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Smart Gate Ticketing System using OCR and Convolutional Neural Networks with Real-time Edge Inferencing: A Case Study of Federal University Dutsin-Ma, Katsina State

Muhammad Yahya[1]*, Zaharaddeen Sani[2] and Umar Iliyasu[3]
[1, 2 & 3]Department of Computer Science and InformationTechnology, Faculty of Computing, Federal University, Dutsin- Ma, Katsina State, Nigeria.
*Corresponding Author Email: ymuhammad1@fudutsinma.edu.ng

ABSTRACT
This research proposal aims to develop a Smart Gate Ticketing System utilizing Optical Character Recognition (OCR) and Convolutional Neural Networks (CNNs) with real-time edge inferencing, specifically tailored for the Federal University Dutsin-Ma in Katsina State, Nigeria. The proposed system seeks to address the significant operational inefficiencies and security vulnerabilities inherent in the current manual gate ticketing process. By automating the recognition and verification of vehicle license plates, the system aims to enhance operational efficiency, reduce long wait times, and minimize the risk of fraud. Unique to this research is the focus on environmental resilience, taking into account the prevalent weather conditions in Northern Nigeria, such as heavy rainfall, lightning, and sandstorms, which have previously been neglected in similar studies. The integration of OCR and CNN technologies will enabled high-accuracy real-time recognition and validation of vehicle entries. Edge computing will ensure low latency and high efficiency by processing data locally at the source. The study involved comprehensive data collection, model training, and system evaluation to ensure robustness and reliability. The anticipated outcome is a scalable, cost-effective solution that not only meets the current needs of the university but also sets a precedent for similar applications in other institutions and public facilities. This research contributed significantly to the advancement of smart technology integration in ticketing and access control systems.

Keywords:
Automatic Number Plate Recognition,
Computer Vision,
Convolutional Neural Networks,
Optical Character Recognition,
Object Detection

INTRODUCTION

The rise of smart technologies and the Internet of Things (IoT) has significantly impacted daily life, especially in sectors like transportation, healthcare, and security (Rejeb *et al.*, 2023). Ticketing systems are among the areas experiencing transformation, as intelligent solutions are increasingly adopted to improve efficiency and user experience (Mouha, 2021). Traditional ticketing systems often encounter problems such as long queues, fraud, and manual errors. These issues are being addressed by automated systems that utilize advanced technologies like Optical Character Recognition (OCR) and Convolutional Neural Networks (CNN) (Aras & Guvensan, 2023).

Many developed countries are implementing these technologies for smart gate ticketing, policy enforcement, and vehicle theft prevention (Leka et al., 2023). This trend has spurred research focused on creating accurate, reliable, and efficient systems (Leka et al., 2023; Aras & uvensan, 2023). However, challenges remain, including limited dataset sizes, lack of robustness, and poor model generalizability (Singh, 2023). Notably, demographic and environmental factors such as rainfall, lightning, and sandstorms—common in northern Nigeria, where the Federal University of Dutsin-Ma is located—have not been adequately addressed in previous studies (Padmasiri *et al.*, 2022; Yash *et al.*, 2023; Jawale *et al.*, 2023). These factors hinder clear vehicle plate detection, affecting model accuracy and efficiency. Addressing them is essential for improving the robustness of current models.

The Federal University of Dutsin-Ma has historically relied on a manual gate ticketing system, which hasresulted in long queues, human errors, and vulnerability to fraud. These issues compromise operational efficiency and the user experience, highlighting the need for innovative solutions to streamline processes, reduce vulnerabilities, and enhance security. This necessity has prompted a critical evaluation of current practices and the exploration of advanced, intelligent ticketing systems to upgrade the institution's gate management infrastructure.

To address these challenges, the Federal University of

Dutsin-Ma developed a Smart Gate Ticketing System using OCR and computer vision techniques. The goal is to create and implement an Automatic Number Plate Recognition (ANPR) system that operates in real-time with edge inference capabilities. The proposed model specifically considered environmental factors like rainfall, lightning, and sandstorms, which are prevalent in Northern Nigeria and have not been sufficiently addressed in prior research. These conditions often result in unclear vehicle plate detection, negatively impacting model performance (Tao *et al.,* 2024).

OCR technology enables the automatic reading and processing of printed or handwritten text from images, making it vital for ticket validation. When combined with CNNs deep learning algorithms highly effective in image recognitionthe system can achieved high accuracy in real-time edge inferencing (Memon *et al*., 2020). This allows ticket validation to occur instantly at the entry gate, eliminating the need for centralized processing, reducing latency, and improving user experience.

