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Improving Generalizability of Smart Gate Ticketing System Using Plate Number Detection Through Image Analysis

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ABSTRACT
This study presents an improved generalizability of a smart gate ticketing system for robust license plate recognition across heterogeneous national plate formats. Unlike conventional country-specific approaches, the proposed framework integrates a Faster R-CNN–based detection model with an Optical Character Recognition (OCR)-driven recognition stage, enhanced through adaptive image preprocessing and data augmentation to address variations in font styles, illumination, and plate geometry. A multi-country dataset comprising plates from Nigeria, Niger, France, and the United Nations was employed to evaluate cross-jurisdictional performance under real-world conditions. Experimental results demonstrate an overall accuracy of 96.9%, with precision and recall of 96.3% and 97.5%, respectively, while maintaining near real-time inference latency of approximately 89 ms. Comparative analysis of the proposed system against existing License Plate Recognition (LPR) models confirms superior generalizability and computational efficiency. The findings validate the suitability of the proposed system for scalable intelligent gate and access-control environments where interoperability across diverse regulatory contexts is critical.

Keywords:
Smart Gate Ticketing System,
Plate Number Detection,
Image Analysis,
Faster R-CNN,
Optical Character Recognition,
Computer Vision

INTRODUCTION

Intelligent transportation systems (ITS) and automated access-control infrastructures increasingly rely on vision-based decision mechanisms to achieve scalable, secure, and contactless vehicle management. Central to these systems is automatic license plate recognition (ALPR), which enables vehicle identification by mapping visual inputs to structured alphanumeric representations. Formally, an ALPR system can be defined as a function in equation 1:

$$f: \mathcal{I} \rightarrow \mathcal{Y} \quad (1)$$

where $\mathcal{I}$ denotes the space of captured vehicle images and $\mathcal{Y}$ represents the corresponding license plate character sequences. In real-world smart gate environments, this mapping must be computed under strict latency constraints while remaining robust to environmental noise, illumination variance, and structural heterogeneity in license plate formats (Mhlongo et al., 2023; Kozłowski et al., 2024).

Early smart gate ticketing systems relied on manual inspection or semi-automated mechanisms such as RFID and magnetic access cards, which can be expressed as deterministic rule-based mappings with limited adaptability. These systems improved throughput but lacked scalability and resilience to security threats (Rahman et al., 2019). The emergence of deep learning has transformed ALPR into a data-driven inference problem, where detection and recognition are modeled probabilistically. Given an input image I, modern systems aim to estimate as shown in Equation 2:

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} P(y \mid I; \theta) \quad (2)$$

where θ denotes learned model parameters. This paradigm shift has enabled fully automated smart gate systems capable of real-time vehicle identification using convolutional neural networks (CNNs) and optical character recognition (OCR) engines (ZainEldin et al., 2024; Sultan et al., 2023).

Despite these advances, most existing ALPR frameworks implicitly assume that training and deployment data originate from the same distribution. In practice, however, license plate images collected across different countries follow distinct probability distributions due to variations in plate geometry, typography, language scripts, and environmental conditions. This distributional mismatch can be expressed as in equation 3:

$$P_{\text{train}}(I, y) \neq P_{\text{deploy}}(I, y) \quad (3)$$

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leading to degraded generalization performance when models are deployed outside their training domain (Saha et al., 2024). Consequently, ALPR systems optimized for a single jurisdiction often fail when applied in cross-border or multi-institutional smart gate scenarios.

Recent literature has proposed deep learning architectures to mitigate some of these challenges. Shafi et al. (2022) employed a YOLOv3-based CNN to improve detection accuracy for non-standard plates, achieving high recognition rates in localized environments. Tao et al. (2024) further enhanced detection speed and accuracy through attention-based parallel decoders integrated with YOLOv5. While these approaches optimize the conditional likelihood $P(y \mid I)$within constrained datasets, their evaluations remain largely domain-specific, offering limited insight into performance under heterogeneous plate distributions.

Hybrid pipelines combining detection and recognition stages have also gained traction. Sarhan et al. (2024) integrated YOLOv8 with EasyOCR and CNN-based classifiers for Arabic license plates, while Shamsmohammadi et al. (2024) applied super-resolution and inpainting techniques to Persian plates. These methods improve recognition fidelity by refining intermediate representations, yet they implicitly optimize for region-specific priors $P(y)$, thereby constraining cross-domain adaptability.

