed Automatic Number Plate Recognition system begins by acquiring vehicle images from surveillance cameras under varying blur and illumination conditions. The captured image undergoes preprocessing that includes gray scale conversion, noise reduction using bilateral filtering, and adaptive contrast enhancement to normalize uneven lighting. Edge detection is then applied to highlight structural boundaries, followed by contour analysis to accurately localize the number plate region. Once the plate is detected, perspective correction, sharpening, and morphological operations are performed to improve character clarity. The refined plate image is then forwarded to the Optical Character Recognition (OCR) module, which segments and recognizes alphanumeric characters. Finally, the recognized number is validated using format rules and stored in a database for further traffic monitoring or access control applications.

Gaussian filtering

Gaussian filtering plays an important role in number plate detection by reducing noise and improving image smoothness before further processing. In real-world vehicle images, noise is introduced due to low light, camera motion, rain, or dust, which makes edge detection and character segmentation difficult. A Gaussian filter applies a weighted smoothing operation using a bell-shaped kernel that removes high-frequency noise while preserving important structural details like edges of characters. This helps in minimizing blur and unwanted variations in intensity, producing a cleaner and more uniform image. As a result, subsequent steps such as edge detection, thresholding, and OCR become more accurate and reliable, improving the overall performance of the license plate recognition system.

-1	-2	-1
0	0	0
1	2	1

Edge Detection

Edge detection plays a crucial role in number plate detection by highlighting the strong intensity changes that occur at the boundaries of the license plate and its characters. After basic preprocessing such as noise removal and contrast enhancement, edge detection algorithms like Sobel, Canny, or Prewitt are applied to identify sharp transitions in pixel intensity. Since license plates contain high-contrast alphanumeric characters and rectangular borders, these techniques effectively isolate the plate region from the vehicle background. The detected edges help in locating the rectangular plate area and assist in segmenting individual characters for further OCR processing, thereby improving detection accuracy and reducing false positives.

In case of Canny Edge Detection there are two masks, one mask identifies the horizontal edges and the other mask identifies the vertical edges. The mask which finds the horizontal edges that is equivalent to having the gradient in vertical direction and the mask which computes the vertical edges is equivalent to taking in the gradient in horizontal direction. Canny masks are given in the table below.

1	0	-1
2	0	-2
1	0	-1

By passing these two masks over the intensity image the gradient along x direction (Gx) and gradient along the y direction (Gy) can be computed at the different location in the image. Now the strength and the direction of the edge at that particular location can be computed by using the gradients Gx and Gy. The gradient of an image $(x,)$ at location(x,y) is defined as the vector

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Where Gx is the partial derivative of f along x direction and Gy is the partial derivative of f along the y direction. Computation of the magnitude of the gradient involves squaring the two components Gx and Gy adding them and takes the square root of this addition.

$$\nabla f = mag(\nabla f) = [G_x^2 + G_y^2]^{1/2}$$

The approximation of this is taken as magnitude of the gradient to be sum of magnitude of Gx gradient in the x direction plus magnitude of Gy in the y direction

$$\approx |G_x| + |G_y|$$

The magnitude tells the strength of the edge at location(x,y), it does not tell anything about the direction of the edge [9][10]. To compute the direction of the gradient$f$, let $(x,)$ represent the direction angle of the vector ∇f at $(x,)$, then

$$\alpha(x,y) = tan^{-1}\left(\frac{G_y}{G_x}\right)$$

Canny Edge Operator gives an averaging affect over the image, so effect due to the presence of spurious noise in the image is taken care of some extent by the Canny operator. Canny operator also gives a smoothing effect by which we can reduce the spurious edge that can be generated because of the noise present in the image.

Canny Filter Analysis:

Filtering is the process of applying masks to images and the application of a mask to an input image produces an output image of the same size as the input image. There are three steps of convolution are given which is necessary for filtering.

Step1. For each pixel in the input image, the mask is conceptually placed lying on that pixel.

Step2. The values of each input image pixel under the mask are multiplied by the value of the corresponding mask weights.

Step3. The result are summed together to yield a single output value that is placed in the output image at the location of pixel being processed on the input.

