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Automatic License Plate Recognition (ALPRON) Using Optical Character Recognition Method

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ABSTRACT

Manual parking systems are prone to inefficiencies and human error, especially with increasing vehicle density. This study proposes ALPRON, an automatic license plate recognition system using Optical Character Recognition (OCR) to automate motorcycle parking management. The system integrates Raspberry Pi 4, USB cameras, and Tesseract OCR to detect and recognize license plates in real-time. Performance testing was conducted under varying distances, lighting intensities, and camera angles. The results show that the system achieves a peak recognition accuracy of 98.75% at 70 cm, in bright lighting, and a 0° camera angle. These findings suggest that ALPRON is a potentially cost-effective and efficient solution for smart parking applications, particularly in controlled campus environments. While current limitations include daylight dependency and difficulty recognizing skewed angles plates, future improvements will address these through infrared support and deep learning enhancements.

I. INTRODUCTION

In recent years, the advancement of digital technology has transformed how intelligent systems are deployed in public service sectors, including vehicle parking management. Manual parking systems, which require human input for license plate recording, are prone to human error, time inefficiency, and are often inadequate for high-traffic environments. As vehicle ownership increases globally, the need for efficient, real-time, and automated solutions becomes critical.

Automatic Number Plate Recognition (ANPR) is an emerging technology that utilizes digital image processing and Optical Character Recognition (OCR) to automatically identify vehicles based on their license plate images. The integration of ANPR systems into intelligent transportation infrastructure has been widely explored in law enforcement, toll collection, and security access systems [1], [2], [3], [4], [5]. ANPR systems generally consist of a digital camera, a processing unit, and software capable of detecting, segmenting, and recognizing license plate characters [6], [7]. OCR technology, particularly when combined with real-time image processing, allows the system to convert alphanumeric characters into digital text that can be stored, verified, and used for automated decisions [8].

Numerous studies have examined the development and deployment of ANPR systems. For instance, Sugeng and Syamsuddin [2] implemented an ANPR prototype using K-Nearest Neighbour (K-NN) algorithms on a Raspberry Pi, while Sheeba et al. [3] proposed an IoT-based approach for license plate extraction. Michael [1] used neural networks and the Viola-Jones method for mobile-based plate recognition, and Solichin and Rahman [6] applied Learning Vector Quantization on mobile platforms. Ranglani and Lachwani [7] presented a modular ANPR model utilizing OCR for character recognition. Although these studies demonstrate significant advancements, many of them are limited in terms of real-time performance under varying lighting and environmental conditions, especially in outdoor motorcycle parking scenarios.

Several technical challenges persist in existing systems. First, most implementations are optimized for four-wheeled vehicles and require high-power processing units or expensive infrastructure, which are not feasible in low-cost environments such as campus motorcycle parking lots. Second, recognition accuracy can significantly drop under low-light conditions or when license plates are partially obstructed. Third, limited studies address seamless integration with user-side applications such as QR-based verification and mobile notifications for parking access.

To address these challenges, this research introduces ALPRON (Automatic License Plate Recognition), a low-cost, embedded ANPR solution using Raspberry Pi 4 and an ELP USB camera, integrated with OCR technology and IoT components for real-time motorcycle plate detection and gate control. Unlike prior systems, ALPRON focuses on affordable hardware, minimal computational overhead, and accuracy across various operational conditions such as lighting intensity, camera angle, and distance. The system also features a user-friendly mobile interface with QR verification and real-time notification services, adding practical value in small-to-medium-scale parking facilities.

The novelty of this research lies in its context-specific focus on two-wheeled vehicle recognition within academic parking facilities, with improved efficiency and detection reliability. Additionally, the system demonstrates the practical fusion of OCR, embedded computing, and user interface integration. This addresses a gap in existing literature, particularly in the context of embedded, real-time ANPR systems for two-wheeled vehicle parking.

The objective of this study is to design, implement, and evaluate an OCR-based vehicle plate detection system (ALPRON) using Raspberry Pi to enhance automated parking operations, particularly for motorcycle parking scenarios with limited infrastructure.