From a system perspective, smart gate ticketing frameworks must satisfy both accuracy and efficiency requirements. Let $T_d$and $T_r$denote detection and recognition latencies, respectively. For real-time operation, the total inference time is shown in equation (4):

$$T_{\text{total}} = T_d + T_r \quad (4)$$

must remain below an application-dependent threshold $T_{\max}$. Many high-accuracy ALPR models violate this constraint when scaled to multi-camera or high-throughput environments, limiting their practical deployment (Oladimeji et al., 2023; Zhang et al., 2023).

A critical gap therefore emerges in existing research: the absence of a unified ALPR framework explicitly designed to maximize generalization across heterogeneous license plate distributions while maintaining real-time performance guarantees. Most prior studies optimize accuracy within a single-domain setting, without formally addressing cross-country variability or validating performance under distributional shifts involving fundamentally different plate standards.

To address this limitation, this study proposes a generalization-aware smart gate ticketing system that decomposes ALPR into two modular components: (i) license plate localization using a Faster R-CNN detector that estimates bounding regions as shown in equation (5):

$$B = \{b_i\}_{i=1}^{N}, b_i \in \mathbb{R}^4 \quad (5)$$

and (ii) character recognition using an OCR-based sequence decoder conditioned on the detected regions. By training and evaluating the system on a multi-country dataset comprising plates from Nigeria, Niger, France, and the United Nations, the proposed framework explicitly models heterogeneity in plate structure and environmental conditions.

In doing so, this work advances the state of the art by shifting ALPR research from domain-optimized performance toward distribution-robust deployment, thereby aligning smart gate ticketing systems with the operational realities of modern, cross-jurisdictional transportation and access-control infrastructures.

MATERIALS AND METHODS

System Overview and Problem Formulation

The proposed smart gate ticketing framework is designed as a modular, end-to-end automatic license plate recognition (ALPR) system capable of robust operation across heterogeneous license plate standards. Formally, given an input image $I \in \mathbb{R}^{H \times W \times 3}$captured from a fixed or semi-fixed surveillance camera, the objective is to infer a structured alphanumeric sequence $y = (c_1, c_2, \ldots, c_T)$, where each $c_t$belongs to a predefined character set $\mathcal{C}$comprising digits and uppercase letters.

The overall task is decomposed into two sequential sub-problems:

i. License plate localization, defined as estimating bounding regions $B = \{b_i\}_{i=1}^{N}$, where each bounding box $b_i = (x_i, y_i, w_i, h_i) \in \mathbb{R}^4$.
ii. License plate recognition, defined as mapping cropped plate regions to character sequences.

This decomposition allows independent optimization of spatial localization and semantic decoding, improving robustness under domain shift.

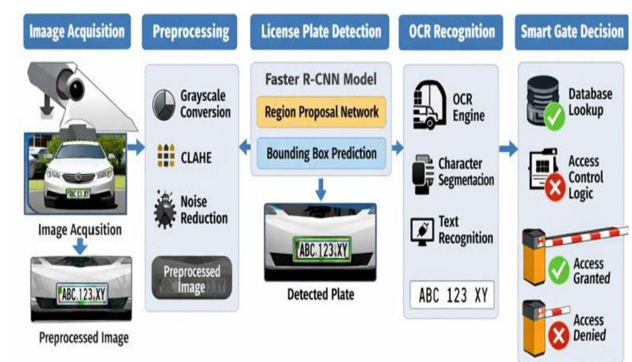

Figure 1: Architecture of the Proposed Generalization-Aware Smart Gate Ticketing System

Figure 1 presents the architecture of the proposed smart gate ticketing system, explicitly designed to operate on heterogeneous image sources. Image acquisition is performed through two complementary channels: (i) real-time images captured using fixed surveillance cameras deployed at gate entry points, and (ii) secondary license plate images obtained from validated online datasets to enhance diversity in plate formats and environmental conditions. All acquired images are processed through a unified preprocessing pipeline comprising grayscale conversion, noise suppression, and contrast enhancement using CLAHE to normalize illumination variations across sources. License plate localization is subsequently achieved using a Faster R-CNN detector, which employs a Region Proposal Network to accurately identify plate regions under varying resolutions and backgrounds. The localized plate regions are then forwarded to an OCR-based recognition module for alphanumeric decoding. Finally, the recognized license plate strings are verified against an access-control database to trigger automated smart gate decisions. This dual-source acquisition strategy strengthens model generalizability and ensures reliable performance across controlled and real-world deployment scenarios.