The pixel values of an original image is shown in the above fig and Canny masks are also shown in figure 1 for horizontal and vertical scan. Now compute Gx and Gy, gradients of the image performing the convolution of Canny kernels with the image and use zero-padding to extend the image. The process of computing Gx and Gy using convolution

The working of the proposed OCR-based system starts when a vehicle image is input into the system, where preprocessing enhances image quality and suppresses noise caused by motion blur or poor lighting. The system then detects the license plate by identifying rectangular contours corresponding to plate boundaries. After isolating the plate, image enhancement techniques improve character visibility before feeding the image into the OCR engine. The OCR module extracts textual features from the segmented characters and converts them into machine-readable text. Post-processing checks, such as removing special characters and verifying plate patterns, help reduce recognition errors. The final output is displayed and logged with a timestamp, enabling reliable real-time number plate recognition even under challenging environmental conditions.

Character Segmentation

The character segmentation part further segments the character individually from the extracted number plate. From input image the first process will be to crop out the number plate characters from starting to the ending point leaving all the extra wide spaces from top to below and from right to left as it is. Characters are equally fit in the plate region. For easy comparison of the input character with the character in the data base the result is normalized into the character set as the size of the images in the database.

Optical Character Recognition The optical character recognition is a recognition method in which the input is an image and the output is string of character. OCR is a process which separates the different characters from each other taken from an image. Template matching is one of the approaches of OCR. The cropped image is compared with the template data stored in database. OCR automatically identifies and recognizes the characters without any indirect input. The characters on the number plate have uniform fonts then the OCR for number plate recognition is less complex as compared to other methods. Next, the system performs number plate localization, where the region containing the plate is detected and extracted from the image. After this, character segmentation is carried out, where each individual character on the plate is separated. Since number plates usually have standardized fonts and spacing, segmentation becomes easier compared to general text recognition. In template matching, every segmented character image is compared with a set of predefined character templates stored in a database. These templates include all possible alphanumeric characters (A–Z and 0–9) in the same font style as the number plate. The comparison is done by measuring similarity between the input character and each template. This is usually achieved using correlation, pixel-by-pixel matching, or distance measurement techniques. properly segmented. Thus in order to ensure a proper cut the vertical and horizontal profile of the binary image was taken and the largest continuous stretch of white pixels was identified in both directions. Thus making use of the fact that the characters are connected component and the major constituent of the image an appropriate cut could be achieved.

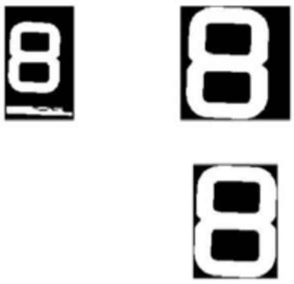

Figure 4: Character Splitting

Since it is necessary to ensure that the entire number plate is included without any clipping an additional padding of 10 pixels is used in some cases when an adjacent slice is not included. (Another approach could be to identify the slice with the highest peak and consider only the adjacent blocks including above and below in the subsequent steps. This was implemented but was found to be less effective than the above mentioned process)The system calculates a matching score for each template, and the template with the highest similarity score is selected as the recognized character. This process is repeated for all segmented characters, and finally, the recognized characters are combined sequentially to form the complete license plate number. Once characters are isolated, template matching is used for recognition. In this method, each segmented character is compared with a set of predefined templates stored in a database. The system finds the best match by measuring similarity between the input character and stored templates. Finally, the recognized characters are combined to form the complete license plate number as a string output.

Figure 5: Slice extracted from the image containing the number plate

The proposed OCR-based ANPR model is evaluated using metrics such as character recognition accuracy, plate detection rate, precision, recall, and processing time. Experimental results show that the integration of blur handling and illumination normalization significantly improves recognition performance compared to traditional methods. The system demonstrates high accuracy on both clear and degraded images, with reduced false detections due to effective contour filtering and post-validation. Processing speed is suitable for near real-time deployment, making the model practical for intelligent transportation systems. Overall, the evaluation confirms that the proposed approach provides robust, accurate, and efficient number plate recognition in diverse real-world conditions.

