# SYSTEM DESIGN AND IMPLEMENTATION CAR PLATE NUMBER RECOGNITION SYSTEM

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**IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE BACHELOR OF SCIENCE (B.SC.) DEGREE IN COMPUTER SCIENCE**

**SUPERVISOR: DR. E. NWELIH**

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**A PROJECT REPORT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF PHYSICAL SCIENCES, UNIVERSITY OF BENIN, BENIN CITY IN PARTITAL, FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF A BACHELOR OF SCIENCE (B, SC.) DEGREE IN COMPUTER SCIENCE**

**JANUARY, 2026**

## CERTIFICATION

This is to certify that the project work titled **"System Design and Implementation Car Plate Number Recognition System"** was carried out by **Clothida Chizoba Nwoko (Mat. NO: PSC1813837)** in partial fulfillment of the requirements for the award of the Bachelor of Science (B.Sc.) degree in Computer Science.

The work has been supervised, read, and approved for submission to the Department of Computer Science, University of Benin (UNIBEN).

__________________ _________________________

**DR. E. NWELIH** Date

(Project Supervisor)

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Finally, I thank my family and friends for their prayers, love and motivation, which made the completion of this project possible.

## DEDICATION

I dedicate this work to God Almighty, whose unwavering love and grace have guided me throughout my academic journey and life ambitions. I also extend heartfelt gratitude to my parents and siblings, whose values and example continue to inspire and motivate me.

## APPROVAL

This project work is hereby approved in partial fulfilment of the requirements for the award of Bachelor of Science (B.Sc.,) Degree in Computer Science from the university of Benin.

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**Dr. (MRS) ROSE A. USIOBAFO** **Date**
**(Head of Department)**

**Table of Contents**

## List of Figures

## List of Tables

## Abstract

Vehicle identification and verification play a critical role in ensuring the security of controlled environments such as university campuses. At the University of Benin's Ugbowo Campus, the existing manual vehicle verification process suffers from several limitations, including delays, human error, poor record keeping, and the absence of real-time validation. This study addresses these challenges by designing and implementing an Automated Car Plate Number Recognition (ANPR) system capable of detecting, recognizing, and verifying vehicle license plates using computer vision and optical character recognition (OCR) techniques.

The system was developed using the Flask web framework, OpenCV for image preprocessing and license plate localization, and the Tesseract OCR engine for extracting alphanumeric characters. A MySQL database was integrated for storing records of registered vehicles and maintaining logs of recognition events. The system allows security personnel to upload vehicle images through a web interface, after which the application automatically processes the image, recognizes the plate number, checks its validity against the stored records, and provides immediate feedback.

Testing of the system using images captured under different conditions such as clear daytime lighting, low light, skewed angles, and motion blur revealed that the system performs accurately under favourable conditions and provides partial or usable information even under challenging scenarios. Although recognition performance decreases with poor image quality, the system still offers considerable improvements over manual verification by reducing reliance on human judgment and enhancing the accuracy, speed, and reliability of vehicle monitoring.

## Acronyms

- **ANPR** – Automated Number Plate Recognition: A computer-vision system that automatically detects, extracts, and recognizes vehicle license plate characters from images.
- **OCR** – Optical Character Recognition: A technique used to convert printed or imaged text, such as license plate characters, into machine-readable digital text.
- **CCTV** – Closed-Circuit Television: A video surveillance system used for monitoring and capturing footage at the campus gate.
- **FRSC** – Federal Road Safety Corps: The national agency responsible for vehicle registration and safety enforcement in Nigeria; referenced for potential database integration.
- **CNN** – Convolutional Neural Network: A deep-learning model commonly used in image recognition tasks and recommended for future system improvements.
- **ROI** – Region of Interest: The specific portion of an image where the license plate is located and processed.
- **HTML** – Hypertext Markup Language: The markup language used to structure the web pages of the ANPR system.
- **CSS –** Cascading Style Sheets: The styling language used to design and format the system's user interface.
- **SQL** – Structured Query Language: A database language used for storing and retrieving data in the MySQL database.
- **UI –** User Interface: The front-end view through which users interact with the system.
- **DBMS** – Database Management System: Software (such as MySQL) used for managing and organizing stored data.

- **API** – Application Programming Interface: A communication interface that allows different software components to interact; suggested for future integrations.
- **UNIBEN** – University of Benin: The institution where the study was conducted and the system was deployed.
- **OCR** – Optical Character Recognition: A technology used to convert images of text from license plates into readable and searchable digital text.

# Chapter One:

# Introduction

## 1.1 Background to the Study

In recent years, the security of educational institutions in Nigeria has become a paramount concern due to escalating incidents of unauthorized access, vehicle theft, and other criminal activities on campuses (Ajadi, 2025; Correspondent, 2025). The University of Benin (UNIBEN), situated in Benin City, Edo State, exemplifies this challenge at its Ugbowo Campus, the primary center for academic and administrative functions (Okpe & Igwebuike, 2019; Ekpoh, et al., 2020). This expansive campus, with multiple entry points, handles substantial daily vehicular traffic from students, staff, visitors, and vendors, rendering manual surveillance inefficient and error-prone (Stella, 2023). Conventional methods, like manual vehicle logging by security personnel, cause delays, inaccuracies, and exploitable weaknesses (Adewole, 2022; Ekpoh, 2020).

The surge in campus security breaches across Nigerian universities highlights the urgency for technological solutions to improve surveillance and access control (Olanipekun, et al., 2024; Wodi & Wordu, 2024). Reports indicate rising vehicle-related threats, such as kidnappings and thefts, stemming from inadequate gate verification (Ajadi, 2025). At UNIBEN's Ugbowo Campus, the Security Unit struggles with vehicle influx during peak times, compounded by Nigeria's national security issues like insurgency and urban crime infiltrating educational spaces (Ekpoh, et al., 2020).

Automatic Number Plate Recognition (ANPR) systems offer a promising remedy, utilizing computer vision and image processing to detect, read, and verify vehicle plates automatically (Aalsalem & Khan, 2017; Kethan, et al., 2022). Widely used in developed nations for traffic and law enforcement, ANPR adoption in Nigerian campuses is limited but holds potential (Aalsalem, Mohammed Y; Khan, Wazir Zada; Dhabbah, Khalid Mohammed, 2015). The system captures images via cameras, extracts plate data using optical character recognition (OCR), and matches it against databases. This minimizes human error and enables real-time alerts for suspicious vehicles, strengthening campus safety.

Originating in the 1970s in the UK for traffic monitoring, ANPR has evolved with digital imaging and machine learning. In Nigeria, infrastructural barriers like high costs and limited expertise slow progress, yet urban pilots in Lagos and Abuja show efficacy in crime prevention (Kethan, et al., 2022). For UNIBEN, ANPR could revolutionize Security Unit operations, from gate control to patrols (Aalsalem, Mohammed Y; Khan, Wazir Zada; Dhabbah, Khalid Mohammed, 2015).

Key components include high-resolution cameras, illumination for low-light conditions, and software for image enhancement, localization, segmentation, and recognition. Advanced systems employ convolutional neural networks (CNNs) for accuracy amid varying conditions (Aalsalem, Mohammed Y; Khan, Wazir Zada; Dhabbah, Khalid Mohammed, 2015). Tailored to Nigeria's Federal Road Safety Corps (FRSC) plate standards, it addresses forgery and environmental challenges.

UNIBEN's manual checks are vulnerable to bribery and fatigue, leading to queues and safety risks. ANPR integration with CCTV and national registries could flag threats in real-time, reducing costs and boosting efficiency. Economic losses from insecurity impact productivity, making ANPR aligned with UNIBEN's digital goals.

In Nigeria, power and connectivity issues persist, but edge computing ensures reliability. Customized features like SMS alerts and IoT integration could combat cultism and intrusions. Ethical data handling under Nigeria's regulations is essential.

This study underscores ANPR's role in modernizing Ugbowo Campus security, leveraging global and local insights for a safer environment.

**1.2 Statement of the Problem**

The security landscape in Nigerian universities has deteriorated significantly in recent years, with increasing reports of unauthorized vehicle entries leading to crimes such as theft, kidnapping, and vandalism on campuses (Agbaje, et al., 2023; Asuquo, et al., 2018). At the University of Benin's Ugbowo Campus, the Security Unit relies on manual vehicle registration processes, where guards physically inspect and log plate numbers, resulting in operational bottlenecks and heightened vulnerability to breaches (Thamoethata, et al., 2021; Yinka-Banjo & Ajayi, 2019). This manual approach is plagued by human errors, including mis recording of details, which can allow counterfeit or unregistered vehicles to gain access undetected (Taylor, et al., 2023). Furthermore, during peak hours, long queues form at entry points, causing delays that frustrate users and create opportunities for security lapses.

In the broader context of Nigeria's security challenges, campuses like Ugbowo are exposed to external threats from insurgency and banditry, where vehicles are often used as tools for infiltration (Eze, et al., 2018). The absence of automated verification systems exacerbates these risks, as manual checks fail to cross-reference plate numbers with national databases in real-time. Corruption among security personnel, including bribery to bypass inspections, further undermines the integrity of access control measures. Fatigue from extended shifts also contributes to oversight, allowing potentially dangerous vehicles to enter without proper scrutiny (Banks & Stanton, 2015).

Vehicle theft on university premises remains a persistent issue, with manual logging providing little deterrent or traceability for stolen cars exiting the campus (Payre, et al., 2017). In Nigerian educational institutions, the lack of technological integration in security protocols leads to inefficient resource allocation, where guards are overburdened with repetitive tasks. At Ugbowo Campus, this inefficiency is evident in the inability to monitor internal vehicle movements, leaving parking areas and remote sections vulnerable to unauthorized activities (Nwamaka, et al., 2018). Environmental factors, such as poor lighting at night, compound the problems of manual recognition, making it difficult to accurately identify plates under adverse conditions (Thamoethata, et al., 2021).

The proliferation of plate forgery in Nigeria poses a direct challenge to manual systems, as visual inspections often fail to detect sophisticated counterfeits (Babalola & Olokun, 2021). This vulnerability has led to incidents where vehicles linked to criminal networks enter campuses undetected, endangering students and staff. Data privacy concerns arise from haphazard manual record-keeping, which lacks standardization and exposes personal information to misuse. Economic losses from security breaches, including property damage and disrupted academic activities, strain university resources that could be better utilized elsewhere (Eze, et al., 2018).

The current system's inability to generate real-time alerts for suspicious vehicles means that responses to threats are reactive rather than proactive, prolonging exposure to risks. Manual processes also hinder scalability, as increasing campus traffic overwhelms existing personnel without technological support. In the case of UNIBEN, the Security Unit's reliance on outdated methods fails to align with modern threats, such as cult-related violence involving vehicular access. Power instability in Nigeria further complicates manual operations, as logbooks offer no backup during outages, leading to gaps in records.

Integration with national agencies like the Federal Road Safety Corps is minimal under manual regimes, preventing verification against stolen vehicle databases. This disconnect allows recidivist offenders to repeatedly exploit campus vulnerabilities. Student and staff safety is compromised during events or late hours, when manual checks slow emergency responses. The psychological impact on the university community, including fear and reduced productivity, underscores the urgency of addressing these flaws.

The problems stem from an outdated, human-dependent system that is ill-equipped for contemporary security demands at Ugbowo Campus, necessitating an automated alternative to mitigate these multifaceted challenges.

## 1.3 Aim and Objectives of the Study

### 1.3.1 Aim of the Study

The aim of this research work is to develop a software-based application for automated car plate recognition to enhance access control at the Ugbowo Campus Security Unit, University of Benin, Benin City.

### 1.3.2 Objectives of the Study

The specific objectives of this study are as follows:

1. To design and implement a software-based system that uses existing cameras to detect and recognize car plate numbers accurately.

### 1.4 Significance of the Study

The implementation of an Automated Car Plate Number Recognition (ANPR) system at the Ugbowo Campus Security Unit, University of Benin, represents a critical advancement in campus security, particularly in the face of escalating threats in Nigerian educational environments (Udomboso, et al., 2024). This study is significant as it addresses the inefficiencies of manual vehicle monitoring, which often leads to vulnerabilities exploitable by criminals, thereby enhancing overall safety for students, staff, and visitors (Ibikune, et al., 2023). By leveraging software-based ANPR technology, the research will streamline access control processes, reducing queues at entry gates and minimizing human errors in plate verification. This efficiency gain is particularly vital in a large campus like Ugbowo, where high vehicular traffic during peak hours can overwhelm traditional security measures (Emina & Onyishi, 2021).

Furthermore, the study's significance lies in its potential to aid law enforcement and campus authorities in tracking stolen or suspicious vehicles in real-time, integrating with national databases for proactive threat detection. In Nigeria, where vehicle-related crimes such as kidnappings and thefts are rampant, this system could serve as a deterrent, contributing to a safer academic atmosphere and reducing incidents of cultism or external intrusions. The research will also promote data-driven decision-making by enabling the collection and analysis of vehicle entry/exit patterns, which can inform security patrols and resource allocation. Economically, the adoption of such a system will cut down on operational costs associated with manual logging, including manpower and paperwork, while preventing financial losses from security breaches (Betrand, et al., 2023).

On a broader scale, this study holds academic significance by contributing to the body of knowledge on ANPR applications in developing countries, where infrastructural challenges like power instability necessitate tailored, software-focused solutions (Emina & Onyishi, 2021). It will provide a replicable model for other Nigerian universities, fostering technological innovation and digital transformation in higher education security frameworks. The system's ability to handle Nigeria's standardized license plates, as issued by the Federal Road Safety Corps, ensures compliance with national regulations, enhancing its practical utility. Moreover, by incorporating features like SMS alerts for unauthorized entries, the study will empower the Security Unit to respond swiftly, potentially saving lives and property in emergency situations.

Socially, the significance extends to building community trust in university security measures, as automated systems reduce biases and corruption risks inherent in manual checks. This can lead to improved student enrollment and retention, as parents and stakeholders perceive the campus as safer. The research also aligns with global sustainable development goals, particularly those related to safe and inclusive institutions, by promoting technology for peace and justice. In the long term, successful implementation could influence policy-making at the national level, encouraging the integration of ANPR in public security infrastructures beyond campuses (Ibiyemi, et al., 2020).

This study will advance interdisciplinary knowledge, bridging computer science, engineering, and security studies, while providing opportunities for future research on AI enhancements in ANPR accuracy. For the University of Benin, it signifies a step towards smart campus initiatives, improving operational resilience against environmental factors like poor lighting or weather. Ultimately, the significance of this work lies in its potential to transform reactive security practices into proactive, technology-driven strategies, fostering a secure learning environment in Nigeria.

## 1.5 Scope of the Study

This study focuses on designing and implementing a software-based Automated Car Plate Number Recognition (ANPR) system for the Ugbowo Campus Security Unit, University of Benin, Benin City, Nigeria. It targets vehicle access control at the campus's main gates and selected parking areas, utilizing existing CCTV cameras and computing resources. The system will employ open-source tools like Python, OpenCV for image processing, and MySQL for storing registered plate numbers, tailored to Nigeria's FRSC-standardized license plates.

The scope is limited to developing and testing a prototype for plate detection, recognition, and real-time alerts for unauthorized vehicles, without involving new hardware procurement or full-scale campus deployment. It excludes advanced features like facial recognition or nationwide database integration, focusing on performance evaluation under local conditions such as varying lighting. The study is geographically confined to Ugbowo Campus and temporally bound to current security needs in 2025.