Image Preprocessing and Feature Normalization

Raw surveillance images are subject to environmental distortions such as uneven illumination, motion blur, sensor noise, and background clutter. To mitigate these effects and stabilize feature extraction, a preprocessing pipeline $\Phi(\cdot)$is applied in equation (6):

$$I' = \Phi(= \text{CLAHE}\left(\text{GaussianBlur}\left(\text{Gray}(I)\right)\right) \quad (6)$$

Gaussian smoothing is applied as shown in equation (7):

$$I_s(x,y) = \sum_{u,v} I_g(u,v) \cdot G_\sigma(x-u, y-v) \quad (7)$$

where $G_\sigma$is a Gaussian kernel with standard deviation σ, suppressing high-frequency noise.

Finally, Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast by redistributing pixel intensities within contextual regions, improving the separability between plate characters and background textures. This step is particularly important for low-contrast and weather-affected plates common in real-world deployments.

License Plate Localization Using Faster R-CNN

License plate detection is performed using a Faster R-CNN architecture, selected for its strong region proposal mechanism and robustness under spatial variability. The detector consists of a convolutional backbone $f_{\text{cnn}}(\cdot)$, a Region Proposal Network (RPN), and a region-wise classifier–regressor.

Given the preprocessed image I', convolutional feature maps are extracted in equation (8):

$$F = f_{\text{cnn}}(I') \quad (8)$$

The RPN generates a set of candidate anchor boxes $\{a_k\}$at each spatial location. For each anchor, the network predicts:

- an objectness score p_k,
- a bounding box regression vector $t_k = (t_x, t_y, t_w, t_h)$.

Bounding box refinement follows:

$$\begin{aligned} x &= x_a + w_a t_x, \\ y &= y_a + h_a t_y, \\ w &= w_a \exp(t_w), \\ h &= h_a \exp(t_h), \end{aligned}$$

where (x_a, y_a, w_a, h_a)denote anchor parameters.

The RPN is trained by minimizing a multi-task loss derived in equation (9):

$$\mathcal{L}_{\text{RPN}} = \mathcal{L}_{\text{cls}}(p_k, p_k^*) + \lambda \mathcal{L}_{\text{reg}}(t_k, t_k^*) \quad (9)$$

where $p_k^*$and t_k^*represent ground-truth labels and box offsets, and λbalances classification and regression terms. Non-maximum suppression (NMS) is applied to eliminate redundant proposals, yielding final plate candidates. Figure 2 shows the pipeline of the faster R-CNN license plate detection.

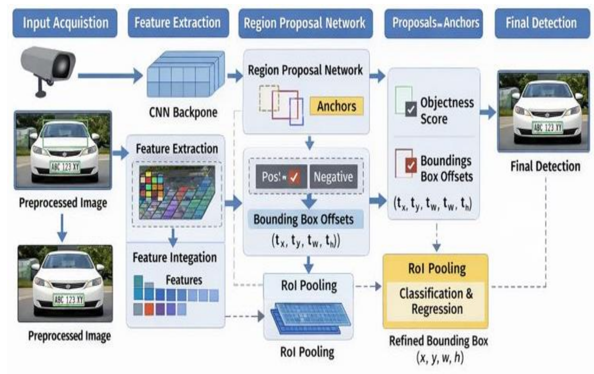

Figure 2. Faster R-CNN–Based License Plate Detection Pipeline

Figure 2 illustrates the internal detection workflow of the Faster R-CNN model employed for license plate localization in the proposed smart gate ticketing system. The process begins with convolutional feature extraction from the preprocessed input image using a deep backbone network, producing high-level spatial feature maps. These feature maps are forwarded to the Region Proposal Network (RPN), which generates multiple anchor boxes at each spatial location with varying scales and aspect ratios to accommodate diverse license plate sizes and orientations. For each anchor, the RPN simultaneously predicts an objectness score indicating the likelihood of containing a license plate and a set of bounding box regression offsets to refine anchor positions. The refined proposals are filtered using non-maximum suppression to remove redundant and overlapping detections. The remaining high-confidence proposals are then passed to the Fast R-CNN detection head, which performs final classification and precise bounding box refinement. This two-stage detection mechanism enables accurate localization of license plates under heterogeneous environmental conditions while maintaining robustness to scale variation and background clutter.