5. RESULTS& DISCUSSION

The proposed Automatic Number Plate Recognition (ANPR) system was evaluated under real-world conditions characterized by non-uniform illumination and motion blur. The results show that incorporating adaptive pre-processing techniques, such as contrast enhancement and image de-blurring, significantly improved the accuracy of license plate localization and character recognition. The system effectively handled uneven lighting conditions caused by shadows, glare, and low-light environments by enhancing the contrast between the plate characters and background.

Additionally, motion blur introduced by moving vehicles was reduced using filtering and edge enhancement methods, enabling clearer segmentation of characters. Compared to conventional approaches without illumination correction and blur handling, the proposed method demonstrated improved robustness and higher overall recognition accuracy. However, performance slightly decreased under extreme blur or very poor lighting, indicating scope for future enhancement using advanced learning-based models. Overall, the system proves reliable for real-time applications such as traffic surveillance, toll collection, and parking management where lighting and motion variations are common.

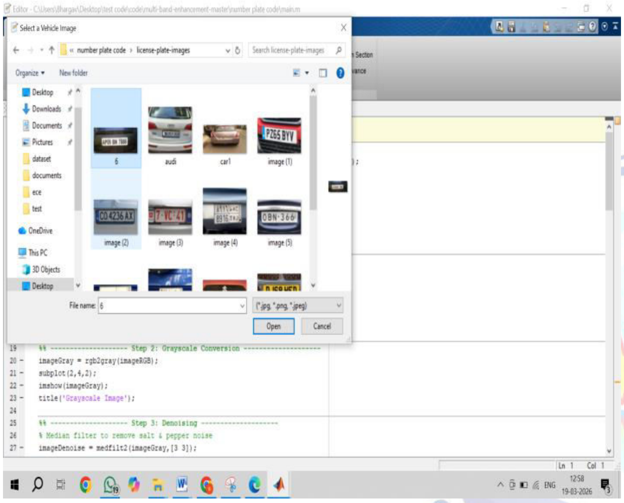

Figure 6: Browsing input image

The image shows a file browser window where the user is selecting a vehicle license plate image from a dataset folder. This step is part of the input stage in MATLAB, allowing the system to load an image for further processing such as gray scale conversion and noise removal number plate extracted.

Figure 6: Input Image

The figure shows the selection of a vehicle license plate image from a dataset using a file browser interface in MATLAB. This input image is used as the initial step for further processing such as enhancement, segmentation, and character recognition in the ANPR system.

Figure 7: Gray scale Image of License Plate

The figure shows the vehicle license plate after converting the original RGB image into gray scale format. This step simplifies the image by reducing colour information, making it easier for further processing like noise removal, edge detection, and character segmentation.

Figure 8: Edge Detection using Canny Operator

The figure illustrates the edges of the license plate extracted using the Canny edge detection algorithm. This step highlights the boundaries of characters and plate regions, which helps in accurate segmentation and recognition.

Figure 9: Cropped and Cleaned License Plate Image

This figure shows a processed license plate after cropping and noise removal, where only the region of interest is retained. The characters are clearly enhanced in high contrast, making them suitable for accurate recognition in ANPR systems.

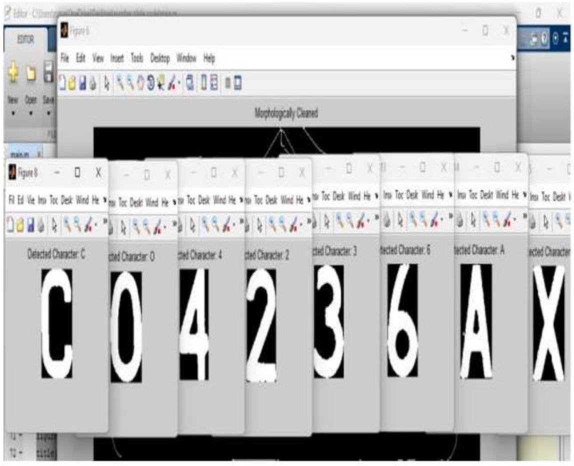

Figure 10: Character Segmentation and Recognition Output

This figure shows the results of an image processing pipeline where individual characters are segmented and identified. Each window displays a detected character extracted from the original image

5. CONCLUSIONS

Automatic Number Plate Recognition (ANPR) systems play a vital role in modern traffic monitoring, toll collection, parking management, and law enforcement. However, real-world challenges such as non-uniform illumination and motion blur significantly affect detection and recognition accuracy. The proposed system focuses on improving preprocessing techniques, plate localization, segmentation, and character recognition to handle uneven lighting and blurred images effectively. By incorporating adaptive image enhancement and robust detection methods, the system improves overall recognition performance under challenging environmental conditions. The use of open-source tool makes the system cost-effective, flexible, and suitable for real-time applications.