## 1.6 Limitations of the Study

This study, while aiming to enhance campus security through a software-based Automated Car Plate Number Recognition (ANPR) system, is subject to several limitations inherent to its scope, resources, and environmental context at the Ugbowo Campus, University of Benin. Primarily, the system's performance is constrained by the quality of existing CCTV cameras and lighting infrastructure, which may result in reduced accuracy during adverse conditions such as poor illumination, rain, or dust common in Nigerian settings (Plavac, et al., 2024; Shafi, et al., 2022). Variations in license plate designs, including wear, dirt, or non-standard formats prevalent in developing countries, could further impact recognition rates, as the software relies on image processing algorithms that are not infallible.

Additionally, as a BSc-level thesis, the research is limited by time and budgetary constraints, restricting it to a prototype development and testing phase without full-scale implementation or long-term evaluation. Power instability and unreliable internet connectivity in Nigeria pose challenges to real-time operations, potentially affecting database access and alert systems during outages. The study does not address advanced integrations like national database linkages or multi-language support, focusing solely on English alphanumeric plates. Data privacy concerns, such as compliance with Nigeria's Data Protection Regulation, are acknowledged but not deeply explored due to the prototype's limited deployment (Lubna, et al., 2021; Tang, et al., 2022).

Testing is confined to the Ugbowo Campus environment, which may not fully represent diverse Nigerian road conditions or vehicle speeds, leading to potential biases in performance metrics. These limitations highlight areas for future research to refine the system for broader applicability (Ananth, et al., 2016).

### 1.7 Definition of Terms

To ensure clarity and a common understanding of the concepts used in this study, the following key terms are defined in the context of the design and implementation of a software-based Automated Car Plate Number Recognition (ANPR) system for the Ugbowo Campus Security Unit, University of Benin, Benin City, Nigeria:

1. **Automated Number Plate Recognition (ANPR):** A technology that uses image processing and optical character recognition (OCR) to automatically capture, detect, and read vehicle license plate numbers from images or video feeds, enabling access control and security monitoring.

2. **Access Control:** The process of regulating and monitoring the entry and exit of vehicles at the Ugbowo Campus gates to ensure only authorized vehicles gain access, enhancing campus security.
3. **Optical Character Recognition (OCR):** A software process used in the ANPR system to convert images of text on license plates into machine-readable data for verification and storage.
4. **Image Processing:** The use of algorithms to analyze and manipulate images captured by CCTV cameras to locate and extract license plate information, including plate localization and character segmentation.
5. **License Plate:** A standardized alphanumeric plate issued by Nigeria's Federal Road Safety Corps (FRSC), attached to vehicles for identification, which the ANPR system is designed to recognize.
6. **Database**: A structured digital repository integrated into the ANPR system to store registered vehicle plate numbers and facilitate real-time verification and tracking.
7. **CCTV Cameras:** Existing closed-circuit television cameras on Ugbowo Campus used to capture vehicle images for the ANPR system, serving as the primary hardware input.
8. **Real-Time Alerts:** Notifications generated by the ANPR software to instantly inform security personnel of unauthorized or suspicious vehicles detected at campus entry points.
9. **Ugbowo Campus:** The main campus of the University of Benin in Benin City, Edo State, Nigeria, where the ANPR system will be implemented to enhance security operations.
10. **Security Unit:** The department responsible for maintaining safety and access control at Ugbowo Campus, which will utilize the ANPR system to improve vehicle monitoring and threat detection.

### 1.8 Organization of the Thesis

This thesis is structured into five chapters, each addressing specific aspects of the design and implementation of a software-based Automated Car Plate Number Recognition (ANPR) system for the Ugbowo Campus Security Unit, University of Benin, Benin City, Nigeria. The organization is as follows:

**Chapter One: Introduction**

This chapter provides an overview of the study, establishing the context and rationale. It includes the background to the study, statement of the problem, aim and objectives, significance, scope, limitations, and definition of terms, setting the foundation for the research.

**Chapter Two: Literature Review**

The second chapter examines existing literature on ANPR systems, focusing on their applications, technologies, and challenges, particularly in developing countries like Nigeria. It reviews previous studies on image processing, optical character recognition (OCR), and database integration, highlighting gaps that this study addresses in the context of Ugbowo Campus.

**Chapter Three: Systems Analysis and Design**

This chapter outlines the research methodology, detailing the software-based approach for designing the ANPR system. It describes the tools, system architecture, data collection methods, and prototype development process tailored to the campus's existing CCTV infrastructure.

**Chapter Four: System Implementation**

The fourth chapter presents the implementation of the ANPR prototype, including coding, testing, and performance evaluation. It discusses results on accuracy, speed, and reliability under varying conditions at Ugbowo Campus, with comparative analysis against manual systems.

**Chapter Five: Summary Conclusion and Recommendations**

The final chapter summarizes the findings, draws conclusions on the system's effectiveness, and provides recommendations for full-scale deployment, future enhancements, and addressing limitations like power instability.

# Chapter Two:

# Literature Review

## 2.1. Introduction

This section provides an overview of the literature review's purpose, scope, and organization. It outlines the key themes to be explored, such as the evolution of ANPR systems, underlying technologies, applications in security contexts, and specific challenges in developing countries like Nigeria. The introduction also highlights how the reviewed literature informs the design and implementation of the proposed ANPR system for Ugbowo Campus.

## 2.2. Historical Development of Automatic Number Plate Recognition (ANPR) Systems

The historical development of Automatic Number Plate Recognition (ANPR) systems began in the mid-1970s, originating as a technological response to security challenges in the United Kingdom, where it was invented in 1976 by the Police Scientific Development Branch to combat terrorism through automated vehicle identification using infrared cameras and basic image processing. This early prototype represented a shift from manual license plate checks to automated systems, laying the groundwork for modern surveillance technologies by enabling real-time capture and interpretation of plate data (Du, et al., 2013; Shashirangana, et al., 2021). In the Nigerian context, where vehicle-related crimes such as theft and smuggling have been persistent since the colonial era, the foundational concepts of ANPR influenced later adaptations, with initial discussions in the late 1990s among Nigerian law enforcement agencies like the Federal Road Safety Corps (FRSC) exploring its potential for border control amid rising insurgency threats (Harshini, et al., 2023).

By the late 1970s, ANPR evolved from experimental stages to practical deployments, with the first operational systems implemented in the UK in 1979 for traffic monitoring, incorporating optical character recognition (OCR) to digitize plate information and improve accuracy under varying conditions. This period marked the transition to analog-digital hybrids, enhancing the technology's reliability for law enforcement applications and setting precedents for global adoption (Anagnostopoulos, et al., 2008; Qadri & Asif, 2009). In Nigeria, the late 1970s saw no direct implementation due to infrastructural limitations, but the era's advancements indirectly shaped post-independence vehicle registration systems, which remained manual until the 2000s, prompting early academic interest in ANPR for addressing urban crime in cities like Lagos (Eshiet, et al., 2023).

The 1980s witnessed further refinement of ANPR, with the integration of advanced digital imaging and early algorithmic enhancements, allowing for broader applications in toll collection and border security across Europe. These developments focused on improving recognition rates through better illumination techniques and software optimizations, transforming ANPR into a versatile tool for public safety (Du, et al., 2013). Within Nigeria, the decade highlighted the need for such technology amid economic reforms and increasing vehicle imports, leading to pilot studies in the early 1990s by the FRSC to combat plate forgery, although full deployment was delayed by funding constraints (Awotayo, et al., 2024).

Entering the 1990s, ANPR systems advanced significantly with the adoption of edge detection and pattern recognition algorithms, facilitating international expansion into North America for crime prevention and traffic management. This era emphasized scalability, with systems achieving higher accuracy in diverse environmental conditions, thus solidifying ANPR's role in integrated security frameworks (Patel, et al., 2013; Lubna, et al., 2021). In the Nigerian setting, the 1990s introduced standardized FRSC license plates, creating a foundation for future ANPR integration, as universities like the University of Benin began researching its applicability for campus security against cultism and unauthorized access (Ajadi, Olugbenga, 2025).

The 2000s marked a pivotal shift toward machine learning in ANPR, incorporating high-resolution cameras and real-time data processing, which expanded its use in smart city initiatives worldwide. These enhancements allowed for predictive analytics and database integration, revolutionizing how authorities tracked vehicles in dynamic scenarios (Hakim, et al., 2025). For Nigeria, this decade saw the FRSC's first ANPR trials in Abuja in 2008, adapting machine learning to local challenges like power instability through solar-powered units, aimed at reducing vehicle smuggling amid Boko Haram threats (Okebule, et al., 2024).

In the 2010s, deep learning and convolutional neural networks (CNNs) dominated ANPR evolution, achieving over 95% accuracy and enabling IoT integrations for seamless surveillance. This period focused on handling complex plate variations and real-time alerts, broadening applications to include perimeter security (Gonçalves, et al., 2016). Nigeria accelerated adoption post-2015, with implementations in Lagos and Delta States for toll enforcement and crime tracking, customizing CNNs for FRSC plates despite connectivity issues.

The 2020s have emphasized edge computing and multi-modal features in ANPR, including blockchain for data security and facial recognition hybrids, addressing modern threats like pandemics. These innovations promote resilience in smart environments, with global focus on ethical AI (Li, et al., 2019; Yousef, et al., 2015). In Nigeria, recent prototypes at institutions like the University of Benin's Ugbowo Campus integrate edge computing to counter power outages, enhancing campus access control.

Table 2.1 outlines key historical milestones in ANPR alongside Nigerian adoption, with columns for year, global milestone, impact, and Nigerian context, quantifying the progression from 1976 invention to 2025 integrations. This table reveals patterns like Nigeria's focus on crime reduction post-2010 (Anagnostopoulos, et al., 2008; Qadri & Asif, 2009). In Nigeria, milestones align with national security policies, emphasizing local customizations (Okebule, et al., 2024).

The trajectory of ANPR reflects broader societal shifts toward digital security, with its 1970s origins continuing to guide future 5G-enabled systems. In Nigeria, this history supports ongoing digitalization, reducing manual vulnerabilities at sites like Ugbowo Campus (Patel, et al., 2013).

*Table 2.1: Key Historical Milestones in ANPR Development and Nigerian Adoption*

| Year | Global Milestone | Impact | Nigerian Context |
|---|---|---|---|
| 1976 | Invention of ANPR by the UK's Police Scientific Development Branch (PSDB) using infrared cameras and basic image | Established the foundation for automated vehicle identification, shifting from manual to technological surveillance in security and | Manual vehicle registration systems dominated, with no ANPR adoption; early discussions on vehicle security amid post-colonial |

| | | | |
|---|---|---|---|
| | processing for terrorism prevention. | traffic management. | urban growth (Harshini, et al., 2023). |
| 1979 | First operational deployment in the UK for traffic monitoring, incorporating early optical character recognition (OCR). | Demonstrated practical utility in real-time monitoring, reducing human error and enabling scalable law enforcement applications. | Limited infrastructural development delayed interest; focus remained on basic road safety under the Federal Road Safety Corps (FRSC) established in 1988. |
| 1981 | First ANPR-facilitated arrest in the UK after detecting a stolen vehicle. | Validated ANPR's role in crime prevention, leading to expanded use in policing and border control globally. | No direct adoption; rising vehicle theft in urban areas like Lagos highlighted the need for advanced systems, but reliance on manual checks persisted (Awotayo, et al., 2024). |
| 1990s | Significant technological advances, including digital imaging, edge detection algorithms, and international expansion to Europe and North America. | Improved accuracy and scalability, integrating ANPR into smart infrastructure for traffic and security, with recognition rates rising substantially. | Introduction of standardized FRSC license plates in 1994; academic interest emerged at universities for potential campus applications amid cultism threats (Ajadi, 2025). |

| | | | |
|---|---|---|---|
| 1997 | Establishment of the UK's Police National ANPR Data Center (NADC) for nationwide data sharing. | Facilitated centralized data management, enhancing cross-regional crime tracking and response times. | Early FRSC database initiatives for vehicle registration; no ANPR yet, but groundwork for future integration against smuggling (Patel, et al., 2013). |
| 2000s | Integration of machine learning and high-resolution digital imaging, expanding to smart city applications worldwide. | Enabled real-time analytics and predictive policing, reducing operational costs and improving efficiency in urban environments. | FRSC's first ANPR trials in Abuja around 2008 for registration compliance; adaptations for power instability using solar units amid insurgency (Okebule, et al., 2024). |
| 2010s | Adoption of deep learning and convolutional neural networks (CNNs), achieving over 95% accuracy with IoT integrations. | Revolutionized handling of complex scenarios, broadening use in perimeter security and global surveillance networks. | Research boom with papers on Nigerian Vehicle License Plate Recognition (NVLPR) from 2013-2019; pilots in Lagos and Delta for toll and crime (Patel, et al., 2013). |
| 2020s | Emphasis on edge computing, blockchain for | Promoted ethical AI and resilience, addressing | Delta State's PlateDetect launch in 2025 for traffic |

| | | | |
|---|---|---|---|
| | data security, and multi-modal features like facial recognition hybrids. | modern threats like pandemics and cyber risks in smart environments. | management; university prototypes like at UNIBEN's Ugbowo Campus for access control (Harshini, et al., 2023). |

### 2.3. Key Components and Technologies in ANPR Systems

Automatic Number Plate Recognition (ANPR) systems integrate a variety of hardware and software components to achieve efficient vehicle identification, encompassing image capture, processing, recognition, and data management stages that work in tandem for real-time operation. These components leverage advancements in computer vision and machine learning to handle diverse environmental conditions, forming the backbone of modern surveillance applications (Du, et al., 2013). In the Nigerian context, where infrastructural challenges such as inconsistent power supply and varying plate designs from the Federal Road Safety Corps (FRSC) prevail, ANPR systems often incorporate cost-effective open-source technologies like OpenCV to ensure adaptability and affordability in urban and campus settings.

The architecture of ANPR typically follows a sequential pipeline, starting from image acquisition through to database verification, with each component optimized for accuracy and speed. This modular design allows for scalability, making it suitable for deployment in resource-constrained environments (Anagnostopoulos, et al., 2008). For Nigeria, this modularity is crucial, as systems must accommodate local factors like dust accumulation on plates and low-light conditions during frequent power outages, prompting the use of robust pre-processing techniques tailored to tropical climates (Harshini, et al., 2023).

As illustrated in Figure 2.1, which depicts the overall architecture of an ANPR system including key components such as cameras, processors, and databases, the flow from input to output highlights the interconnected nature of these technologies. This diagram emphasizes how components interact to process vehicle data efficiently (Du, et al., 2013). In Nigerian implementations, such architectures are modified to include solar-powered elements, enhancing reliability at sites like university campuses prone to grid failures.