OCR is crucial for digitizing text from physical documents, transforming images with written or printed text into machine-readable data (Memon *et al.*, 2020). This automation enhances data management efficiency by making large volumes of text searchable and editable (Alowais *et al.,* 2023). The OCR process includes preprocessing (noise reduction, binarization, normalization), feature extraction (identifying lines, curves, intersections), and classification (matching features to known character templates) (Alahmadi & lshangiti, 2024; Ma *et al*., 2020). Modern OCR systems, enhanced by machine learning—especially deep learning—can adaptively learn various fonts, styles, and even handwritten text, achieving high accuracy under diverse conditions (Orji *et al.*, 2023). OCR applications are widespread, including digitizing historical manuscripts, automating mail sorting, enabling assistive technology for the visually impaired, and streamlining business processes.

Computer vision, a rapidly evolving field of artificial intelligence, enables machines to interpret and make decisions based on visual inputs, covering tasks like image classification, object detection, segmentation, and facial recognition (Soliman *et al.*, 2024). At the core of many computer vision systems are CNNs, which emulate the human visual system's pattern recognition abilities (Manakitsa *et al.*, 2024). CNNs comprise multiple layers: convolutional layers apply filters to input images to produce feature maps, each detecting different features (edges, textures, colors) (Zhao & Zhang, 2024); pooling layers reduce spatial dimensions by down-sampling, decreasing computational load and increasing robustness (Nirthika *et al.*, 2022); fully connected layers perform high-level reasoning and classification based on extracted features (Krichen, 2023). CNNs are especially effective for image recognition due to their ability to automatically learn complex spatial hierarchies, making them suitable for real-time object detection, automated surveillance, medical image analysis, and advanced driver assistance systems (Zhao *et al.*, 2024). Their use ensures high accuracy and reliability in interpreting visual data, making them a cornerstone in intelligent systems development (Manakitsa *et al.*, 2024).

The proposed Smart Gate Ticketing System at the Federal University of Dutsin-Ma aims to address several key challenges: reducing long wait times at entry points, minimizing the risk of counterfeit tickets, and improving overall security. The system is designed to function efficiently within the resource constraints typical of edge computing environments, ensuring both cost-effectiveness and scalability. The study will demonstrated the feasibility and benefits of deploying a Smart Gate Ticketing System using OCR and CNN technologies, examining the system's architecture, implementation, and performance in the university context. This case study will provide valuable insights for broader application in similar environments. By pioneering this solution, the university aims to sets an example for other institutions and public facilities, contributing to the wider adoption of smart technology in ticketing and access control systems.

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Research Gap

Despite significant advancements in the use of Optical Character Recognition (OCR) and Convolutional Neural Networks (CNNs) for smart gate ticketing systems, current research often overlooks the unique environmental challenges prevalent in Northern Nigeria, such as heavy rainfall, lightning, and sandstorms, which can obscure vehicle license plates and hinder accurate recognition. Most existing models are developed and tested in relatively stable and controlled environments, lacking robustness against these adverse conditions. Additionally, the integration of real-time edge computing for instantaneous ticket validation at entry points has not been fully explored, leaving a gap in addressing latency and processing efficiency. This study aim to bridges these gaps by developing a resilient and scalable Smart Gate Ticketing System tailored to the specific environmental and operational needs of the Federal University of Dutsin-ma, thereby enhancing accuracy, reliability, and user experience.

MATERIALS AND METHODS

The research design for developing the Smart Gate Ticketing System integrated both experimental and quantitative approaches to ensure a rigorous evaluation of the proposed system. This design is structured around five key phases: data collection, preprocessing, model development, system integration, and evaluation. Each phase plays a critical role in the overall development and validation of the system.

SGTS Work flow

The workflow for the Automatic Number Plate Recognition (ANPR) system involves a sequence of steps designed to accurately capture, process, and recognize vehicle license plates from video data. The process starts with video data collection and proceeds through frame capturing, image preprocessing, plate region detection, plate extraction, character recognition, and finally, output generation. This structured approach ensures that the system operates efficiently and accurately in real-time. Each step is crucial for maintaining the integrity and accuracy of the recognition process, from initial data acquisition to final character output. By systematically breaking down the workflow, the ANPR system can handle the complexities of different environmental conditions and plate variations, ensuring robust performance and reliability in practical applications.