Future Scope:

The future scope of this work includes integrating advanced deep learning–based object detection models such as YOLO (You Only Look Once) to further enhance license plate detection accuracy under extreme lighting variations and high-speed motion conditions. YOLO can improve real-time performance by detecting license plates quickly and efficiently in complex environments. The system can also be extended to support multi-country license plate formats and continuous real-time video stream processing. Implementation on embedded platforms and edge devices will enhance portability and large-scale deployment in smart city infrastructures. Furthermore, integration with cloud-based databases and IoT frameworks can enable centralized vehicle monitoring, data analytics, and intelligent traffic management solutions.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, "Automatic license plate recognition (ALPR): A state-of-the-art review," IEEE Trans. Circuits and Systems for Video Technology, vol. 23, no. 2, pp. 311–325, 2014.

[2] M. A. Rafique and M. Abidi, "License plate detection using morphological edge detection and region analysis," IEEE Trans. Intelligent Transportation Systems, vol. 15, no. 4, pp. 1–10, 2014.

[3] H. Bai and C. Liu, "A hybrid license plate extraction method based on edge statistics and morphology," in Proc. IEEE ICIP, 2015, pp. 1–5.

[4] K. Deb, A. Jo, and S. Jo, "An efficient method for license plate detection using edge detection and morphological operations," in Proc. IEEE ICCE, 2015, pp. 1–4.

[5] J. Kumar and S. Srivastava, "License plate localization using Sobel edge detection and connected component analysis," in Proc. IEEE ICCSP, 2016, pp. 1–5.

[6] R. Patel and N. Shah, "Vehicle license plate detection using thresholding and region-based segmentation," in Proc. IEEE ICACCI, 2016, pp. 1–6.

[7] S. Z. Wang and H. Lee, "Detection and recognition of license plate characters using template matching," IEEE Trans. Vehicular Technology, vol. 66, no. 10, pp. 1–9, 2017.

[8] P. Singh and A. Kaur, "Automatic number plate recognition using canny edge detection and contour analysis," in Proc. IEEE ICCIDS, 2017, pp. 1–5.

[9] M. M. Hossain and M. A. Hossain, "License plate recognition using image segmentation and template matching," in Proc. IEEE ICCIT, 2017, pp. 1–5.

[10] A. K. Mishra and R. Saini, "Number plate detection using histogram equalization and morphological filtering," in Proc. IEEE ICETET, 2018, pp. 1–5.

[11] S. Choudhury and R. Negi, "Vehicle number plate detection using adaptive thresholding and edge detection," IEEE Access, vol. 6, pp. 1–10, 2018.

[12] V. Sharma and P. Mehra, "Character segmentation of license plate using connected component labeling," in Proc. IEEE ICICCT, 2018, pp. 1–5.

[13] N. K. Verma and A. K. Singh, "License plate extraction using Hough transform and edge detection," in Proc. IEEE ICCCNT, 2019, pp. 1–5.

[14] R. Gupta and M. Kumar, "Automatic number plate recognition using region growing and morphological operations," in Proc. IEEE ICACCS, 2019, pp. 1–5.