II. METHOD

This research employs an applied research design to develop a real-time Automatic License Plate Recognition (ALPRON) system using Optical Character Recognition (OCR) for detecting two-wheeled motorcyle license plates, with testing conducted in a controlled campus parking environment. The research process follows sequential stages commonly adopted in applied system design methodologies for ANPR systems, ensuring a systematic development pipeline.

A. Research Chronology

The research chronology is shown in Figure 1.

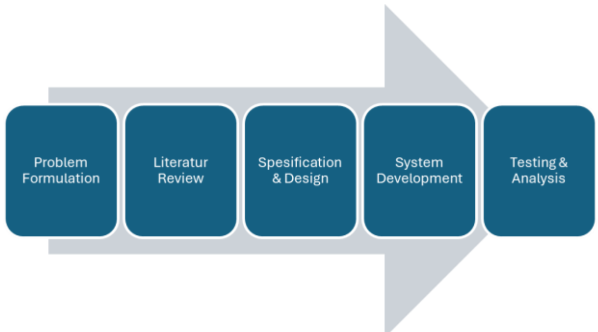


Figure 1. Research Chronology

The design and development of ALPRON followed a structured sequence beginning with the formulation of the problem, which involved identifying inefficiencies in existing manual parking systems. This was followed by a comprehensive literature review focusing on Automatic Number Plate Recognition (ANPR), Optical Character Recognition (OCR), and embedded systems, providing the theoretical foundation for the proposed solution. Based on this foundation, the next phase involved defining system specifications and designing both hardware and software components necessary for real-time OCR performance. The system was then developed through the implementation of integrated modules for license plate recognition, QR code verification, and automatic barrier control, with adjustments made iteratively based on testing outcomes. Subsequently, a series of tests were conducted to measure detection accuracy under varying distances, camera angles, and lighting conditions. Finally, the system's performance was analysed by evaluating recognition rates and system responsiveness across different environmental scenarios.

B. OCR Algorithm Design

The core of the system uses Tesseract OCR integrated with Python (via Pytesseract library). The OCR pipeline is shown in Figure 2.

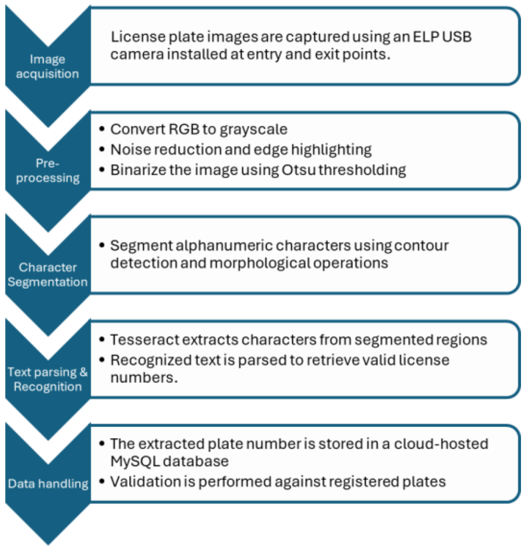


Figure 2. The OCR Pipeline

The OCR pipeline implemented in ALPRON begins with image acquisition, where license plate images are captured using an ELP USB camera positioned at the vehicle entry and exit points. The captured images undergo a series of pre-processing steps, including conversion from RGB to grayscale, application of Gaussian blur and Laplacian edge detection to reduce noise and enhance edges, and binarization using Otsu thresholding to isolate character regions effectively [9]. The image at each stage of image pre-processing can be seen in Figure 3.

(a) grayscale (b) binarization (c) extracted

Figure 3. Pre-processing image

Following pre-processing, character segmentation is performed by detecting contours and applying morphological operations to extract individual alphanumeric characters. These segmented characters are then processed through the Tesseract OCR engine, which recognizes and parses the text to retrieve valid license plate numbers. Finally, the extracted plate data is transmitted to a cloud-based MySQL database for storage and validated against a list of registered vehicle plates to determine access eligibility.

C. System Architecture

The architecture of ALPRON is shown in Figure 4.