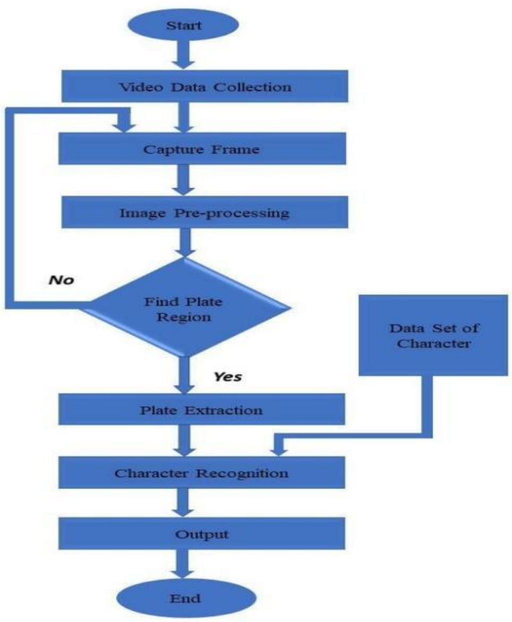

Figure 1: SGTS Workflow

SGTS Architecture

The architecture of the Automatic Number Plate Recognition (ANPR) system was designed to effectively capture, process, and recognize vehicle license plates from images. This comprehensive pipeline integrates various stages from data collection to training and testing to ensure high accuracy and efficiency. The system was divided into three main phases: Data collection, training, and testing. Each phase consists of specific tasks aimed at detecting and recognizing license plates and their characters.

As shown in Figure 2, the data collection phase is the foundational stage where extensive and diverse data were gathered to build a robust dataset for training the ANPR system. This phase involves two key components: license plate detection and character confirmation/recognition. In license plate detection, 163 images of vehicles with visible license plates were collected from various sources, out of these images a total of 426 images were generated using three different data augmentation techniques. These techniques where applied to ensure a wide range of conditions such as different lighting, angles, and weather. The comprehensive dataset was crucial for training effective detection and recognition models. The dataset was splitted using the train_test_split function of the scikit-learn library in a 70:15:15 ratio, where 70% of the images were allocated for training the OCR and CNN models, 15% for validation during model tuning, and the remaining 15% reserved for final testing and performance assessment.

In the Training phase, the collected dataset is utilized to train the detection model. The first step is license plate detection, where the YOLOv8 is trained using the 263 license plate images to accurately locate the rectangular regions containing license plates within the images. This model learns to identify the boundaries and position of license plates regardless of variations in the input images. The next step is character detection, which involves training a CNN model to segment and detect each character within the license plate region. This segmentation is critical for isolating each character for subsequent recognition. Finally, PaddleOCR was applied to the segmented platesor individual characters for text extraction. This technique classifies each detected character into its corresponding alphanumeric value, enabling the system to convert the segmented characters into readable text.

The Testing phase evaluates the performance of the trained models on new, unseen data to ensure their accuracy and reliability in real-world applications. This phase starts with the system receiving a new input image of a vehicle. The trained license plate detection model processes this image to identify and isolate the license plate region. Once the license plate is detected, the character segmentation and detection model segment the plate into individual characters, separating each one for further processing. These segmented characters are then fed into the character recognition model, which converts them into a coherent string representing the license plate number. This final recognized license plate number is displayed as the output. The testing phase is crucial for assessing the model's performance metrics, such as accuracy, precision, recall, and F1-score, ensuring that the system can operate effectively and efficiently in real-time applications.

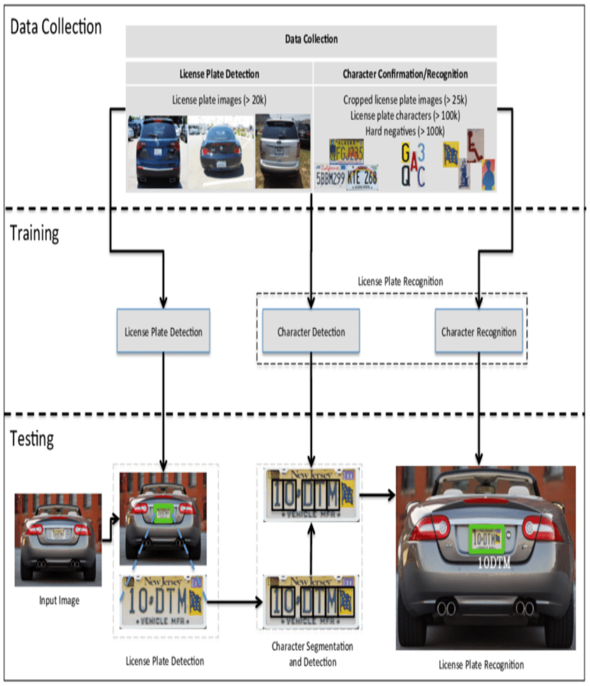

Figure 2: SGTS Architecture

RESULTS AND DISCUSSION

This section evaluates the performance of the YOLOv8-based detection model developed for the Smart Gate Ticketing System (SGTS) at the Federal University of Dutsin-Ma. To assess robustness, performance metrics such as accuracy, precision, recall, and F1-score were calculated across multiple training iterations. Computational dynamics, including learning curves and loss convergence, were analyzed to evaluate training stability and efficiency.