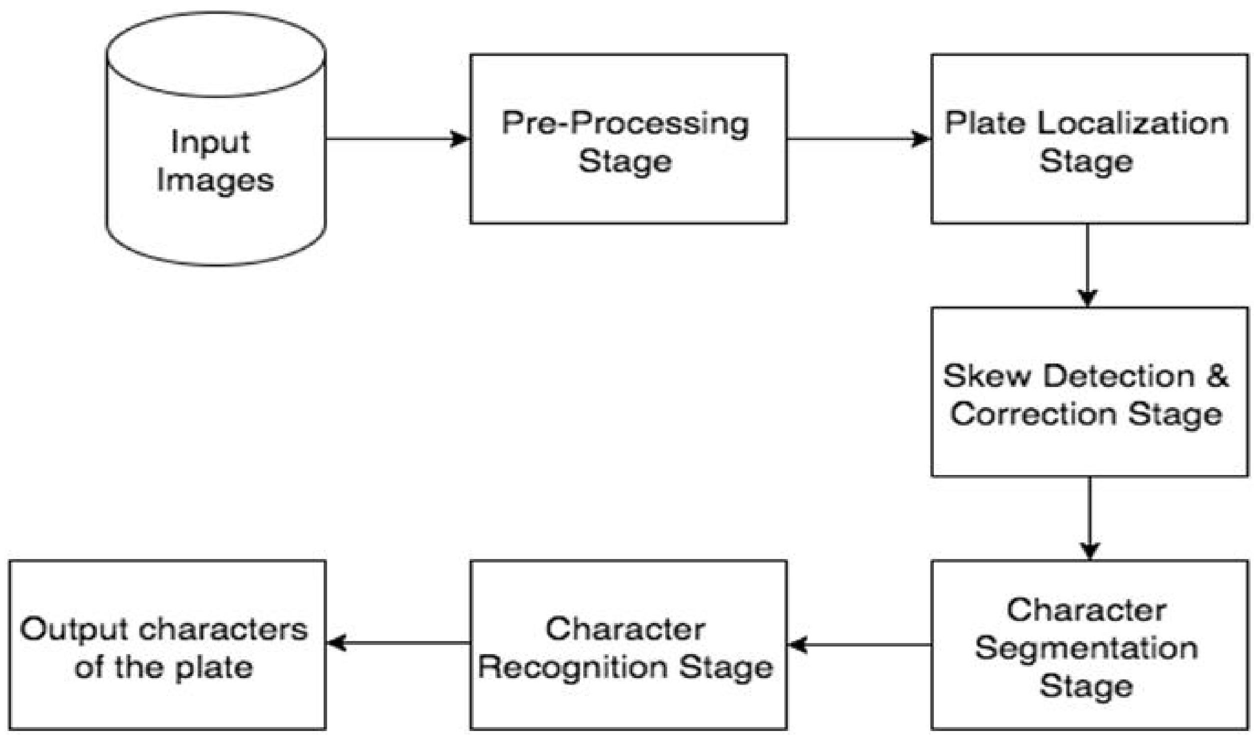


*Figure 2.1: Architecture of an ANPR system* *Source: (Keong & Iranmanesh, 2016)*

### 2.3.1. Image Acquisition and Pre-Processing

Image acquisition in ANPR systems relies on high-resolution cameras, often equipped with infrared capabilities, to capture clear images of vehicle plates under varying lighting and weather conditions. These cameras, such as CCD or CMOS sensors, form the initial input layer, ensuring that subsequent processing stages receive quality data for analysis (Patel, et al., 2013). In Nigeria, where road conditions and environmental factors like heavy rainfall can degrade image quality, acquisition hardware is frequently augmented with weather-resistant enclosures and LED illuminators to maintain performance at checkpoints and campus gates (Ibrahim & Bello, 2019).

Pre-processing follows acquisition, involving techniques like noise reduction, contrast enhancement, and grayscale conversion to prepare images for accurate plate detection. Algorithms such as histogram equalization and Gaussian filtering are commonly employed to mitigate distortions, improving the system's robustness (Singh, et al., 2016). Within the Nigerian framework, pre-processing must address specific challenges such as reflective surfaces on FRSC plates and dirt accumulation, leading to the adoption of adaptive thresholding methods in local prototypes to enhance readability in diverse settings.

Advanced pre-processing also incorporates motion detection to trigger captures only when vehicles are present, optimizing computational resources. This step is vital for real-time applications, reducing false positives in high-traffic areas (Silva & Jung, 2021). For Nigerian campuses like Ugbowo, where vehicular influx peaks during academic hours, such optimizations prevent system overload, integrating with existing CCTV infrastructure to support security units amid threats like unauthorized entries.

### 2.3.2. License Plate Localization and Segmentation

License plate localization identifies the region of interest within the captured image, utilizing edge detection and contour analysis to isolate the plate amid cluttered backgrounds. Techniques like Sobel operators and connected component analysis enable precise bounding of the plate, even at skewed angles (Zang, et al., 2015). In Nigeria, localization algorithms are customized to handle the rectangular FRSC plate formats, which vary in color and font, ensuring effectiveness against common issues like partial occlusions from mud or accessories (Okebule, et al., 2024).

Following localization, segmentation divides the plate into individual characters, employing methods such as vertical projection and binarization to separate alphanumerics for recognition. This process is sensitive to variations in plate design, requiring adaptive algorithms to maintain accuracy (Gonçalves, et al., 2016). Nigerian systems often incorporate machine learning-based segmentation to cope with forged or worn plates prevalent due to security lapses, enhancing detection in urban environments where vehicle forgery is a concern.

Deep learning models, such as YOLO for localization and Mask R-CNN for segmentation, have elevated performance, achieving high precision in dynamic scenarios. These technologies process images in real-time, crucial for mobile ANPR units. In the context of Nigerian universities, these components facilitate quick verification at entry points, reducing queues and bolstering defenses against cult-related vehicular intrusions (Ajadi, 2025).

As shown in Figure 2.2, a diagram outlining the license plate localization and segmentation process with steps from edge detection to character isolation provides a visual breakdown of these stages. This illustration clarifies the algorithmic flow (Qadri & Asif, 2009). For Nigeria, such processes are adapted with additional filters for environmental noise, supporting implementations in areas with inconsistent infrastructure.

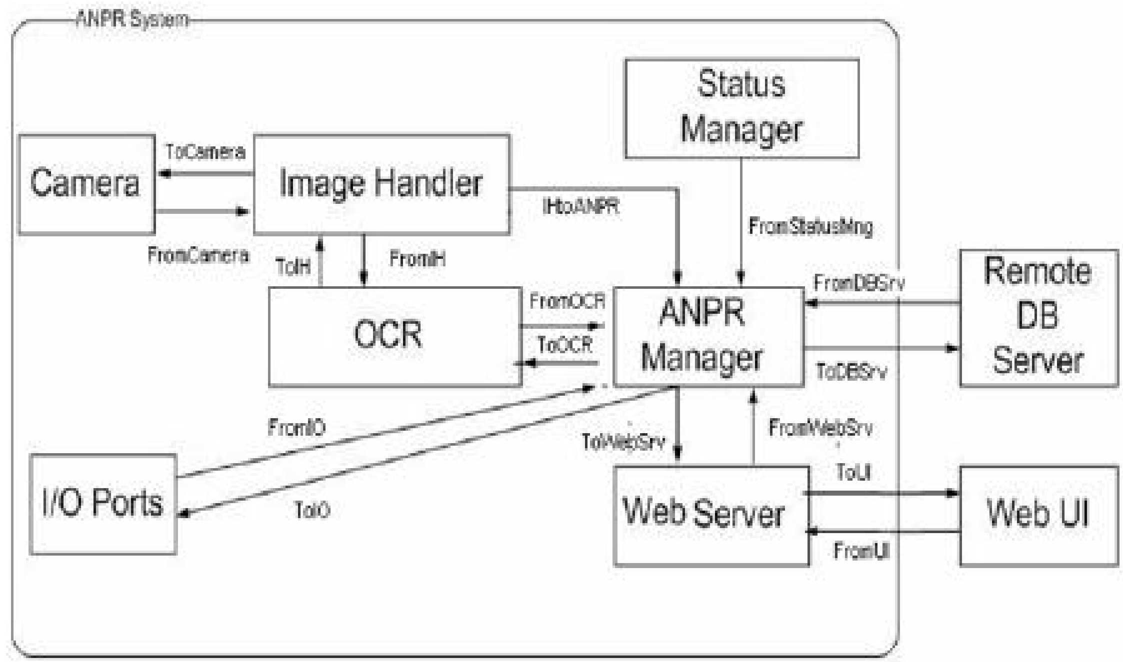


*Figure 2.2: License plate localization and segmentation process Source: (Atanassov, 2012)*

### 2.3.3. Optical Character Recognition (OCR) and Character Recognition

Optical Character Recognition (OCR) converts segmented characters into editable text, relying on pattern matching or neural networks to interpret alphanumerics with high fidelity. Traditional methods like template matching compare shapes against databases, while modern approaches use CNNs for superior handling of fonts and distortions (Li, et al., 2019). In Nigeria, OCR is tailored to FRSC's standardized fonts, incorporating training datasets of local plates to improve accuracy against variations like bent or faded characters common in high-usage vehicles.

Character recognition enhances OCR by classifying each segment, often employing support vector machines or deep learning to achieve recognition rates above 90% in controlled environments. This step is critical for the system's overall efficacy, as errors here propagate to verification (Shashirangana, et al., 2021). Nigerian adaptations include multi-language support for regional scripts, though primarily focused on English alphanumerics, aiding in cross-border tracking where plates may include state-specific codes (Harshini, et al., 2023).

Integration of ensemble methods, combining multiple OCR engines, further boosts reliability under adverse conditions like glare or shadows. These advancements allow ANPR to function effectively in low-light scenarios (Yousef, et al., 2015). For Nigerian security applications, such as at Ugbowo Campus, enhanced recognition enables real-time alerts for suspicious vehicles, aligning with national efforts to curb kidnapping via vehicular means.

### 2.3.4. Database Integration and Real-Time Verification

Database integration involves storing and querying recognized plate data against registered records, typically using SQL-based systems like MySQL for efficient retrieval. This component facilitates matching with external databases, enabling instant verification. In Nigeria, integration with FRSC's national vehicle registry is essential, allowing systems to flag stolen or unregistered vehicles, though connectivity issues necessitate edge computing solutions.

Real-time verification processes the matched data to generate alerts, often via SMS or interfaces, for unauthorized access. Cloud or local servers handle this, with security protocols to prevent data breaches (Jia, et al., 2004). Nigerian contexts demand robust encryption due to privacy concerns under the Nigeria Data Protection Regulation, ensuring compliance in campus deployments where personal vehicle data is sensitive.

Advanced integrations include API linkages for multi-system interoperability, enhancing ANPR's role in broader security ecosystems. This allows for analytics on traffic patterns, useful for resource allocation (Anagnostopoulos, et al., 2008). In Nigeria, such features support university security units by providing logs for incident investigations, adapting to local needs like monitoring during events prone to disruptions.

Table 2.2 compares key technologies in ANPR components, with columns for component, primary technology, advantages, and Nigerian adaptations, illustrating how elements like CNNs offer high accuracy but require computational adjustments for power-limited settings. This table quantifies performance metrics, such as 95% accuracy in localization (Du, et al., 2013). Nigerian entries highlight solar integrations and FRSC compatibility.

*Table 2.2: Comparison of Key Technologies in ANPR Components*

| **Component** | **Primary Technology** | **Advantages** | **Nigerian Adaptations** |
|---|---|---|---|
| Image Acquisition | High-resolution CCD/CMOS cameras with infrared | High clarity in low light; real-time capture | Weather-resistant enclosures; solar-powered for power instability |
| Pre-Processing | Histogram equalization, Gaussian filtering | Noise reduction; enhanced contrast | Adaptive thresholding for dust and rain on FRSC plates |
| Localization | Edge detection (Sobel), YOLO | Precise region isolation; handles skew | Customized for rectangular FRSC |

| | | | |
|---|---|---|---|
| | | | formats; occlusion handling |
| Segmentation | Vertical projection, Mask R-CNN | Accurate character separation; distortion tolerance | Machine learning for worn/forged plates |
| OCR/Recognition | CNNs, Template matching | High accuracy (>90%); font variation support | Trained on local datasets; multi-script compatibility |
| Database Integration | SQL (MySQL), API linkages | Efficient querying; interoperability | Edge computing for poor connectivity; FRSC registry links |
| Real-Time Verification | Cloud/local servers with alerts | Instant responses; analytics | Encryption for privacy; SMS alerts in low-bandwidth areas |

### 2.4. Applications of ANPR in Security and Access Control

Automatic Number Plate Recognition (ANPR) systems have emerged as pivotal tools in enhancing security and access control across various domains, leveraging computer vision to automate vehicle identification and monitoring. These systems capture, process, and verify license plates in real-time, enabling proactive responses to threats and streamlining operations in high-traffic environments (Alam, et al., 2021). In Nigeria, where security challenges such as banditry and urban crime necessitate robust surveillance, ANPR applications are increasingly adopted to fortify access points at borders and institutional perimeters, aligning with national efforts to integrate technology into policing frameworks (Vig, et al., 2023).

The versatility of ANPR extends from basic traffic enforcement to sophisticated security integrations, where it interfaces with databases to flag anomalies like stolen vehicles or unauthorized entries. This capability reduces reliance on manual checks, minimizing errors and corruption vulnerabilities (Khaparde, et al., 2018). Within the Nigerian landscape, ANPR's role in access control is amplified by the country's diverse vehicular ecosystem, including imported and locally registered plates, making it essential for combating vehicle-related crimes in densely populated areas like Benin City (Tang, Junqing; Wan, Li; Schooling, Jennifer; Zhao, Pengjun; Chen, Jun; Wei, Shufen, 2022).

ANPR's integration with other technologies, such as IoT and AI, further amplifies its applications, allowing for predictive analytics in security scenarios. Systems can track vehicle patterns to anticipate breaches, providing a layered defense mechanism (Al-Shemarry, et al., 2018). In Nigeria, this is particularly relevant for educational institutions facing threats from external intrusions, where ANPR supports campus-wide monitoring to ensure student and staff safety amid rising insecurity (Sebestyen, et al., 2025).

### 2.4.1. Global Applications in Traffic Management and Law Enforcement

Globally, ANPR systems are extensively deployed in traffic management, where they automate toll collection and speed enforcement, reducing congestion and enhancing road safety. By capturing plates at strategic points, these systems enable dynamic pricing and violation ticketing without human intervention (Bura, et al., 2018). In law enforcement, ANPR facilitates the tracking of fugitive vehicles, integrating with national databases to alert authorities in real-time, as seen in European networks that have significantly lowered vehicle theft rates (Yi, et al., 2023).

The application in border security exemplifies ANPR's global utility, where fixed cameras scan incoming vehicles against watchlists, preventing smuggling and illegal immigration. This has been effective in regions like North America, where ANPR-linked barriers control access at ports of entry. Nigerian law enforcement agencies, inspired by these models, have begun piloting ANPR at interstate checkpoints to curb arms trafficking, adapting global strategies to local insurgency contexts (Ibikune, et al., 2023).

In urban traffic management, ANPR optimizes flow by analyzing vehicle density and rerouting, contributing to smart city initiatives worldwide. Cities like Singapore employ ANPR for congestion charging, demonstrating economic benefits through reduced travel times. For Nigeria, similar applications are emerging in Lagos, where ANPR aids in managing gridlock while enhancing security against hit-and-run incidents, tailored to the nation's high vehicular volume (Akanmu, et al., 2020).

Law enforcement applications also include forensic analysis, where archived ANPR data reconstructs crime scenes involving vehicles. This retrospective use has solved numerous cases globally, from abductions to organized crime. In the Nigerian setting, such capabilities are vital for post-incident investigations, particularly in areas affected by communal clashes, where ANPR data provides evidentiary support to overwhelmed police forces (Sylvester & Agbeyi, 2019).