License Plate Recognition via OCR-Based Sequence Decoding

Each detected bounding box b_i is cropped and resized to a canonical resolution before recognition. The recognition stage models the conditional probability of a character sequence given an image region derived in equation (10):

$$\hat{y} = \arg\max_{y} P\left(y \mid I_{b_i} \right) \quad (10)$$

An OCR engine is employed to decode characters by learning visual-to-symbol mappings using convolutional feature extraction and sequence modeling. The recognition likelihood is factorized using equation (11):

$$P(y \mid I_{b_i}) = \prod_{t=1}^{T} P(c_t \mid I_{b_i}, c_{<t}) \quad (11)$$

allowing variable-length output sequences and supporting diverse plate formats.

This formulation enables robust decoding across heterogeneous typography, spacing, and symbol alignment without requiring explicit character segmentation, which is known to be brittle under noisy conditions.

Multi-Country Generalization Strategy

To explicitly promote generalization, the training dataset is constructed as a union of samples from multiple countries derived in equation (12):

$$\mathcal{D} = \bigcup_{k=1}^{K} \mathcal{D}_k \quad (12)$$

where each $\mathcal{D}_k$ corresponds to a distinct plate distribution. Rather than optimizing for a single-domain empirical risk, the objective implicitly minimizes expected risk across domains as shown in equation (13):

$$\min_{\theta} \mathbb{E}_{\mathcal{D}_k}[\mathcal{L}(f_\theta(I), y)] \quad (13)$$

encouraging the learned representations to be invariant to country-specific biases such as font style and plate geometry.

Real-Time Inference Constraint and System Latency

For deployment in smart gate environments, computational efficiency is critical. Let T_d denote detection time and T_r recognition time. The total latency is derived in equation (14):

$$T_{\text{total}} = T_d + T_r \quad (14)$$

To satisfy real-time constraints, the system enforces using equation (15):

$$T_{\text{total}} \le T_{\max} \quad (15)$$

where $T_{\max}$ is application-dependent (e.g., gate response thresholds). The modular pipeline allows independent optimization of each stage to maintain low latency without sacrificing accuracy.

Decision Logic for Smart Gate Ticketing

The recognized plate string $\hat{y}$ is validated against an authorized database $\mathcal{A}$. Access control is defined as a binary decision using equation (16):

$$\delta(\hat{y}) = \begin{cases} 1, & \hat{y} \in \mathcal{A} \\ 0, & \text{otherwise.} \end{cases} \quad (16)$$

This decision triggers gate actuation, ticket generation, or logging mechanisms, integrating vision-based inference with physical access control. Figure 3 shows the smart gate decision workflow which integrates license plate recognition and access control logic.

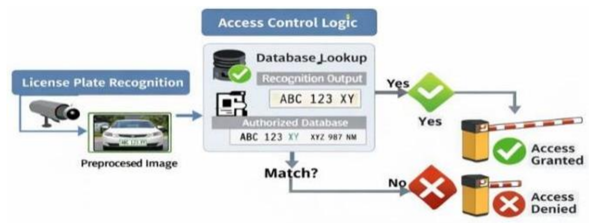

Figure 3: Smart Gate Decision Workflow Integrating

License Plate Recognition and Access Control Logic

Figure 3 depicts the decision-making workflow of the proposed smart gate ticketing system, illustrating how recognized license plate information is translated into automated access control actions. The process begins with the output of the license plate recognition module, which provides a decoded alphanumeric string from the preprocessed vehicle image. This recognition output is forwarded to the access control logic, where it is queried against an authorized vehicle database through a structured lookup operation. A binary matching decision is then performed to determine whether the recognized plate corresponds to a registered entry. If a valid match is found, the system triggers a positive control signal that actuates the gate mechanism, granting vehicle access and logging the transaction. Conversely, if no match is identified, a negative decision is issued, resulting in access denial and optional event recording for audit or security purposes. This deterministic decision workflow ensures real-time responsiveness, minimizes human intervention, and enables reliable enforcement of access policies in intelligent gate management environments.