Evaluation Metrics

The use of performance measures in the evaluation of deep learning related to human health is critical and essential. In this study, we used four performance measures as follows:

i. Accuracy: Is the number of pixels correctly detected during inferences over the total number of pixels detected in a given image. This is mathematically expressed in equation 1:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

ii. Precision: Is the fraction of positive detection among the total number of detected boxes, as expressed in Equation 2.

$$\text{Precision} = TP/(TP + FP) \quad (2)$$

iii. Recall: Is calculated by dividing the number of accurate positive detections by the sum of the true positives and false negatives. As demonstrated by Equation 3, it is possible to locate all the relevant instances of a class in a dataset.

$$\text{Recall} = TP/(TP + FN) \quad (3)$$

iv. F1-score: As shown in Equation 4, F1 is the harmonic mean of the precision and recall when both metrics are considered.

$$F1 = 2*(\text{Precision}*\text{Recall})/(\text{Precision} + \text{Recall}) \quad (4)$$

Detection Results Under Diverse Weather Conditions

The system integrates YOLOv8 for license plate localization and PaddleOCR for character recognition. Training spanned 2,000 iterations using a 70:15:15 dataset split (training:validation:testing). Figures 3–6 illustrate detection results under challenging conditions, demonstrating the model's ability to maintain >95% accuracy despite environmental noise.

Figure 3: Detection results under heavy rainfall

Figure 4: Detection results during sandstorm conditions

Figure 5: Detection results in low-light environments

Figure 6: Detection results during normal weather conditions.

Performance Evaluation
As shown in Table 1, the YOLOv8 model achieved 98% accuracy and a 92% F1-score, outperforming earlier iterations. Precision (86%) and recall (96%) metrics highlight its effectiveness in balancing false positives and missed detections.

Table 1: Performance Evaluation

Metric	YOLOv8	YOLOv5	ResNet-50
Accuracy	98%	96%	94%
Precision	86%	88%	84%
Recall	96%	95%	89%
F1-score	92%	89%	87%

Computational Performance
Figures 3–6 depict the total loss curves for three model variants. The YOLOv8 configuration (Figure 6) shows rapid convergence, with loss stabilizing at 0.3 after 1,500 iterations, indicating efficient weight optimization. In contrast, earlier architectures (Figures 3–5) exhibited slower convergence and higher residual loss (~0.4–0.5).