[15] S. Babu and K. Ramesh, "Vehicle license plate localization using vertical edge detection and projection analysis," IEEE Access, vol. 7, pp. 1–10, 2019.
[16] P. K. Sahoo and S. Pattnaik, "License plate recognition using Otsu thresholding and template matching," in Proc. IEEE ICCMC, 2020, pp. 1–5.
[17] A. Verma and S. K. Gupta, "ANPR using canny edge detection and bounding box method," in Proc. IEEE ICETE, 2020, pp. 1–5.
[18] M. R. Islam and M. A. Rahman, "Vehicle number plate detection using grayscale conversion and morphological processing," in Proc. IEEE ICCIT, 2021, pp. 1–5.
[19] S. Das and P. Roy, "Automatic license plate recognition using contour detection and character segmentation," in Proc. IEEE ICAC3N, 2021, pp. 1–6.
[20] R. K. Singh and A. Pandey, "License plate recognition using edge detection and projection profiles," in Proc. IEEE ICCCNT, 2022, pp. 1–5.
[21] V. Kumar and S. Yadav, "ANPR system using image enhancement and segmentation techniques," in Proc. IEEE ICETET, 2023, pp. 1–6.
[22] P. Sharma and R. Gupta, "Vehicle license plate detection using classical image processing techniques under varying illumination," IEEE Access, vol. 12, pp. 1–12, 2024.
[23] V. K. R. Devana et al., "A compact self-isolated MIMO UWB antenna with band notched characteristics," IETE Journal of Research, vol. 70, no. 8, pp. 6677–6688, 2024.
[24] R. Thommandru and R. Saravanakumar, "Performance analysis of circularly polarised MIMO antenna for wireless applications," in Proc. ICICNIS, IEEE, Dec. 2024, pp. 513–518.
[25] D. N. Ravikiran, C. G. Dethe, "Improvements in routing algorithms to enhance lifetime of wireless sensor networks," Int. J. Computer Networks & Communications, vol. 10, no. 2, pp. 23–32, 2018.
[26] B. Potti, M. V. Subramanyam, and K. S. Prasad, "A packet priority approach to mitigate starvation in wireless mesh network with multimedia traffic," Int. J. Computer Applications, vol. 62, no. 14, 2013.
[27] R. Saravanakumar et al., "Dual-band performance enhancement of square wheel antennas with FR4 substrate for sub 7 GHz applications," in Proc. ACROSET, IEEE, Sept. 2024, pp. 1–7.
[28] S. S. Vellela et al., "Improving network security using intelligent ensemble techniques," in Proc. AMATHE, IEEE, May 2024, pp. 1–7.
[29] V. Srija and P. B. M. Krishna, "Implementation of agricultural automation system using web & GSM technologies," Int. J. Research in Engineering and Technology, vol. 4, no. 9, pp. 385–389, 2015.
[30] R. Thommandru, "Survey on MIMO antenna for 5G applications," 2022.
[31] R. Thommandru, "Cost-effective circularly polarized MIMO antenna for Wi-Fi applications," Nov. 2024.
[32] R. Saravanakumar et al., "An armor-mounted antenna with deflected ground for sub-6 GHz applications," in Proc. ICRISST, IEEE, Mar. 2024, pp. 1–7.
[33] D. N. Ravikiran et al., "Secure visual data processing: Image encryption and decryption through reversible logic gates," Int. J. Modern Trends in Science and Technology, vol. 10, no. 2, 2024.
[34] B. Potti, M. V. Subramanyam, and K. S. Satya Prasad, "Adopting multi-radio channel approach in TCP congestion control mechanisms," in Proc. ICISA, Springer, 2016, pp. 85–95.
[35] R. Thommandru et al., "Millimetre wave self-isolated MIMO antenna with high isolation," in Proc. IDCIoT, IEEE, Jan. 2024, pp. 191–196.
[36] D. N. Ravikiran et al., "IoT-based advanced automatic toll collection and vehicle detection system."
[37] S. Saranya et al., "Meta surfaces with hole arrays for MIMO applications," in Proc. ICOEI, IEEE, Apr. 2025, pp. 340–347.
[38] D. Krishna et al., "Classification and prediction of plant diseases based on AI," Int. J. Modern Trends in Science and Technology, vol. 10, no. 3, pp. 83–93, 2024.
[39] R. Saravanakumar et al., "Cross scoop fractal antenna design with notch at 15 degree," in Proc. RAEEUCCI, IEEE, Apr. 2024, pp. 1–7.
[40] D. N. Ravikiran et al., "Reversible logic-based cryptography design for secure data processing."