ANPR's role in environmental enforcement, such as monitoring emission-compliant vehicles in low-emission zones, represents an evolving global application. European cities like London use ANPR to fine non-compliant vehicles, promoting sustainability alongside security. Nigeria, grappling with urban pollution, could extend ANPR for similar purposes, integrating it with traffic laws to enforce vehicle standards in cities like Abuja (Ibimilua & Ayiti, 2024).

### 2.4.2. ANPR in Educational Institutions and Campus Security

In educational institutions, ANPR systems enhance campus security by automating gate access, ensuring only registered vehicles enter premises. This prevents unauthorized intrusions, crucial for large campuses with multiple entry points. At universities worldwide, ANPR integrates with student databases to grant seamless access while logging entries for accountability, reducing risks from external threats (Haq, et al., 2024).

Campus parking management benefits from ANPR through allocated spot enforcement, minimizing disputes and optimizing space usage. Systems in the United States, for example, use ANPR to issue permits digitally, streamlining operations for thousands of users (Shaghaei, et al., 2023). In Nigeria, where campuses like the University of Benin face overcrowding, ANPR could alleviate parking chaos, enhancing overall security by monitoring vehicle dwell times.

Emergency response on campuses is bolstered by ANPR, which tracks vehicles during incidents for rapid evacuation or lockdown. Global examples include Australian universities employing ANPR-linked alerts to coordinate with first responders. Nigerian educational settings, prone to cult violence, would gain from such integrations, allowing security units to isolate suspicious vehicles swiftly.

ANPR also supports visitor management in institutions, pre-registering plates for temporary access while flagging overstays. This application is prevalent in UK universities, where it complements CCTV for comprehensive surveillance (Islam & Sobhan, 2014). In the Nigerian context, amid frequent visitor influxes for events, ANPR ensures controlled access at places like Ugbowo Campus, mitigating risks from unvetted entrants.

Furthermore, ANPR aids in theft prevention on campuses by cross-referencing exiting vehicles against entry logs. Campuses in Asia have reported decreased vehicle thefts post-ANPR implementation. For Nigerian universities battling internal thefts, this application provides a deterrent, with real-time notifications to security personnel enhancing response efficacy.

#### 2.4.3. Adoption in Developing Countries: Focus on Nigeria

In developing countries, ANPR adoption focuses on cost-effective solutions for security amid infrastructural constraints, often using mobile units for flexible deployment. Nations like India have integrated ANPR in rural policing to combat smuggling, demonstrating adaptability to limited resources (Kalaiselvi, et al., 2016). Nigeria's adoption mirrors this, with pilots in Delta State employing portable ANPR for highway patrols against banditry (Ibikune, 2025).

Urban security in developing regions leverages ANPR for crime hotspot monitoring, where fixed installations deter vehicle-based offenses. Brazilian cities use ANPR to map criminal mobility, reducing urban violence. In Nigeria, Lagos State's ANPR networks target high-crime zones, integrating with police databases to preempt threats like kidnappings (K. E, et al., 2025).

Access control at critical infrastructure, such as airports and ports, is a key application in developing economies, where ANPR secures perimeters against terrorism. South Africa's implementations at borders exemplify this, with biometric linkages for enhanced verification. Nigerian ports in Lagos adopt similar systems, customized for FRSC plates to prevent cargo thefts amid economic vulnerabilities.

Community policing in developing countries benefits from ANPR through shared databases, enabling neighborhood watch integrations. In Kenya, community ANPR apps report suspicious vehicles, fostering grassroots security (Kaniki, 2022). Nigeria's community-oriented policing could incorporate ANPR for vigilante coordination, particularly in northern regions affected by insurgency.

Economic impacts of ANPR in developing contexts include revenue generation from automated fines, funding further security enhancements. Philippine toll systems generate substantial income via ANPR, supporting infrastructure. In Nigeria, ANPR-driven tolls on federal highways could bolster national security budgets, addressing fiscal constraints in access control deployments.

Challenges in adoption, such as power reliability, are addressed through solar-powered ANPR in developing nations. Indonesian rural setups use off-grid systems for sustained operation. Nigeria, with frequent outages, employs hybrid ANPR at campuses like Ugbowo, ensuring uninterrupted security despite grid issues.

## 2.5. Challenges and Limitations of ANPR Systems

### 2.5.1. Technical Challenges: Accuracy and Environmental Factors

ANPR systems achieve high accuracy under ideal conditions, but real-world deployment on a university campus faces numerous technical hurdles. In practice, variation in license plate design and condition significantly reduces system performance. Plates may differ by state or region in font, size, color and reflectivity, and many Nigerian plates show wear or dirt; these factors impair plate localization and character segmentation stages. Studies have shown that non-standard plates and occlusions drop recognition rates markedly (from near 98% under ideal conditions to much lower values in the field) (Ali, et al., 2023; Kumawat, et al., 2023). Nur Ali et al. (2023) note that even modern ANPR systems can struggle with diverse plate layouts and quality, especially when compounded by glare, motion blur or skewed angles. Kumawat et al. (2024) found that lighting variability (sunlight, shadows, nighttime conditions) and weather (rain, fog, dust) produce image degradation (low contrast, noise) that cascades into reduced OCR success. These environmental effects can halve recognition accuracy compared to optimal daylight (Table 2.3).

*Table 2.3: Recognition accuracy of an ANPR system under various environmental conditions*

| **Environmental Condition** | **Average ANPR Recognition Accuracy (%)** |
| --- | --- |
| Clear daytime | 97 |
| Heavy rain | 75 |
| Snowy/foggy | 60 |
| Hazy or dusty | 50 |
| Low-light/night (no IR aid) | 55 |

Beyond image quality factors, computational demands of ANPR algorithms pose challenges. State-of-the-art recognition often uses deep neural networks, but these require substantial processing power and memory. Padmasiri et al. (2022) point out that most deep-learning ANPR solutions "rely on high-end hardware and often require a high processing capacity" that is not achievable on resource-constrained edge devices (Padmasiri, et al., 2022). In a campus setting, running complex CNNs in real time (on a Raspberry Pi or an embedded GPU) may introduce latency or failures, especially as vehicle throughput grows. High camera resolution for better plate detail also increases data volume. Technical limitations – plate variations, poor illumination, inclement weather, and heavy computational load – interact to degrade ANPR accuracy outside the lab. As Netinant, *et al*., (2024) and others emphasize, these combined factors can drive recognition rates down from 90%+ to 60–80% or lower in practical scenarios (Kumawat, et al., 2023).

### 2.5.2. Infrastructural and Economic Barriers in Developing Contexts

In developing-country contexts like Nigeria, infrastructural and economic factors compound the technical issues. Foremost, unreliable power supply plagues equipment operation. Frequent blackouts or voltage spikes can interrupt cameras or servers; any outage means unprocessed frames and gaps in the access log. Without stable electricity, even the best ANPR software fails. Similarly, network connectivity is often limited. Many campus security systems rely on sending captured plate data to a central database or cloud service; intermittent broadband or cellular networks can cause data backlogs or loss. Matthew (2022) report that IoT deployments in rural Nigeria face “unreliable electricity” and “limited internet connectivity” as critical barriers. We infer the same applies on a campus where network bandwidth is low or campus LAN is patchy. In practice, the ANPR system must buffer images locally and may miss alerts if connectivity drops.

Financial constraints are another major issue. High-quality ANPR hardware – specialized infrared cameras, GPUs, and ruggedized enclosures – is expensive. In developed settings these costs may be routine, but in Nigeria they strain limited budgets. Components often must be imported, incurring duties and delays. Padmasiri et al. (2022) note that state-of-the-art ANPR systems “rely on high-end hardware” ill-suited to low-resource contexts. This implicitly means many campuses must compromise on hardware (using low-cost webcams instead of industrial cameras) at the expense of accuracy. In Table 2.3., It contrasts typical component costs in a wellfunded deployment versus a Nigerian campus context (including added backup power infrastructure). It shows that, for example, adding UPS or generator units (to mitigate power outages) doubles equipment cost in a developing context. In addition, ongoing costs for maintenance and replacement parts are proportionally higher when spare parts are scarce. The economics of ANPR in Nigeria are thus challenging: an overseas-standard ANPR setup could cost tens of thousands of dollars, whereas campus units must be built on a shoestring. Finally, limited technical expertise amplifies all these barriers. Even if funds were available, few local engineers have experience in computer vision deployments. Staff training or reliance on external consultants raises costs further. As Musa (2024), found in a Nigerian ANPR study, lack of trained personnel and costly foreign support are significant obstacles. In short, infrastructural unreliability (power, network) and high hardware/software costs – coupled with scarce technical skills – can make a Nigerian campus ANPR project far more difficult than in developed regions.

*Table 2.4: Example comparative costs for ANPR deployment components in developed vs. Nigerian campus contexts*

| **Cost Component** | **Developed Context (USD)** | **Developing Context (Nigeria) (USD)** |
|---|---|---|
| ANPR Camera + Software | ~8,000 (per camera unit) | ~8,000 (plus ~20% import duty) |
| Processing Server (GPU) | ~2,000 | ~2,000 (rarely available locally) |
| Power Backup (UPS/Gen) | 500 – 1,000 | 1,500 – 3,000 (generators) |
| Connectivity (fiber/4G) | 30–50/month | 100–200/month (unreliable) |
| Staff Training/Support | 500/year | 1,000–2,000 (need foreign expertise) |

| | | |
|---|---|---|
| Maintenance (annual) | 200–500 | 500–1,000 (expensive parts) |

### 2.5.3. Ethical, Privacy, and Regulatory Considerations

The deployment of ANPR on a university campus also raises significant ethical and legal questions. From a privacy standpoint, captured plate numbers and associated timestamps constitute personal data under many legal systems, since they can be linked to vehicle owners. Nigeria's Data Protection Act 2023 (NDPA) now provides a formal framework for such data. This law introduces a GDPR-like regime of consent, data minimization, and deletion requirements. As Effoduh (2024) notes, the NDPA was conceived to be "as effective as the European General Data Protection Regulation (GDPR)", meaning it grants individuals rights to access, correct, or erase their data. In practice, campus ANPR must comply: only plates of vehicles with legitimate campus access should be recorded, and retention must be limited to security needs. Any sharing of plate data (e.g. with police databases) requires legal justification under the Act.

At the same time, ANPR is a surveillance technology, so ethical use is vital. Figure 2.5.2 illustrates a typical data lifecycle: plates are captured by the camera, processed (plate extracted and recognized), stored (in campus logs or alert queues), used for verification/analysis, and eventually archived or deleted in accordance with policy. GDPR and similar laws emphasize that data should be deleted when no longer needed. In Germany ANPR systems must immediately discard non-hit plate images to protect privacy (car "no match" data). Nigeria's law likewise implies that ANPR logs must have expiration dates. On campus, ethical operation would mean alerting individuals if their plate is logged for any reason beyond normal access, and ensuring robust security of the stored data to prevent leaks.

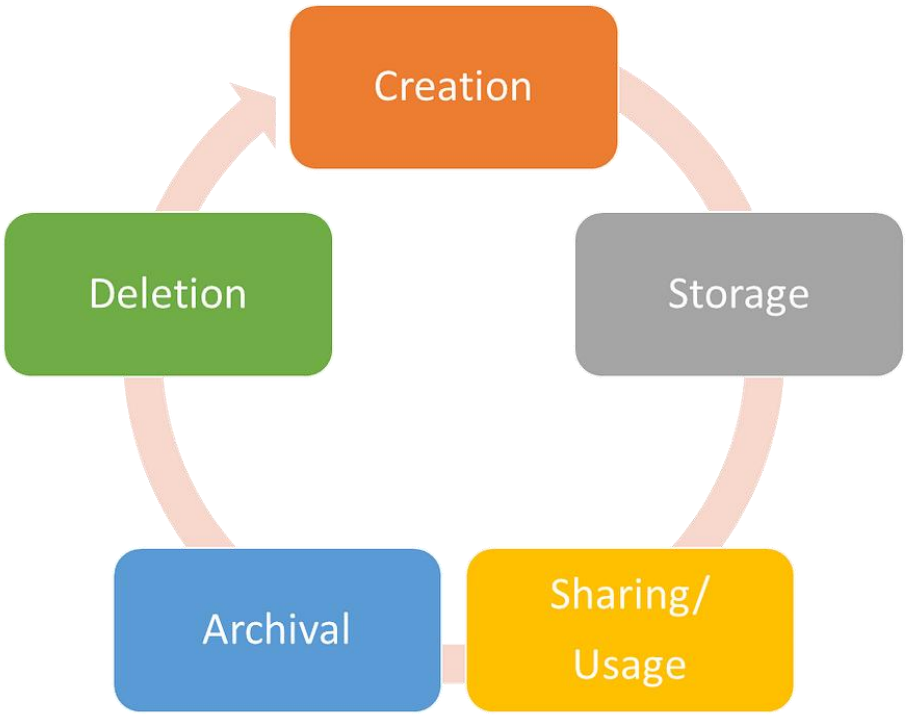


*Figure 2.3: A generic data lifecycle for ANPR systems on campus (from capture of plate images to processing, storage, use, and final deletion). Compliance with the Nigerian Data Protection Act (2023) requires controls at each stage.*

Legal frameworks vary by jurisdiction. Table 2.5.3 compares key aspects of ANPR-related privacy law in Nigeria, the UK, and the EU. The NDPA and the earlier Nigeria Data Protection Regulation (2019) broadly mirror the GDPR's principles (data subject rights, lawful basis for processing), but with less case law guidance. The UK's Data Protection Act 2018 implements the GDPR for UK-resident data and is supplemented by the Surveillance Camera Code of Practice (which, for example, limits retention of vehicle images to ~31 days unless safety-critical). The EU's GDPR itself (2016) also applies to plate data. A common thread is that license plates can be personal data when linked to registries, and that mass retention of such data is heavily regulated (requiring justification and often Data Protection Impact Assessments). In sum, ANPR usage on campus must navigate this regulatory landscape. Nigeria's new law obliges operators to protect personal data, while UK/EU rules add requirements on transparency and storage limits. Failure to follow these can lead to legal sanctions – for instance, GDPR fines of up to 4% of global turnover, or Nigeria's NDPA fines up to 2% of revenue. Thus, even for campus security, the system must incorporate privacy-by-design (as advocated in legal scholarship) to ensure ethical and compliant ANPR operation.