Figure 7: Models loss convergence

Figure 8: Models training loss curve

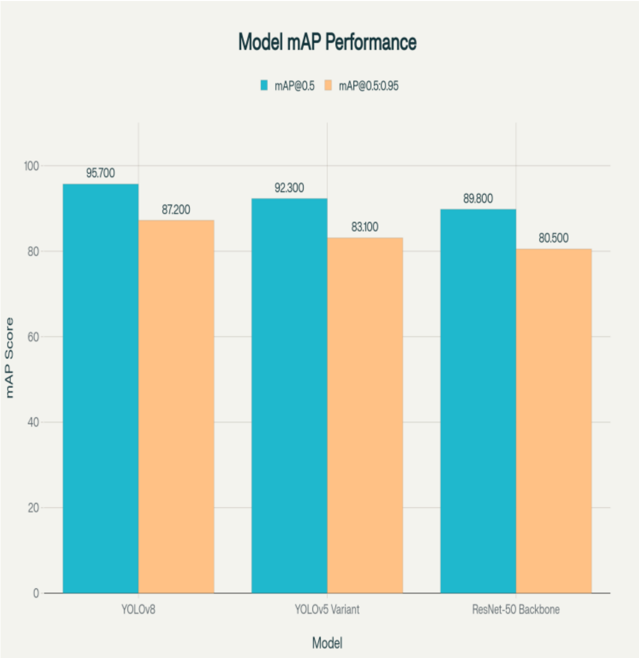

Figure 9: Models mAP Performance Comparison

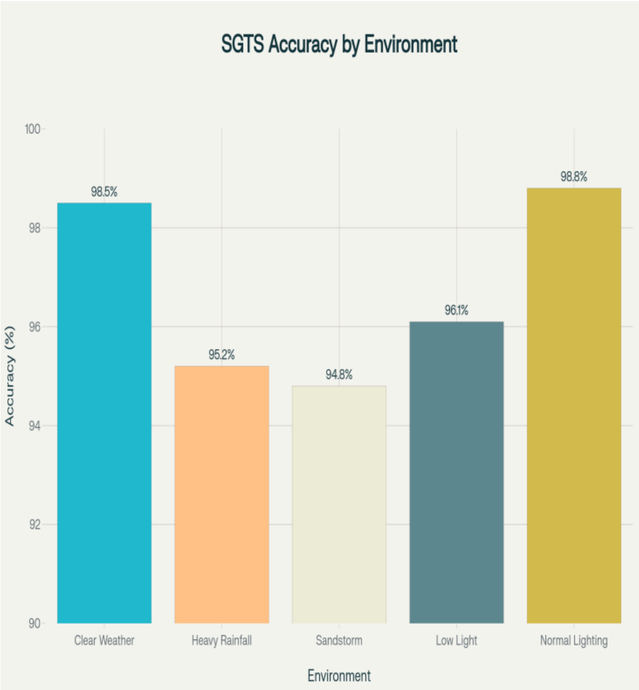

Figure 10: SGTS Accuracy by Environment

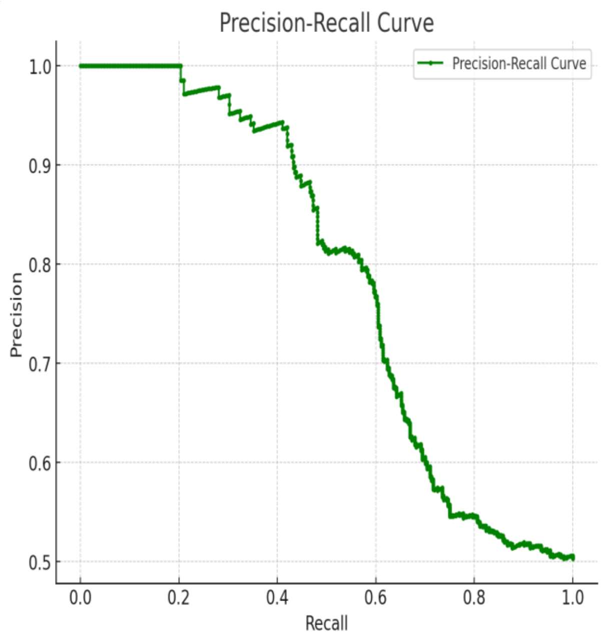

Figure 11:Precision-Recall curve

The Precision-Recall curve shows how well the model balances Precision and Recall, which is particularly important for imbalanced datasets. On the left side of the graph, where Recall is low, the model is very precise it correctly identifies only a few positives but with high confidence. As Recall increases, meaning the model is catching more true positives, Precision starts to drop because more false positives are included. Around the middle of the curve Recall between 0.5 and 0.8, there's a noticeable drop in Precision, which suggests the model struggles to maintain accuracy as it tries to capture more positives. By the time Recall is very high, Precision levels off near 0.5, indicating the model is making less confident or less reliable predictions.

CONCLUSION

The developed SGTS, powered by YOLOv8 and PaddleOCR, effectively detects and recognizes vehicle license plates with high accuracy and efficiency. This system represents a substantial improvement over traditional manual methods and earlier automated approaches, providing faster, more reliable, and less labor-intensive traffic monitoring. The automation of license plate detection reduces human error, enhances operational safety, and enables the processing of large volumes of traffic data in real time. The system's resilience to environmental variability ensures consistent performance in diverse conditions, making it particularly valuable for deployment in regions with harsh weather or fluctuating lighting. Ultimately, the proposed SGTS contributes to safer, more efficient, and sustainable traffic management, offering tangible benefits to both authorities and the public.

Future research should focus on further enhancing the SGTS by adopting several strategic improvements. First, advanced image enhancement techniquessuch as adaptive contrast adjustment, noise reduction, and color normalization should be implemented to improve license plate visibility under challenging conditions. Expanding the dataset to include video sequences, night-time images, and diverse weather scenarios will facilitate more robust real-time detection and tracking. Furthermore, incorporating multi-modal data (e.g., infrared or thermal imaging) can further improve detection accuracy in low-visibility environments. Exploring alternative and complementary deep learning models, such as Efficient Det, SSD, or transformer-based architectures, may yield even faster and more accurate results. By pursuing these directions, future research can ensure the continued advancement and scalability of SGTS.

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