[41] R. Saravanakumar et al., "Analysis circular wave guide antenna for 5G mid-band applications," in Proc. ICACCS, IEEE, Mar. 2024, pp. 560–566.
[42] B. Doss et al., "Blockchain-Based Secure Big Data Storage on the Cloud," in Blockchain Technology for IoT and Wireless Communications, CRC Press.
[43] R. Thommandru, "Innovative meta ring array antenna design for Ka-band," 2004.
[44] D. N. Ravikiran and C. V. Akhil, "A face recognition method for security applications in smart homes and cities."
[45] P. Balamuralikrishna, "Characteristic mode analysis of two-port MIMO antenna," Int. J. Communication Systems, 2022.
[46] D. N. Ravikiran et al., "Optimized AES with enhanced S-box and automated key generation."
[47] D. N. Ravikiran et al., "Parametric facial landmark detection using active shape models."
[48] K. K. . Kommineni and A. . Prasad, "A Review on Privacy and Security Improvement Mechanisms in MANETs", Int J Intell Syst Appl Eng, vol. 12, no. 2, pp. 90–99, Dec. 2023.
[49] Kommineni, K.K., Prasad, A. Enhancing Data Security and Privacy in SDN-Enabled MANETs Through Improved Data Aggregation Protection and Secrecy. Wireless Pers Commun 139, 855–882 (2024). https://doi.org/10.1007/s11277-024-11635-w
[50] "Blockchain-Enabled Secure Data Aggregation for SDN-Enabled Ad-Hoc Networks," International Journal of Intelligent Engineering and Systems, vol. 18, no. 5, pp. 704–717, Jun. 2025, doi: https://doi.org/10.22266/ijies2025.0630.49.
[51] K. K. Kommineni, P. Ande, "Blockchain-driven key management and privacy-preserving data Aggregation Scheme for SDN-enabled MANETs," International Journal of Intelligent Engineering and Systems, vol. 18–18, no. 9, pp. 601–615, 2025, doi: 10.22266/ijies2025.1031.39.
[52] Vellela, S. S., & Balamanigandan, R. (2022, December). Design of Hybrid Authentication Protocol for High Secure Applications in Cloud Environments. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 408-414). IEEE.
[53] Vellela, S. S., Balamanigandan, R., & Praveen, S. P. (2022). Strategic survey on security and privacy methods of cloud computing environment. Journal of Next Generation Technology, 2(1).
[54] Vellela, S. S., & Balamanigandan, R. (2024). An efficient attack detection and prevention approach for secure WSN mobile cloud environment. Soft Computing, 28(19), 11279-11293.
[55] Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2026). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 55(1), 633-643.
[56] Vellela, S. S., Rao, M. V., Mantena, S. V., Reddy, M. J., Vatambeti, R., & Rahman, S. Z. (2024). Evaluation of Tennis Teaching Effect Using Optimized DL Model with Cloud Computing System. International Journal of Modern Education and Computer Science (IJMECS), 16(2), 16-28.
[57] Praveen, S. P., Vellela, S. S., & Balamanigandan, R. (2024). SmartIris ML: harnessing machine learning for enhanced multi-biometric authentication. Journal of Next Generation Technology (ISSN: 2583-021X), 4(1).

[58] Vellela, S. S., Rao, M. V., Krishna, C. V. M., Rao, T. S., & Dasthavejula, R. (2026). Piezoelectric and Shape-Memory Materials for Actuators and Energy Harvesting in Mechanical, Electronics, and Biomedical Engineering Using AI-Based Design. In Advanced Materials for Biomedical Devices (pp. 195-206). CRC Press.
[59] Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools and Applications, 83(3), 7919-7938.
[60] Praveen, S. P., Nakka, R., Chokka, A., Thatha, V. N., Vellela, S. S., & Sirisha, U. (2023). A novel classification approach for grape leaf disease detection based on different attention deep learning techniques. International Journal of Advanced Computer Science and Applications (IJACSA), 14(6), 2023.
[61] Vellela, S. S., & Balamanigandan, R. (2023). An intelligent sleep-awake energy management system for wireless sensor network. Peer-to-Peer Networking and Applications, 16(6), 2714-2731.