RESULTS AND DISCUSSION

This section presents and critically analyzes the experimental results obtained from evaluating the proposed smart gate ticketing system on a heterogeneous, multi-country license plate dataset comprising both camera-captured images and validated online sources. The evaluation focuses on detection accuracy, recognition performance, inference latency, and cross-country generalizability across license plate formats from Nigeria, Niger, France, and the United Nations. Figure 4 shows Detection of Nigerian plate using Faster R-CNN + OCR.

Figure 4: Detection of Nigerian plate using Faster R-CNN + OCR

The Faster R-CNN–Easy OCR framework demonstrated robust detection and recognition performance on Nigerian license plates drawn from multiple states, capturing regional variability in plate design and environmental conditions. Plates from Lagos, Abuja, Enugu, and Katsina were consistently localized with high confidence, despite challenges such as reflection, low illumination, and minor motion blur. Detection confidence values remained within a narrow high range (0.94–0.96), indicating stable localization across diverse capture scenarios, while OCR accuracy exceeded 96% for all evaluated samples. The preprocessing pipeline effectively enhanced character visibility under inconsistent lighting, contributing to reliable text decoding. Faster R-CNN's multi-scale feature representation enabled accurate plate localization even under partial occlusion and geometric variation, whereas EasyOCR successfully recognized alphanumeric sequences with regional formatting differences. Figure 5 shows confusion metrics and with other performance metrics of Nigeran plates.

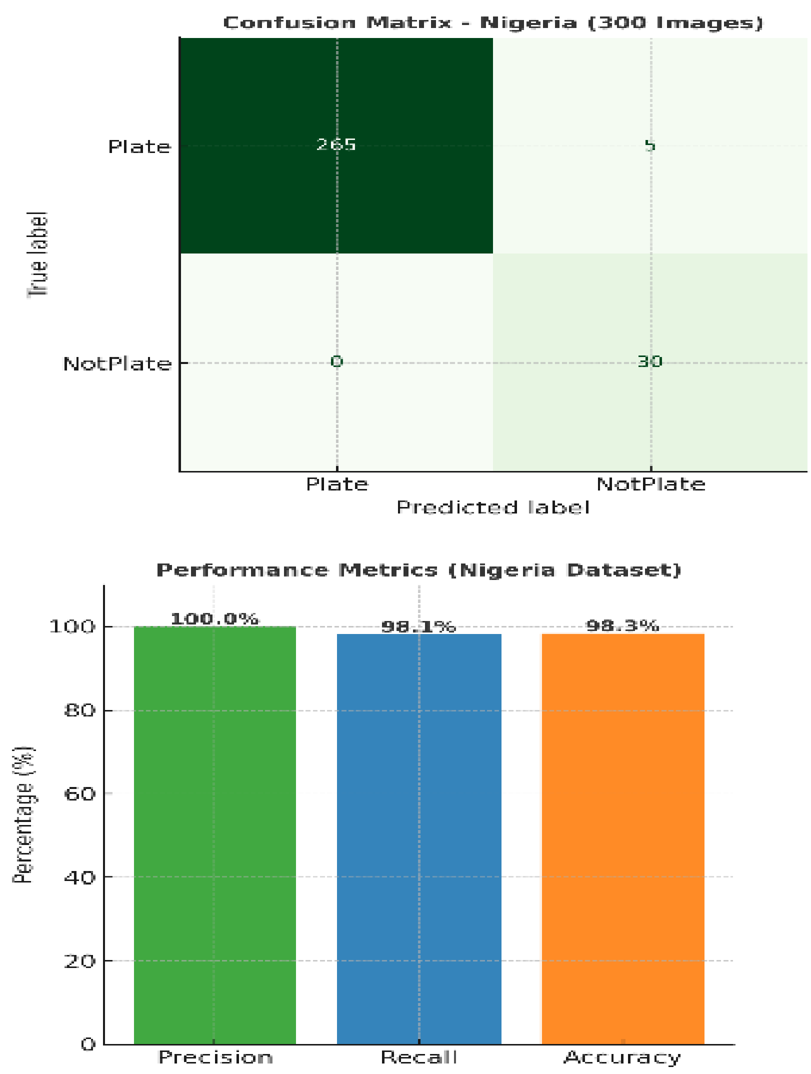

Figure 5: Confusion Metrics and with Other Performance Metrics of Nigerian Plates