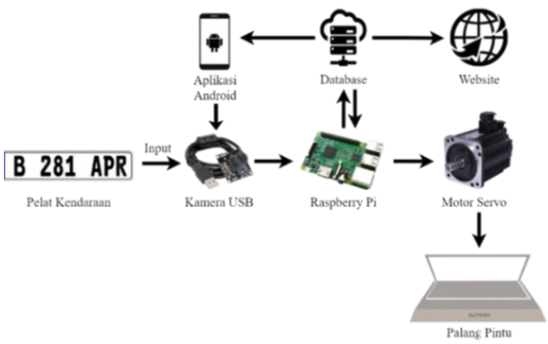


Figure 4. Architecture ALPRON System [10]

The implementation of ALPRON integrates various hardware components designed to support real-time license plate recognition and parking access control. At the core of the system is the Raspberry Pi 4 Model B, which serves as both the processing unit and server, coordinating data flow between sensors, image processing modules, and the database. License plate images are captured using ELP 5MP USB cameras strategically placed at entry and exit points. Vehicle detection is facilitated by infrared proximity sensors, which trigger image acquisition upon vehicle presence. To control physical access, the system employs an MG996R servo motor connected to a gate mechanism, while GM65 barcode scanners are used for QR code verification, primarily during exit operations. LED lights and buzzer modules offer visual and auditory feedback to guide user interaction during the parking process.

On the software side, Python is used to develop and manage core functionalities including image acquisition, OCR processing, and hardware interfacing. MySQL serves as the backend database to store recognized license plate data, user access logs, and validation records. Additionally, an Android-based mobile application complements the system by providing users with real-time notifications, entry-exit logs, and QR-based access credentials. Together, this hardware-software integration enables ALPRON to function as a low-cost, scalable, and user-friendly solution for automated parking systems.

D. Data and Analysis Techniques

The dataset consists of 80 annotated images of 15 dummy motorcycle license plates, each captured under varying distances, angles, and lighting conditions, and featuring diverse characteristics such as black-white backgrounds, province codes (e.g., BE, B, A), and alphanumeric lengths ranging from 6 to 9 characters. Images were captured under three lighting conditions: cloudy (~3,500 Lux), normal daylight (~6,800–7,000 Lux), and direct sunlight (>11,000 Lux). The camera distances were varied at 50 cm, 70 cm, and 100 cm. All images were obtained using an ELP 5 Megapixel USB camera and stored in .jpg format with a resolution of 1920 × 1080 pixels.

The system's performance was evaluated under controlled variations:

- ✓ Distance: Tested at 50 cm, 70 cm, and 100 cm.
- ✓ Lighting: Evaluated cloudy, bright, and very bright.
- ✓ Camera Angle: Varied from 0°, 15°, to 35°.

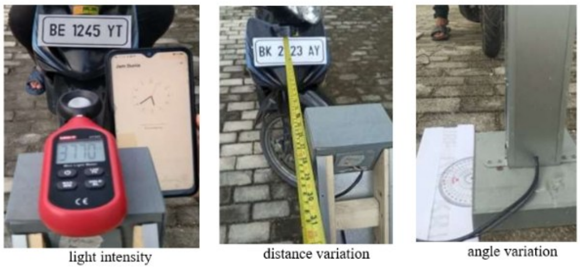
For each test scenario, the metrics measured include:

- ✓ Recognition Accuracy (%): Number of correctly recognized plates / Total test images × 100.
- ✓ Processing Time (s): Time taken from image capture to gate response.

Recognition Accuracy was computed on a plate-wise basis, where a plate was considered correctly recognized only if all characters were accurately identified. Analysis was conducted using descriptive statistics and compared with benchmark performance values reported in previous studies on OCR-based ANPR systems [1], [3], [7].

III. RESULT AND DISCUSSION

This section presents the experimental results and analysis of the Automatic License Plate Recognition (ALPRON) system, tested under various conditions: camera distance, lighting intensity, and angle as shown in Figure 5. The aim was to evaluate the system's ability to recognize motorcycle license plates with accuracy in real-time scenarios.



light intensity distance variation angle variation

Figure 5. Various Conditions of Testing

A. System Performance Overview

The ALPRON prototype was tested in a controlled parking lot at the Institut Teknologi Sumatera, as shown in Figure 6.