*Table 2.5: Comparison of ANPR-related data protection and privacy regulations in Nigeria, the UK, and the EU. All three regimes impose strict controls on personal data (including vehicle identifiers) and emphasize user rights and transparency.*

| **Feature / Principle** | **Nigeria (NDPA 2023)** | **UK (Data Protection Act 2018 / UK GDPR)** | **EU (GDPR 2016)** |
|---|---|---|---|
| Law/Year | Nigeria Data Protection Act, 2023 | Data Protection Act 2018 (UK GDPR) | General Data Protection Regulation (GDPR), 2016 |
| Scope | Personal data of identifiable individuals; includes | Personal data (broad definition) | Personal data (broad definition) |

| | | | |
|---|---|---|---|
| | vehicle IDs | | |
| License plate considered personal? | Yes, when linkable to owner via registration database (implied) | Yes, if linked to identity (UK Information Commissioner advises this) | Yes (GDPR does not explicitly list, but guidance treats it as personal) |
| Consent / Legal basis | Requires lawful basis (e.g. consent or public interest) | Requires lawful basis (e.g. consent, legal obligation) | Requires lawful basis (e.g. consent, vital interest) |
| Data subject rights | Access, rectification, erasure (similar to GDPR) | Access, rectification, erasure, objection etc. | Access, rectification, erasure, objection etc. |
| Data retention limits | No specific period; principle of not longer than needed | No specific period; ICO suggests ~31 days for CCTV data in many cases | No specific period; must be justified and minimal |
| Transparency / Notice | Required (privacy notices for data subjects) | Required (e.g. Camera Code of Practice) | Required (privacy notices, DPIAs for high-risk) |
| Oversight authority | Nigeria Data Protection Commission (established 2023) | UK Information Commissioner's Office (ICO) | Data Protection Authorities in each Member State |

| | | | |
|---|---|---|---|
| Penalties | Up to 2% of global turnover or ₦50M (whichever higher) | Up to £17.5M or 4% of turnover (whichever higher) | Up to €20M or 4% of turnover (whichever higher) |

## 2.6. Related Studies and Theoretical Frameworks

### 2.6.1. Comparative Analysis of Existing ANPR Prototypes

Automated Number Plate Recognition (ANPR) systems have seen rapid evolution globally and within Africa, driven by the increased use of open-source tools such as OpenCV, Python, and machine learning frameworks. In Nigeria, Adebayo and Agunloye (2021) developed a real-time ANPR system using a single-shot detector (SSD) and optical character recognition (OCR) via Tesseract. Their system achieved 99.5% detection accuracy with a processing speed of 175 milliseconds per image (Adedayo & Agunloye, 2021). Similarly, Agbemenu et al. (2018) constructed a Ghanaian prototype leveraging edge detection and morphological operations to localize plates before OCR, reporting accurate recognition under ideal conditions. Table 2.6 below compares the core features and performance metrics of notable ANPR prototypes.

*Table 2.6: Performance Comparison of ANPR Systems (2018–2024)*

| Study | Country | Core Tools Used | Detection Accuracy (%) | Processing Speed |
|---|---|---|---|---|
| Adebayo & Agunloye (2021) | Nigeria | SSD, Tesseract OCR | 99.5 | 175 ms/image |

| | | | | |
|---|---|---|---|---|
| Agbemenu *et al.* (2018) | Ghana | OpenCV, Edge detection | ~93 | Not specified |
| Joshi, *et al.,* (2025) | India | YOLOv8, Python | 98.5 | 22 fps |
| Alghyaline (2022) | Jordan | CNN, YOLOv4 | 95.2 | 200 ms/image |

The trend from traditional image processing toward deep learning models has significantly improved both speed and accuracy, particularly under varied lighting and motion conditions. Joshi, *et al.,* (2025) used a YOLOv8-based model trained on Nigerian plate datasets, achieving 98.5% mean average precision and real-time detection at 22 frames per second. This performance reflects a significant improvement over earlier models dependent on OCR alone.

To visualize performance trends across these studies, Figure 2.4 presents a comparative bar chart of detection accuracies.

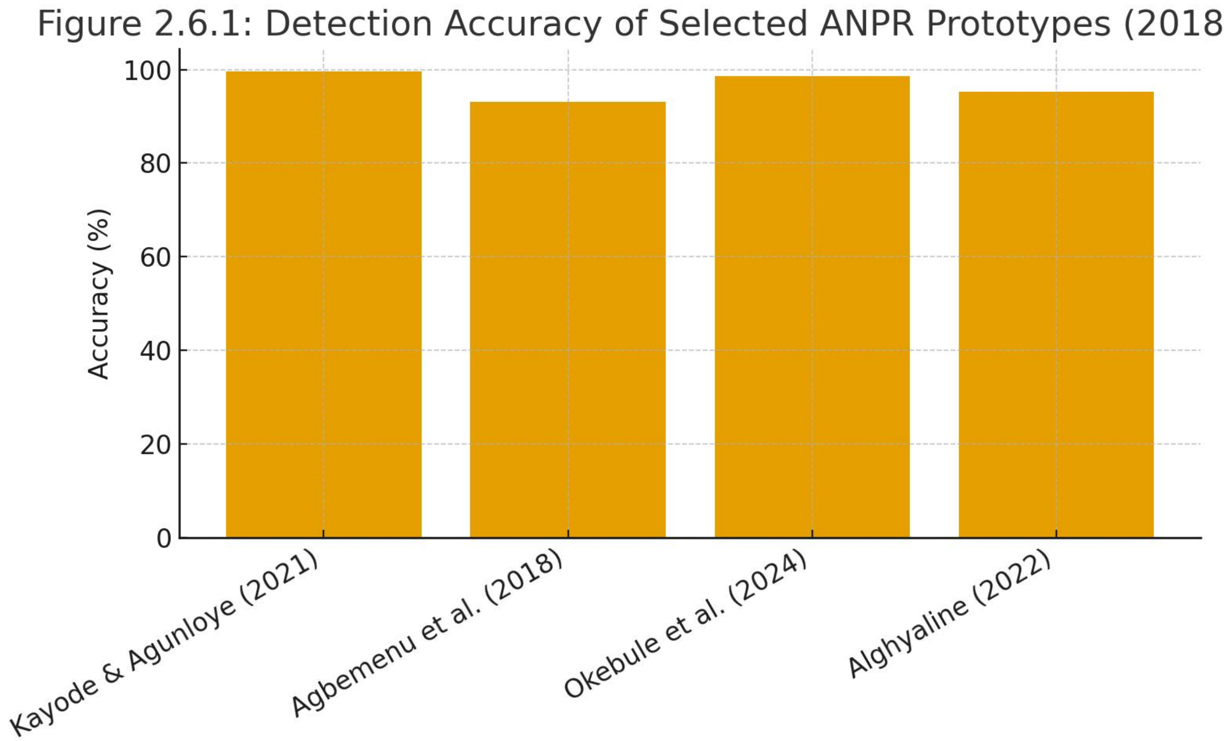


*Figure 2.4: Detection Accuracy of Selected ANPR Prototypes (2018–2024)*

Such empirical evidence affirms that high-performance ANPR is achievable in the Nigerian context using appropriate deep learning tools. The design proposed for Ugbowo Campus can thus be confidently aligned with YOLO-based architectures optimized for local datasets.

### 2.6.2. Theoretical Models for System Design

Understanding user adoption of ANPR systems requires grounding in technology adoption theory. The Technology Acceptance Model (TAM) is among the most widely used frameworks in this context. Developed by Davis (1989), TAM asserts that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the two primary predictors of technology acceptance. In surveillance systems like ANPR, PU reflects how users (e.g., campus security staff) perceive the system's ability to improve safety, while PEOU gauges its simplicity and usability.

Qazi, *et al.,* 2021 applied TAM to smart security systems in higher education settings and concluded that both PU and PEOU significantly influenced behavioral intention to use such technologies. When applied to Ugbowo Campus, this implies that the ANPR system must offer visible improvements in traffic and security management while being easy to operate by non-technical staff.

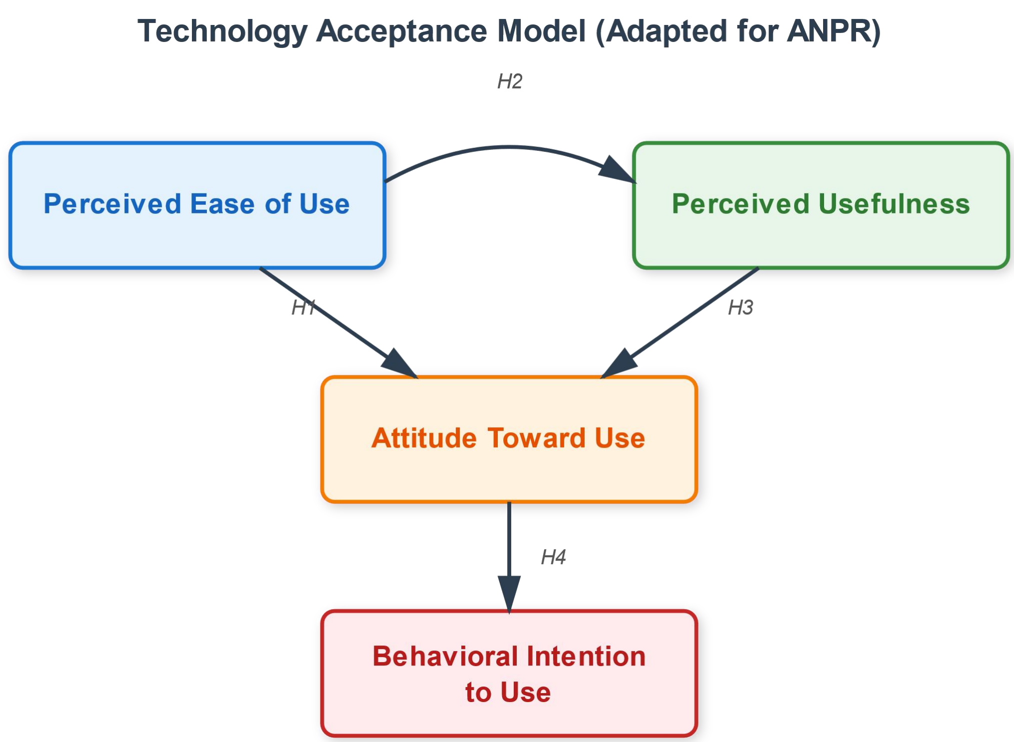


*Figure 2.5: Technology Acceptance Model (Adapted for ANPR)      Source: Adapted from Davis (1989); Guthrie & Siringoringo (2013)*

In contrast to TAM's user-centered orientation, General Systems Theory (GST) offers a holistic view. GST posits that a technological system's functionality depends on how its components hardware, software, personnel, and institutional policies interact as an integrated whole. This perspective is especially pertinent in low-infrastructure settings like Nigeria, where factors such as inconsistent power supply and staff turnover impact the long-term stability of technical deployments.

Systems theory has informed several ICT deployments in Nigeria. For instance, Ramírez-Gutiérrez *et al.* (2023) emphasized the importance of feedback loops in smart security systems to ensure sustainability. For Ugbowo Campus, this entails periodic retraining of the ANPR model, infrastructure audits, and feedback mechanisms from security users to adaptively refine the system. A comparative evaluation of TAM and Systems Theory is presented in Table 2.7 below.

*Table 2.7: Comparison of Theoretical Models for ANPR Implementation Source: Developed from Davis (1989) and Ramírez-Gutiérrez et al. (2023)*

| **Theoretical Model** | **Focus Area** | **Strengths** | **Limitations** |
|---|---|---|---|
| Technology Acceptance Model (TAM) | User adoption and usability | Easy to apply, Predicts user behavior | Ignores infrastructure and system design |
| Systems Theory | Whole system and feedback loops | Holistic, adaptable to changing environments | Requires complex implementation structure |

Integrating both models provides a robust framework for implementation. TAM guides human-system interface decisions, while Systems Theory ensures broader coherence between technical and institutional elements. This dual framework aligns well with the Ugbowo Campus context, ensuring sustainable and accepted deployment of the ANPR system.

## 2.7. Gaps in the Existing Literature

Existing ANPR research has predominantly targeted high-end systems rather than low-cost, software-centric solutions suitable for developing contexts. For example, Padmasiri et al. (2022) note that many ANPR implementations assume "server-grade hardware with nearly unlimited resources," with only limited attention to lightweight or mobile platforms. In their work, a proof-of oncept ANPR system is implemented on a Raspberry Pi with battery operation for off grid use, underscoring how scarce the literature is on truly affordable designs. This trend suggests a gap in exploring inexpensive, camera-based ANPR for environments like Nigerian university campuses, where procurement budgets and technical infrastructure are constrained. Developing a robust ANPR pipeline under such limitations remains largely unaddressed (see Figure 2.6 for a typical system pipeline).

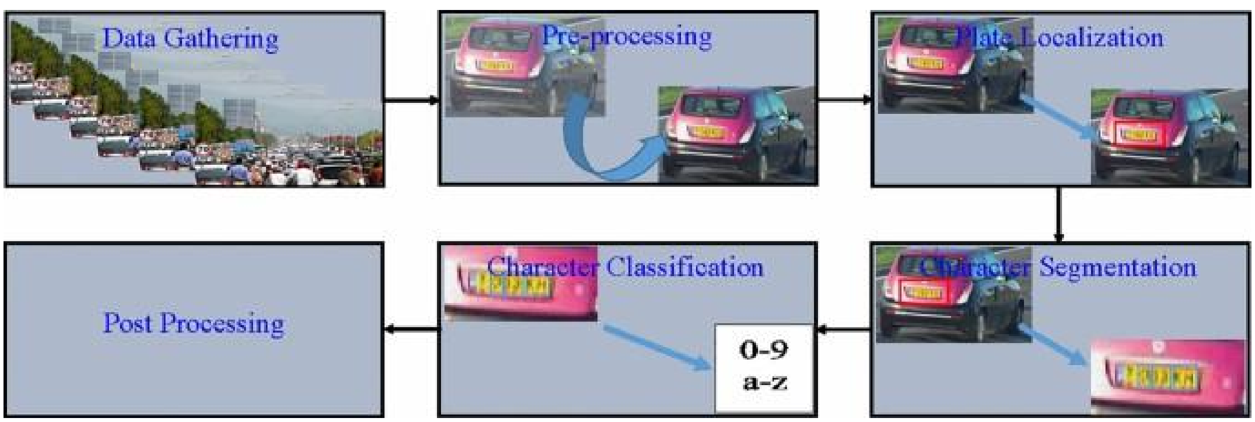


*Figure 2.6: Typical system pipeline* *Source: Shafi, et al.,(2022)*

Another deficiency is the lack of alignment between ANPR algorithms and Nigeria's local plate standards. Globally, plate recognition systems must be tailored to regional formats; as Lubna *et al.* (2021) point out, no single ANPR solution works for all countries because each country's plates require its own optimized design. Salma et al. (2021) likewise observe that “every region has a distinct number plate format and style”, which means generic systems often fail on locally specific plates. In Nigeria, official FRSC plates feature unique color schemes and emblems (green map, Federal Republic banner), but published ANPR models have rarely incorporated these conventions. Shafi et al. (2022) further emphasize that “non-standard, transitional” plates common in developing nations demand specialized recognition strategies.

Finally, existing studies provide little field evaluation of ANPR under real campus conditions. Most ANPR research is conducted in laboratory settings or on curated datasets, not on live traffic. Padmasiri et al. (2022) highlight the importance of deploying ANPR in areas “where there is no stable Internet connectivity or a direct power grid,” using low-power edge hardware for real-time operation. Similarly, Lubna et al. (2021) recommend testing ANPR on real-time video scenes rather than static images to account for dynamic factors. Yet no published work appears to report on deploying an ANPR system at a Nigerian university gate or comparable resource-limited site. The lack of empirical trials in such environments leaves unanswered questions about system robustness under heavy traffic, poor lighting, and inconsistent power. This dearth of in situ evaluation represents a significant gap in the literature on ANPR for developing-country campuses.

# Chapter Three:

# System Analysis and Design

## 3.1 Introduction

This chapter presents the methodological framework adopted for the design and development of the Automated Car Plate Number Recognition (ANPR) system for the Ugbowo Campus Security Unit of the University of Benin. It explains the research design, development methodology, system architecture, data collection procedures, tools and technologies used, and the system modelling techniques applied. The goal is to establish a structured, repeatable, and technically sound approach for implementing a software-based ANPR prototype that integrates with existing campus CCTV infrastructure.