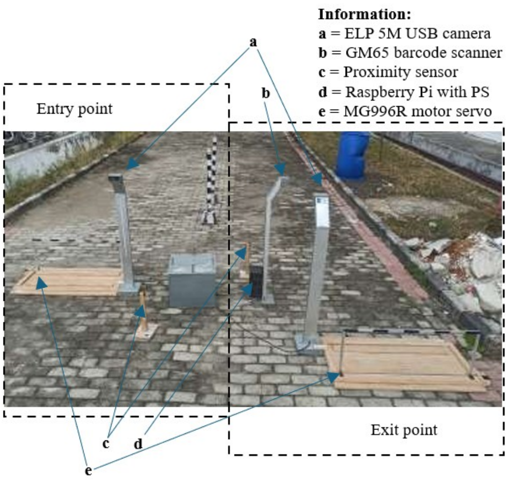


Figure 6. Demonstration of ALPRON

The system successfully operated as a real-time entry-exit recognition system, capable of capturing and processing license plate images using OCR implemented via Tesseract on Raspberry Pi. The overall average detection accuracy achieved was 98.75%, with optimal results recorded at a camera distance of 70 cm under bright lighting conditions at a 0° angle.

B. Effect of Distance on Detection Accuracy

Three different distances (50 cm, 70 cm, 100 cm) were tested to evaluate OCR accuracy as shown in Table 1.

TABLE I
ACCURACY TESTING BASED ON DISTANCE

Distance	Accuracy (%)	Average Processing Time (s)
50 cm	87.5	2.9
70 cm	**98.75**	2.3
100 cm	80.0	4.5

The “Average Processing Time (s)” in Table I represents the mean duration from image capture to OCR output and system response. Measured across multiple trials, the processing time ranged from 2.3 to 4.5 seconds, indicating that ALPRON performs within acceptable limits for real-time use in low-traffic settings like campus parking.

The best performance occurred at 70 cm. At 100 cm, characters became too small, reducing OCR accuracy. At 50 cm, distortion from proximity impacted character geometry. These results align with findings by Kaur and Kaur [11], who demonstrated that optimal distance and resolution balance are critical for robust plate recognition.

C. Influence of Light Intensity

OCR performance was evaluated under three lighting conditions, as shown in Table 2.

TABLE II
ACCURACY TESTING BASED ON LIGHT INTENSITY

Lighting	Intensity (Lux)	Accuracy (%)
Cloudy (low)	< 3,800	60.0
Bright	6,600-7,000	100.0
Very Bright (high)	> 10,000	40.0

Lighting directly affected image clarity and segmentation quality. Overexposure caused glare, while low light reduced contrast. These findings are consistent with studies by Du et al. [4], which emphasized the impact of lighting on segmentation and OCR stages in ANPR pipelines. These results are consistent with studies showing that lighting variation introduces noise and hinders OCR segmentation performance [12], [13]. Super-resolution techniques as proposed by Tsai et al. [12] may further improve detection in low-light conditions and should be considered for future.

D. Influence of Camera Angle

The impact of camera tilt on OCR recognition was tested at angles of 0°, 15°, and 35° as shown in Table 3.

TABLE III
ACCURACY TESTING BASED ON CAMERA ANGLE

Camera Angle	Accuracy (%)
0°	100.0
15°	60.0
35°	0.0

At higher angles, the license plate's rectangular geometry becomes skewed, leading to character deformation. Most recognition errors were caused by character similarities, such as ‘O’ vs ‘0’, ‘I’ vs ‘1’, and ‘B’ vs ‘8’. It’s often exacerbated by angled or overexposed conditions, as illustrated in table 4.

TABLE IV
EXAMPLE OF OCR RECOGNITION ERRORS

Ground Truth	OCR Output	Error Type	Cause
B123OYZ	B1230YZ	O misread as 0	Angle
D541UIC	D541VIC	U misread as V	Angle
B9954EXC	89954EXC	B misread as 8	Angle
B3481IC	B348IIC	1 misread as I	Angle
BE1245YT	BE1265YT	4 misread as 5	High light
B9054EXC	B9954EXC	0 misread as 9	High light
BE1245YT	BE1265YT	4 misread as 6	Low light

The optimal angle is 0°, where the plate image is most orthogonal to the camera lens. Similar angular distortion effects have been noted in ANPR studies using mobile vision systems [14]. Zherzdev and Gruzdev [15] demonstrated that angle normalization significantly boosts performance in DNN-based systems, suggesting the future incorporation of geometric correction modules.