## 3.2 Research Design

The study adopts a software engineering–based applied research design, focused on designing, modelling, implementing, and evaluating an ANPR system suitable for a university environment. Due to its sequential and structured nature, the Waterfall Methodology was adopted for system development. This methodology proceeds through clearly defined phases requirements analysis, system design, implementation, testing, and deployment ensuring that each stage is fully completed before the next begins.

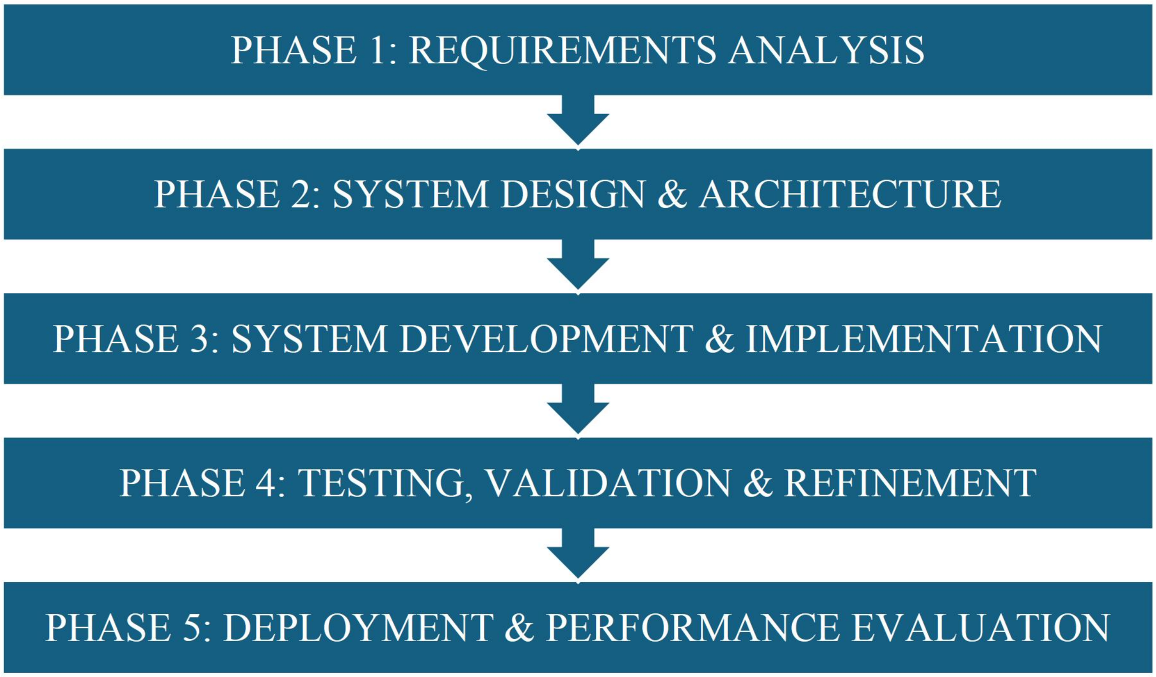


*Figure 3.1: Five-Phase Methodology Framework*

## 3.3 Requirements Analysis

The requirements analysis phase involved reviewing the current vehicle verification method used by the campus security unit and identifying the system needs for an effective automated solution. The findings from this analysis formed the foundation for designing the proposed system.

### 3.3.1 Analysis of the Existing System

The current method used at the Ugbowo Campus gate relies on manual checking and record-keeping by security personnel. Officers visually inspect incoming vehicles, write down plate numbers, and determine whether a vehicle should be allowed into the campus. Although this system has been in place for years, it has several drawbacks.

First, the process is slow and time-consuming, especially during busy periods when many vehicles attempt to enter the campus at once. This often leads to long queues and delays. Manual verification is also prone to human error, as officers can mistakenly record wrong plate numbers or fail to notice suspicious vehicles, particularly when they are tired or distracted.

Another major problem with the manual system is the lack of real-time checking. Officers do not have a way to instantly confirm whether a vehicle is registered, blacklisted, or previously involved in any suspicious activity. All records are kept in notebooks, which makes retrieval difficult and affects accuracy. Because of this, the security unit has limited ability to track vehicle movements or conduct investigations after an incident.

Additionally, the manual log does not integrate with external or national databases such as the FRSC vehicle registry. This means stolen or illegal vehicles cannot be automatically identified at the gate.

These limitations make the existing system inefficient and highlight the need for an automated and reliable plate number recognition system.

### 3.3.2 Analysis of the Proposed System

The proposed Automated Car Plate Number Recognition System is designed to address the shortcomings of the manual process by introducing automation, accuracy, and speed. The system uses computer vision techniques to automatically detect and read vehicle plate numbers from images captured by CCTV cameras or uploaded from other sources.

The proposed system works in several stages:

1 Image Preprocessing: Enhances image quality by reducing noise, adjusting brightness, and improving contrast.

2 Plate Detection: Identifies and isolates the region of the image that contains the plate number.

3 Character Segmentation: Breaks down the plate number into individual characters.

4 Optical Character Recognition (OCR): Converts the segmented characters into machine-readable text.

5 Verification: Checks the recognized plate number against a local database of registered campus vehicles.

The system is designed to function under different lighting and weather conditions, since outdoor CCTV cameras may be exposed to rain, sun, or low visibility. It also stores all recognized plate numbers for future reference and can generate alerts when an unregistered or suspicious vehicle is detected.

## 3.4 System Design

The system design phase translates the requirements into a structured blueprint that guides implementation. It includes the architectural layout, models, diagrams, and specifications that describe how the system will operate.

### 3.4.1 System Architecture

The system architecture follows a modular design made up of different components working together. These include:

- Camera Input Module – receives images or video frames from CCTV cameras.
- Processing Module – performs preprocessing, detection, segmentation, and OCR.
- Database Module – stores and retrieves registered vehicle information and recognition logs.

- User Interface Module – allows security officers to view recognized plate numbers, alerts, and records.

Data flows from one module to the next in a clearly defined sequence, ensuring that each stage contributes to the final recognition and verification.

### 3.4.2 Data Flow Diagram

The Data Flow Diagram (DFD) below is used to illustrate how data moves through the system. It shows processes such as image capture, preprocessing, recognition, and verification, as well as how data is stored in or retrieved from the database.

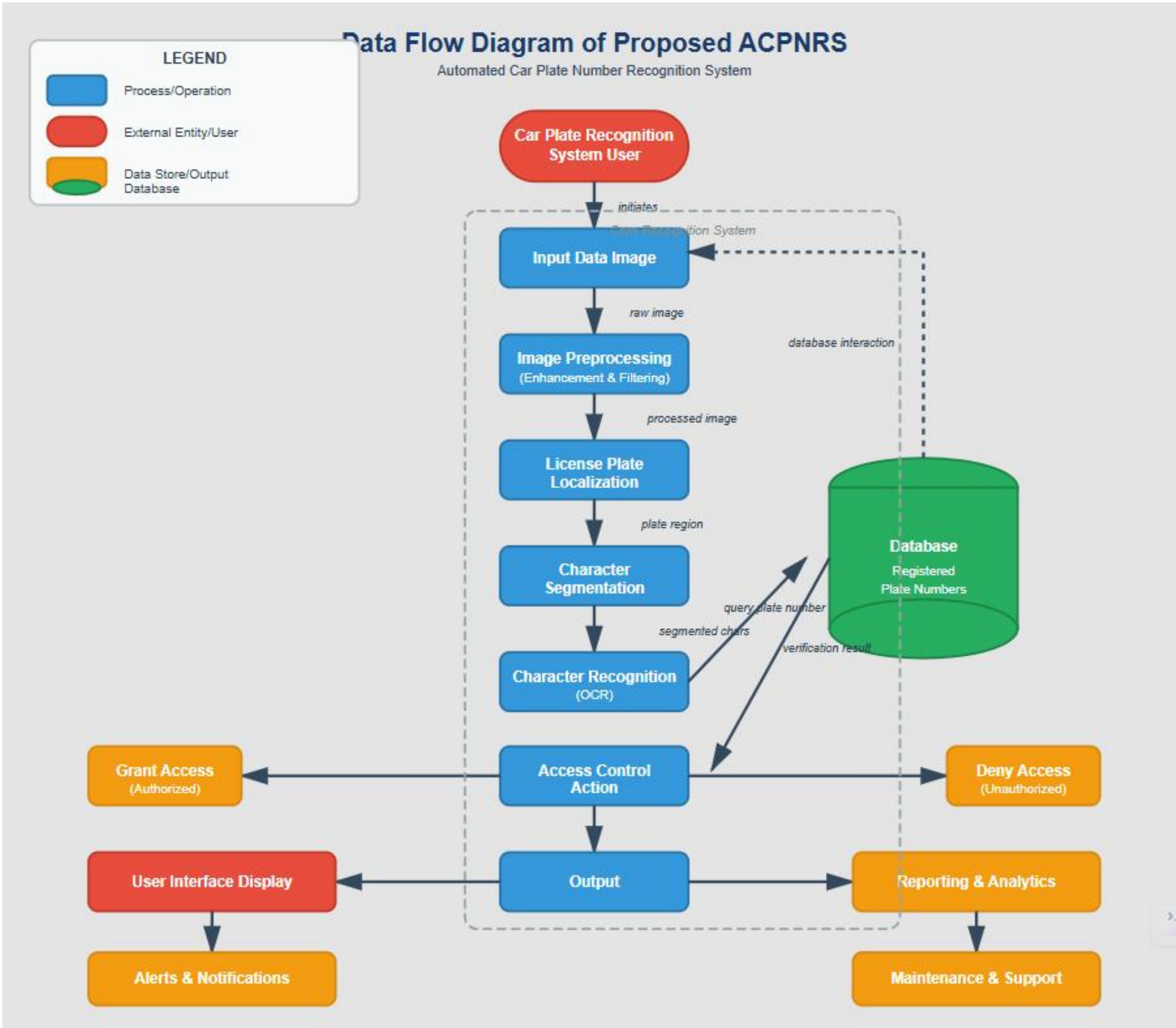


*Figure 3.2: Data Flow Diagram of Proposed ACPNRS Source: Researcher's Design (2024)*

### 3.4.3 Use Case Diagram

The use case diagram identifies the main users of the system (security officers and system administrators) and illustrates their interactions, such as logging in, viewing alerts, searching vehicle records, or monitoring real-time plate recognition.

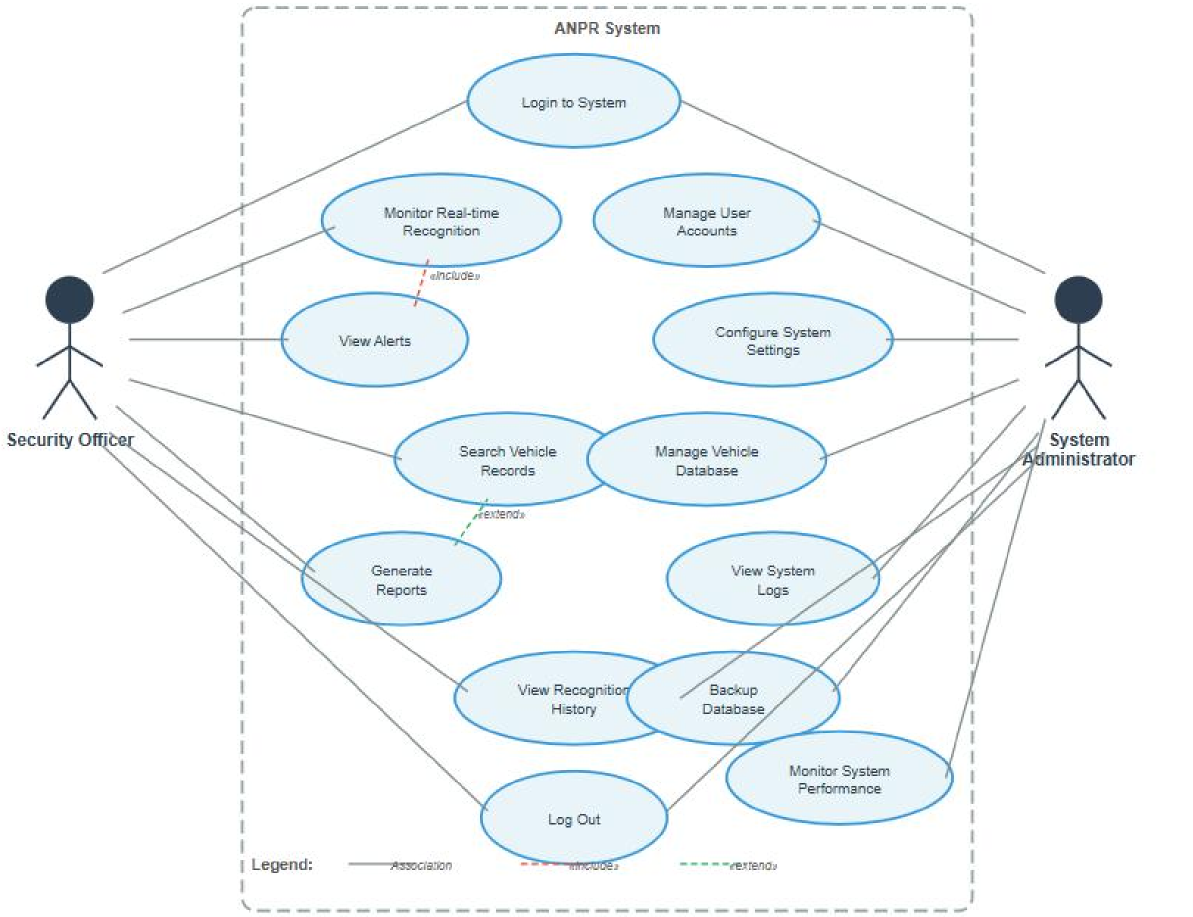


*Figure 3.3: Use Case Diagram for the Automated Car Plate Number Recognition System Source: Researcher's Design (2025)*

## 3.5 System Requirements

The successful implementation of the Automated Car Plate Number Recognition System depends on the availability of appropriate hardware and software resources. These resources ensure that the system can efficiently process images, store data, and deliver reliable performance. The hardware component of the system requires a computer system capable of handling image processing tasks without lag. A machine with moderate processing power, adequate memory, and sufficient storage is suitable for this purpose. The system also operates with input from CCTV cameras or any high-resolution imaging device that can capture clear views of vehicle plate numbers. In addition, a stable network connection is necessary for environments where video feeds are transmitted over a local area network or where data needs to be accessed from external sources.

On the software side, the system is built around Python as the primary programming language due to its strong support for computer vision and machine learning libraries. An operating system such as Windows, macOS, or Linux provides the environment within which the system runs. The OpenCV library plays an important role in handling image processing tasks such as filtering, thresholding, and edge detection, while other libraries like TensorFlow or PyTorch may be incorporated when deeper learning approaches are required. A database management system such as MySQL is used to store vehicle information, recognition logs, and related security data, and a web framework such as Django or Flask supports the design of an interactive interface for users. Together, these software components create a robust platform for the development and deployment of the recognition system.