E. Discussion and Comparative Insights

In comparison to related systems documented in the literature, the ALPRON system offers a well-balanced integration of embedded computing, real-time optical character recognition (OCR), and QR-based access control, making it both technically effective and practically deployable. Unlike previous implementations such as that by Ranglani and Lachwani [7], which relied on conventional PC-based infrastructures, ALPRON demonstrates that comparable accuracy levels can be achieved using compact and cost-efficient embedded hardware, significantly reducing the overall deployment footprint.

The system was specifically designed to address the operational context of two-wheeled vehicle parking, a use case often overlooked in previous research. This was achieved through optimized camera positioning and minimal dependence on environmental conditions. Nonetheless, several limitations persist. The system is currently unable to detect license plates that are obscured by protective covers, lacks infrared capability for nighttime operation, and is constrained by a fixed camera mount that reduces its adaptability to different installation angles and positions.

When compared to earlier approaches utilizing convolutional neural networks (CNNs) and Haar cascades for license plate recognition on general-purpose computing platforms [16], ALPRON maintains comparable recognition performance while operating on a lightweight embedded infrastructure. This indicates its potential suitability for deployment in resource-constrained environments, such as university or institutional parking facilities, where full-scale ANPR systems may be economically or logistically unfeasible.

Recent advances in deep learning have significantly improved ALPR systems, especially in challenging visual scenarios. Notable examples include the use of CNN-based object detection models such as YOLO (You Only Look Once), which have been successfully employed for efficient license plate localization and segmentation [12], [13], [17]. Zherzdev and Gruzdev [15] introduced LPRNet, a lightweight deep learning architecture capable of direct character prediction without requiring prior segmentation. Similarly, Laroca et al. [18] proposed a layout-independent system combining YOLO for detection with Tesseract OCR for recognition, demonstrating strong performance across various plate layouts and environmental conditions.

Furthermore, ALPRON's integration of QR-code validation and cloud-based database synchronization provides additional functionality beyond that of conventional low-cost ALPR systems. This combination enhances both system reliability and user convenience, particularly in closed environments such as campus parkin

This work contributes to the field by demonstrating an OCR-based ALPR system specifically optimized for two-wheeled vehicle recognition on embedded hardware in constrained environments, a niche that remains underexplored in current ANPR literature. To improve the system's robustness and versatility, future iterations of ALPRON should consider incorporating night vision modules, adjustable camera mounts for dynamic angle calibration, and robust license plate localization methods that are not dependent on plate borders, as recommended by Anagnostopoulos et al. [5].

IV. CONCLUSION

This study successfully developed and validated ALPRON, an Automatic License Plate Recognition system that leverages Optical Character Recognition (OCR) for real-time detection of motorcycle license plates in campus parking environments. Implemented on embedded hardware using a Raspberry Pi 4 and the Tesseract OCR engine, ALPRON demonstrated high recognition accuracy with low computational demand. Experimental results showed optimal performance at a 70 cm camera distance, under well-lit conditions (6,800–7,000 Lux), and at a perpendicular angle (0°), achieving a peak recognition accuracy of 98.75%. However, the system's performance significantly declined under overexposed lighting and skewed angles due to image distortion affecting OCR precision. The novelty of ALPRON lies in its context-specific design optimized for two-wheeled vehicle access, emphasizing cost-efficiency, near real-time responsiveness, and seamless integration with user-facing mobile applications. Compared to prior ANPR systems, ALPRON achieves similar accuracy using simpler and more affordable hardware, making it suitable for deployment in resource-constrained environments. Nonetheless, limitations such as dependence on daylight and inability to detect covered plates remain. Future improvements will focus on incorporating infrared imaging, adaptive camera alignment, and deep learning-based recognition to enhance robustness and flexibility. Overall, ALPRON demonstrates viability and scalability as a potential solution for smart motorcycle parking systems in controlled academic environments.

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