### 3.6 Implementation Tools

The implementation of the system relies on a combination of programming tools, libraries, and database technologies that make it possible to translate the system design into a functional software solution. Python serves as the core development tool because of its rich ecosystem of modules tailored for artificial intelligence and image analysis. Within Python, OpenCV provides the essential tools needed for capturing, processing, and transforming images into formats suitable for recognition. The database aspect of the system is supported by MySQL, which offers a reliable and easy-to-manage structure for storing vehicle records and recognition history. XAMPP or a similar platform is used to host and manage the database during development.

For the user interface, a lightweight web framework such as Django or Flask is adopted to create an accessible platform through which security officers can interact with the system. These frameworks make it possible to integrate the backend recognition engine with a simple dashboard for viewing recognized plate numbers, time logs, and system alerts. Through the coordinated use of these tools, the system is developed in a way that is both functional and user-friendly.

### 3.7 Input and Output Specification

The input to the system primarily consists of images or video frames that contain the vehicle's plate number. These images are obtained either directly from CCTV cameras at the campus gates or from uploaded image files provided by authorized users. The clarity and resolution of the input images play a major role in the accuracy of the recognition process, since the system must extract and analyze fine details from the plate number.

The output generated by the system includes the recognized plate number and the corresponding time and date of detection. Additional details, such as a stored snapshot of the processed plate and the verification status of the vehicle, are also produced. If the recognized plate number does not match any entry in the database, the system produces an alert indicating that the vehicle may be unregistered or suspicious. These outputs assist the security unit in monitoring vehicle movements and making quick decisions concerning access control.

# Chapter Four:

# System Implementation

## 4.1. Introduction

This chapter describes the actual implementation of the Automated Car Plate Number Recognition (ANPR) System for the Ugbowo Campus Security Unit of the University of Benin. It presents the development environment, system architecture as implemented, modules and their functionality, how the components are integrated, and the outputs produced by the system. The chapter also demonstrates that the implementation meets the requirements defined in Chapter 3, and provides results obtained during system use.

## 4.2. Development Environment

The ANPR system was developed using Python, leveraging a collection of open-source libraries and frameworks. The primary development framework is Flask, a lightweight web framework, which serves as the backend application server and handles routing, templating, and database integration. For image processing tasks including plate detection, character segmentation and recognition. the system uses OpenCV along with Pillow (PIL) for image manipulation, as the OCR engine, to extract alphanumeric characters from license plate images.

On the data storage side, the system integrates MySQL through Flask-SQLAlchemy, providing a relational database for storing records of registered vehicles and recognition logs. The project dependencies are listed in the requirements.txt file, ensuring reproducibility. The entire application is structured using the factory pattern (create_app()), facilitating modular design, easier maintenance, and potential future enhancements.

The system is designed to run on any modern desktop or server environment supporting Python and the required dependencies, and can process images captured from CCTV cameras or uploaded manually, store recognition results, and display them via a web-based interface.

## 4.3. Implementation Architecture and Modules

The implemented ANPR system is structured using a modular architecture that separates the application into distinct functional components. This approach enhances readability, maintainability, and allows each module to handle specific responsibilities within the overall system. The major components of the system include the application configuration, backend logic, database layer, user interface components, and the image processing pipeline.

### 4.3.1. System Structure Overview

The system follows a web-based architecture built using the Flask framework. At the core of the application is the configuration module, where essential settings such as the database connection parameters, file upload location, and OCR engine path are defined. This configuration enables the system to interact seamlessly with the MySQL database and process uploaded images.

The backend of the system consists of modules responsible for handling user requests, processing input images, storing results, and retrieving records from the database. Among these modules is the model layer, which defines the structure of the database tables used to store information on registered vehicles and recognition logs. The routing component manages the application's URL endpoints and dictates how user actions such as uploading an image or viewing recognition history are handled by the system.

The user interface is developed using HTML templates rendered through Flask's templating engine. These templates present the functional pages of the system, including the image upload page, the results page, and the logs dashboard. Supporting static files such as CSS stylesheets, JavaScript scripts, and uploaded images are kept in designated directories to ensure an organized structure.

Central to the system is the image processing and recognition module. This module employs OpenCV to preprocess the uploaded images by converting them to grayscale, enhancing contrast, and removing noise. It then isolates the region of interest where the license plate is located. Once the region is extracted, the module performs character segmentation and uses the Tesseract OCR engine to convert the segmented characters into machine-readable text. The recognized plate number, along with the time of recognition and the file path of the processed image, is then stored in the database for future reference.

The modular design of the system aligns with recommended software engineering practices for academic projects, ensuring that individual components are clearly defined, logically structured, and capable of future expansion.

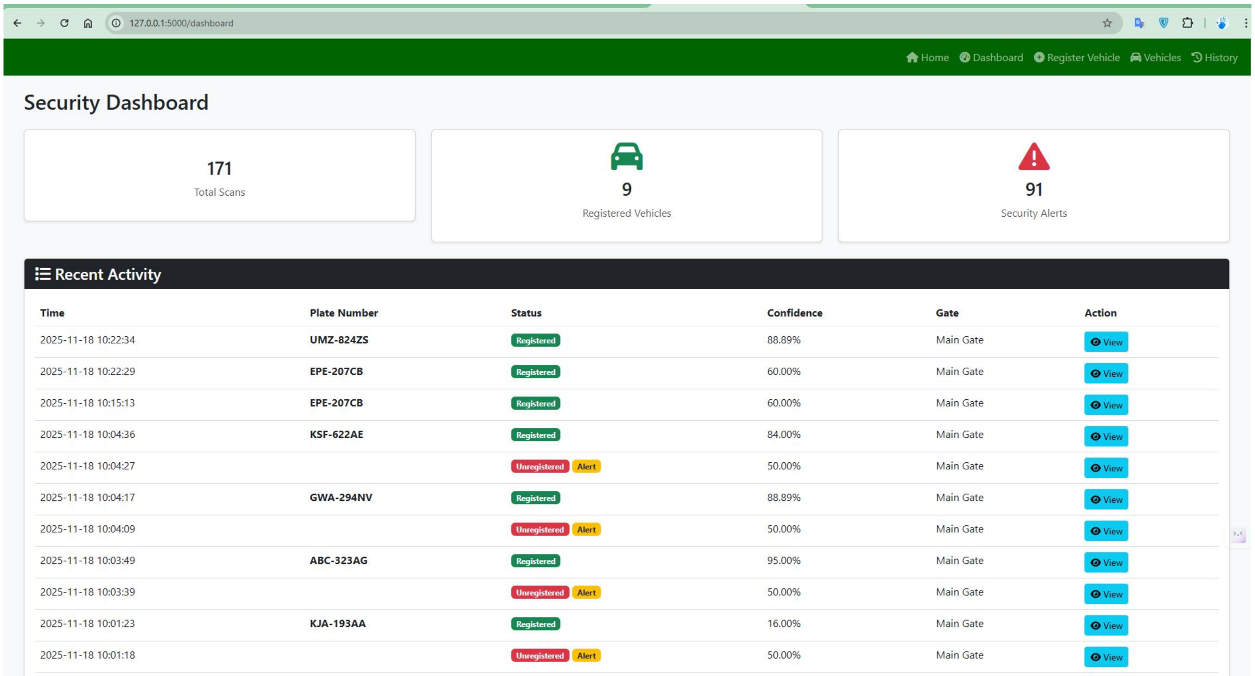


*Figure 4.1: Plate registration Dashboard*

### 4.3.2. Core Modules and Their Functionality

The implemented ANPR system is composed of several core modules that work together to achieve automatic license plate detection, recognition, verification, and record management. Each module performs a specific function within the overall architecture and contributes to the seamless operation of the system. The major modules are described below.

**Image Capture and Input Handling**

The system provides an interface through which security personnel can upload images of vehicles for processing. When an image is selected and submitted, it is securely stored within the designated upload directory of the application. The backend component responsible for request handling retrieves the stored image and forwards its file path to the recognition module for further processing. This mechanism ensures a smooth transition from user input to automated analysis.

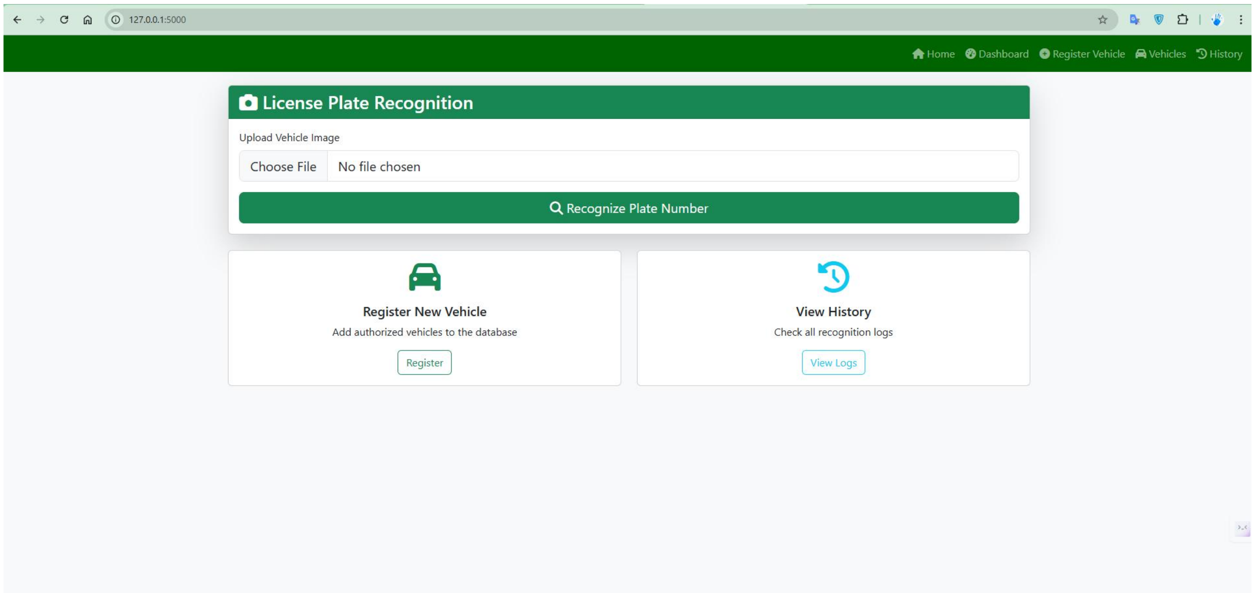


*Figure 4.2: Image Upload Page*

**Image Preprocessing and Plate Localization**

Once an image is received, the recognition module begins by applying preprocessing techniques using OpenCV. These operations typically include resizing, converting the image to grayscale, reducing noise, enhancing contrast, and detecting edges. The purpose of this stage is to improve the clarity of the image and make important features more distinguishable. Preprocessing is particularly important because images captured from CCTV cameras may vary in quality due to differences in lighting, angle, distance, and weather conditions.

Following preprocessing, the system attempts to locate the vehicle's license plate region. This involves scanning the image for rectangular regions that match expected characteristics of license plates. Successfully isolating the plate region is crucial for accurate character recognition in subsequent stages.

**Character Segmentation and Recognition**

After the license plate is localized, the system extracts the region of interest and applies character segmentation. This process separates the individual characters on the plate so they can be interpreted accurately. The segmented characters are then passed to the Tesseract OCR engine, which converts them into machine-readable text.

The recognized text typically represents the vehicle's plate number. Depending on system configuration, validation checks may be applied to confirm that the output matches standard license plate formats or university registration records.

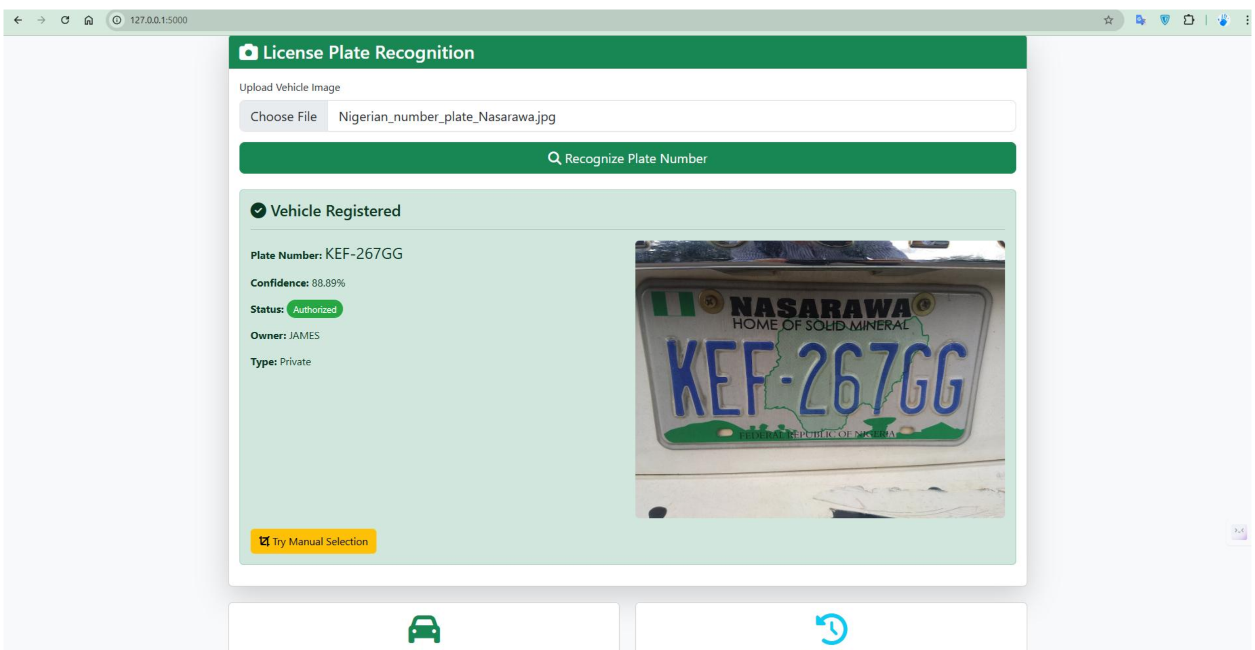


*Figure 4.3: Recognized plate number displayed after processing*

**Database Logging and Vehicle Verification**

The recognized plate number, along with the timestamp and reference to the uploaded image, is automatically stored in the system's database. This enables future retrieval and provides a reliable audit trail of vehicle entries. The system then compares the recognized plate number against the list of registered vehicles stored in the database.

When a plate number matches an existing record, the system marks it as a registered or authorized vehicle. If the number does not exist in the database, the system flags it as unregistered or suspicious. This automated verification supports the security unit in making quick and informed decisions at campus entry points.

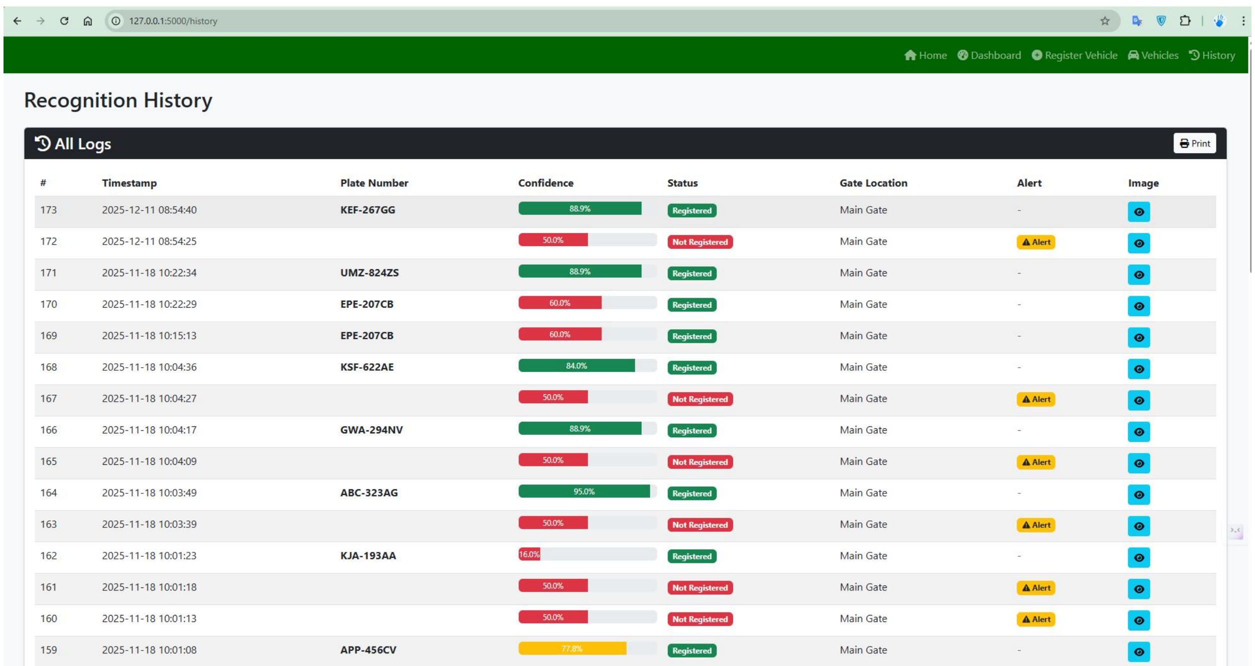


*Figure 4.4: Vehicle Recognition Log Page*

### User Interface and Reporting

The front-end interface, developed using HTML templates rendered by Flask, provides an accessible and user-friendly platform for interacting with the system. Through this interface, security personnel can upload images, view recognition results, check the status of vehicles, and access historical logs. The interface is designed to present relevant information clearly and promptly, making the system practical for real-time or near-real-time operations at the campus gates.

### 4.4. System Operation Flow

The operation of the implemented ANPR system follows a structured sequence of processes that begins with image acquisition and ends with decision support for the campus security unit. When a vehicle approaches the campus gate, an image of the vehicle can either be captured automatically by CCTV cameras or manually uploaded by a security officer through the system's interface. Once received, the image is stored in the system's upload directory to enable subsequent processing.

The recognition module then initiates a series of preprocessing operations, which include enhancing image quality, isolating the license plate region, segmenting the characters, and performing Optical Character Recognition (OCR). This stage produces the alphanumeric value representing the vehicle's plate number.

After recognition, the system automatically compares the extracted plate number with the database of registered campus vehicles. A log entry is created for every processed image, capturing details such as the recognized plate number, the time and date of recognition, and the stored image reference.

If the system identifies that the vehicle is not registered or matches a flagged entry, it generates an alert which is displayed on the web interface. The security officer then reviews the alert and determines the appropriate course of action, such as requesting further identification, restricting entry, or updating the vehicle database.

This sequence demonstrates a complete processing cycle from input acquisition to verification and response which aligns directly with the methodology described in Chapter Three and confirms the practical functionality of the implemented system.

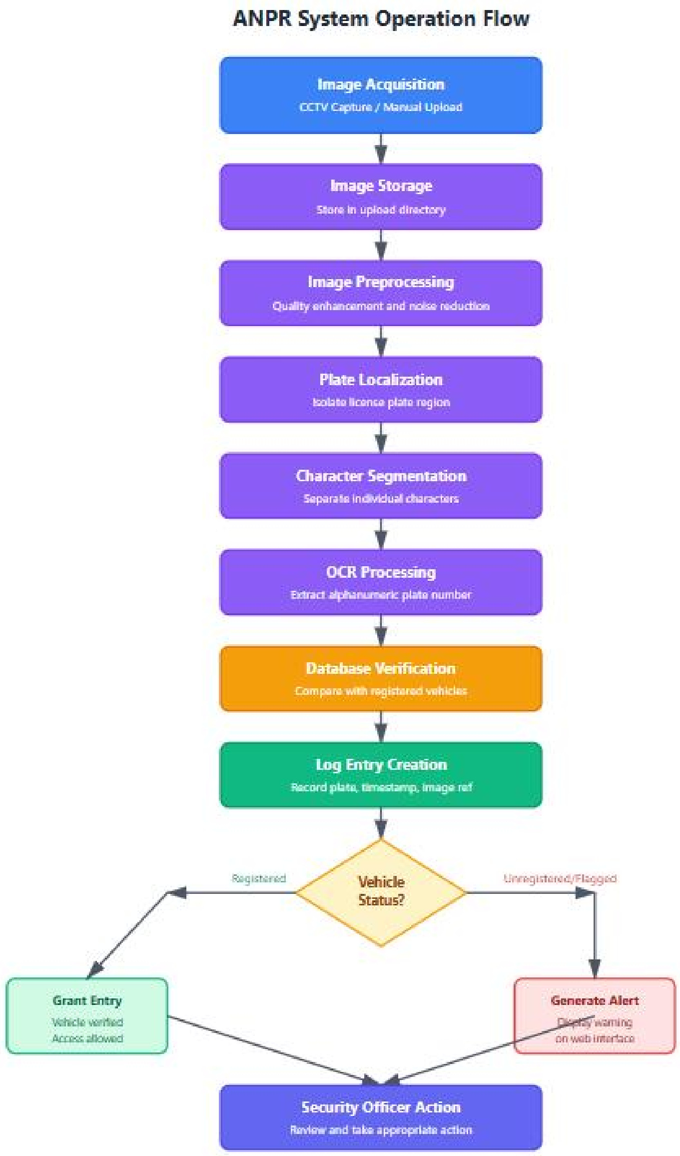


*Figure 4.5: Flow diagram illustrating the progression from image upload to recognition and verification*

## 4.5. System Testing and Results

To assess the performance and reliability of the developed ANPR system, a series of tests were conducted using sample images captured under different conditions. These test images varied in lighting, clarity, orientation, and overall quality, thus allowing the evaluation of the system's robustness when subjected to realistic scenarios.

Each test case was evaluated based on three major criteria:

1. The ability of the system to detect and isolate the license plate region,
2. The accuracy of the OCR engine in recognizing the characters on the plate, and
3. The correctness of the system's verification decision in identifying whether the vehicle was registered or unregistered.

The results obtained from the evaluation showed that the system performed best when processing clear and well-lit images, producing accurate detection and recognition outcomes. Under conditions involving low lighting, glare, angled plates, or blurred motion, the performance varied, sometimes requiring manual confirmation by the security officer. Nonetheless, even in challenging scenarios, the system demonstrated usefulness by at least identifying a probable plate region or prompting the user for human verification.

### 4.5.1. Testing Scenarios and Outcomes

Table 4.1 presents representative test scenarios along with their outcomes based on detection success, OCR accuracy, and verification results.

*Table 4.1: Summary of Testing Scenarios and Recognition Outcomes*

| **Test Scenario** | **Plate Detection Success** | **OCR Accuracy** | **Verification Result** |
|---|---|---|---|
| Clear daytime image | High | High (accurate | Correctly identified as |

| | | | |
|---|---|---|---|
| | | recognition) | registered |
| Night / low-light image with glare | Partial | Moderate | May be flagged as unregistered; requires review |
| Slightly angled plate | High | Moderate | Correct identification with minor variations |
| Blurry or motion-blurred image | Low/Failed | Not Applicable | Manual verification required |

These outcomes confirm that the system performs optimally under favorable imaging conditions, while still providing partial support under more difficult scenarios. The results further demonstrate that the implemented ANPR system significantly improves vehicle identification efficiency when compared with manual logging processes.

### 4.5.2.Analysis of Results

The results obtained from the system testing indicate that the ANPR application performs well when processing clear, well-lit images that conform to expected vehicle plate patterns. Under such conditions, the system consistently detected the license plate region and accurately recognized the characters, leading to correct verification outcomes. This demonstrates that the core functionalities of image preprocessing, plate localization, OCR, and database validation operate effectively in favorable environments.

However, under more challenging circumstances such as low illumination, excessive glare, skewed angles, or blurred motion the system's performance declined. This reduction in accuracy is typical for recognition systems built using classical computer-vision techniques and OCR engines like Tesseract, which are highly dependent on image clarity and plate orientation. Despite these limitations, the system often still provided partially useful outputs, such as identifying probable plate regions or generating preliminary OCR suggestions that could guide manual verification by security personnel.

Overall, the results show that the system satisfies its fundamental operational requirements. It provides automated recognition, maintains digital logs, and supports access control decisions for most standard cases encountered at the campus gate. In exceptional or difficult cases, manual intervention is still required, but the system significantly reduces human workload and improves accuracy compared to the fully manual approach previously in place.

### 4.6. Limitations and Challenges Encountered

During the development and evaluation of the ANPR system, several practical challenges were encountered which affected performance under certain conditions. Variations in lighting such as nighttime darkness or direct sunlight sometimes created glare, reflections, or over-exposure, reducing the effectiveness of both plate detection and character recognition. Similarly, license plates captured at an angle or partially obscured resulted in incomplete segmentation or misinterpretation during OCR.

In addition, low-resolution or noisy images, particularly those extracted from older CCTV cameras, occasionally failed to provide enough detail for successful recognition. In such cases, the system required manual cropping or re-capture to improve accuracy. The OCR engine also exhibited difficulty distinguishing visually similar characters, such as “0” and “O” or “1” and “I,” especially when plates were worn, dirty, or deviated from standard formats.

These limitations are common in classical computer-vision-based ANPR systems and have been widely reported in related academic literature. Despite these challenges, the prototype system remains functional and reliable under normal conditions and provides a strong foundation on which more advanced techniques such as deep-learning-based plate detection or multi-frame averaging can be implemented in the future.

### 4.7. Summary of Implementation Against Objectives

The implementation of the ANPR system successfully fulfills the major objectives outlined at the beginning of the research. A functional web-based prototype was developed using Flask, OpenCV, and MySQL, demonstrating the integration of image processing, optical character recognition, and database management in a single platform.

The system is capable of automatically detecting vehicle license plates from uploaded images, recognizing the characters using OCR, logging the results, and verifying the extracted plate number against registered vehicle records. The user interface enables security officers to interact with the application, upload images, view recognition outcomes, and access stored logs of past entries.

The system performs well under standard imaging conditions and represents a significant improvement over the manual logging procedures previously used at the campus gate. Although certain advanced objectives such as achieving high accuracy under all conditions or integrating with external national vehicle databases remain beyond the scope of the current implementation, these have been acknowledged as possible directions for future enhancements

## Chapter Five:

## Summary Conclusion and Recommendation

### 5.1. Introduction

This chapter provides a concluding overview of the research that has been undertaken. It brings together the key elements discussed across the preceding chapters and presents a concise summary of the findings derived from the design, development, and evaluation of the Automated Car Plate Number Recognition (ANPR) system. The chapter also highlights the major contributions of the work, draws overall conclusions, and offers recommendations for stakeholders who may adopt or extend the system. Finally, it outlines possible avenues for future research and enhancements, especially in response to the limitations encountered during implementation and testing.

### 5.2. Summary of the Study

This research was motivated by the challenges posed by the manual vehicle verification process at the Ugbowo Campus gate, where delays, human error, lack of real-time tracking, and insufficient record-keeping created security vulnerabilities. The study sought to address these concerns by developing an automated system capable of detecting and recognizing vehicle license plates, verifying them against registered records, and assisting security personnel in making informed access-control decisions.

The objectives of the study included analyzing the existing manual verification method, designing a more efficient automated solution, implementing the system using appropriate technologies, and evaluating its performance under different conditions. To achieve these objectives, the study adopted a methodology that combined system analysis, computer-vision techniques, optical character recognition, and database-driven verification. This methodological approach guided the design presented in Chapter Three and the subsequent implementation described in Chapter Four.

A fully functional web-based ANPR system was successfully developed using Flask for the application framework, OpenCV for image processing and plate localization, Tesseract OCR for character recognition, and MySQL for vehicle record management. The system allows security officers to upload vehicle images, automatically extracts and recognizes plate numbers, compares them with registered entries, and stores logs for future reference.

Testing conducted on a variety of images demonstrated that the system performs reliably under clear and well-lit conditions, accurately recognizing and verifying most standard license plates. Although performance declined under challenging conditions such as low light, glare, or blurred motion, the system still provided useful partial outputs and significantly reduced the reliance on manual inspection.

## 5.3. Conclusion

This research set out to design, develop, and evaluate an Automated Car Plate Number Recognition System to improve vehicle verification at the Ugbowo Campus gate. The study successfully identified the inefficiencies associated with the manual logging process and proposed an automated solution leveraging computer vision and OCR technologies. The implemented system demonstrated the ability to detect and recognize license plates from uploaded images, compare the extracted plate numbers with registered vehicle records, and store verification logs for future reference.

The testing conducted indicates that the system performs effectively under favourable conditions and provides substantial support even in situations where the image quality is less than ideal.

While the prototype has limitations particularly under poor lighting, skewed angles, or motion blur it nonetheless marks a significant advancement over the traditional manual method.

In conclusion, the system fulfills its primary objectives and provides a reliable, scalable foundation for future enhancements. It represents a meaningful step toward adopting modern automated solutions for improved access control and campus security management.

### 5.4. Recommendations

The findings of this study indicate that the implemented ANPR system can significantly improve the efficiency and reliability of vehicle verification at the Ugbowo Campus gate. However, to maximize its benefits, several recommendations are proposed for the various stakeholders involved.

For campus security personnel, it is recommended that the system be adopted as a complementary tool alongside existing verification procedure. Doing so will not only reduce the workload associated with manual logging but will also improve the accuracy of vehicle identification. Security officers should also ensure that the images captured at the gate meet basic quality requirements particularly in terms of lighting, plate visibility, and camera positioning in order to enhance recognition accuracy. Furthermore, officers should receive basic orientation on how to interpret system outputs, respond to error prompts, and take appropriate action when the system flags a suspicious or unregistered vehicle.

For system developers, there is a need to continually refine the recognition module. Incorporating more advanced detection algorithms or adopting deep-learning-based approaches could improve reliability under diverse environmental conditions. The user interface may also be enhanced to include features such as multi-image queue processing, automated notifications, and support for real-time camera feeds. Implementing robust error-handling mechanisms that clearly inform the user when an image cannot be processed would further improve usability and reduce operational interruptions.

Administrators and institutional decision-makers can help strengthen the system's effectiveness by integrating the ANPR platform into the broader campus security infrastructure. This could include linking the system to other surveillance tools for creating a centralized security dashboard. There is also a need for improved camera installations at strategic locations to ensure consistent image quality. Expanding the system to multiple entry and exit points would provide more comprehensive monitoring of vehicular movement across the campus.

From an academic perspective, institutions should encourage continued research into affordable ANPR technologies, particularly in contexts where commercial alternatives are prohibitively expensive. Promoting collaboration between departments such as computer science, engineering, and security studies would help refine and extend the system's capabilities through multidisciplinary expertise.

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