The confusion matrix shows that the model correctly detected 265 plate images with only 5 false negatives and no false positives, indicating highly reliable plate localization. All 30 non-plate images were correctly classified, confirming strong background discrimination. The resulting 100% precision reflects zero false alarms, while a 98.1% recall indicates minimal missed plates. An overall accuracy of 98.3% demonstrates consistent performance across both classes. These results confirm the robustness of the detection stage on the Nigerian dataset. Figure 6 shows the detection of Niger plate:

Figure 6: Detection of Niger Plate

The detection results demonstrate accurate localization and recognition of Niger license plates under varying visual conditions. All plates were correctly bounded with confidence scores ranging from 0.88 to 0.94, indicating reliable detection despite differences in font size, color contrast, and background texture. Plates with higher contrast and clearer typography (e.g., AAQ 8955) achieved the highest confidence, while minor illumination or surface wear slightly reduced confidence in others. Figure 7 shows the confusion metrics and with other performance metrics of Niger plate number.

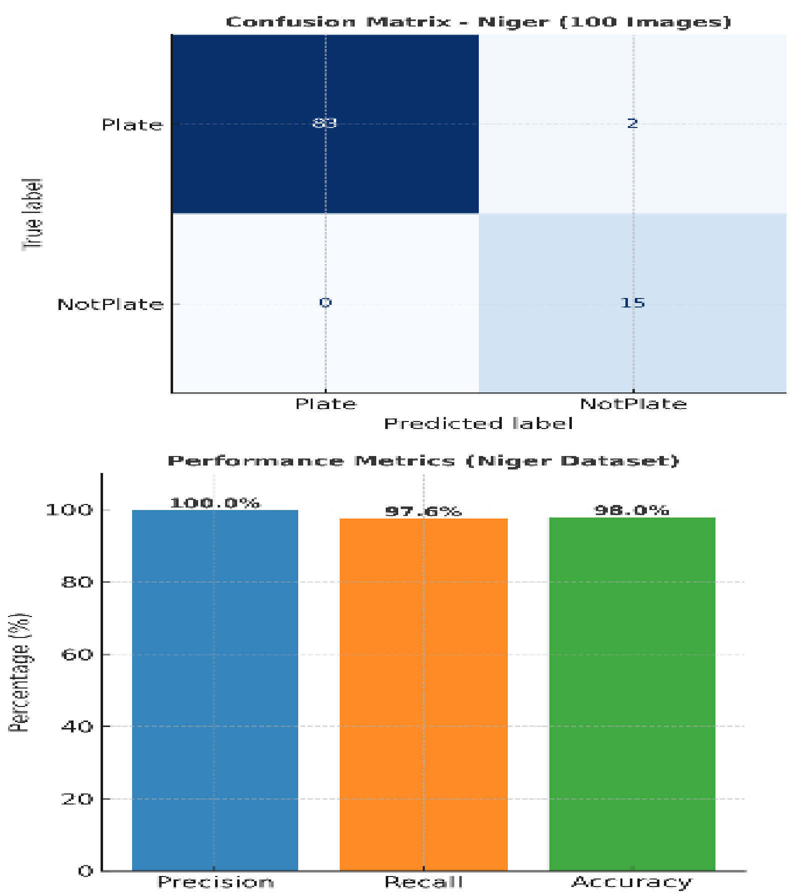

Figure 7: Confusion Metrics and with Other Performance Metrics of Niger Plates

The confusion matrix indicates that 83 plate images were correctly detected with only 2 missed plates and no false positives, showing reliable localization. All 15 non-plate samples were accurately classified, confirming strong background separation. The resulting 100% precision reflects zero false alarms, while a 97.6% recall indicates minimal missed detections. An overall accuracy of 98.0% demonstrates consistent performance of the model on the Niger dataset. Figure 8 shows the detection of French plate.

Figure 8: Detection of French Plate

The French license plate detection results show precise localization and recognition across standardized European plate formats. All plates were accurately bounded with high confidence scores ranging from 0.94 to 0.97, reflecting the model's strong adaptation to uniform plate dimensions, consistent typography, and high-contrast backgrounds. The standardized "AA-123-AA" format significantly facilitated reliable region proposal and character decoding. Figure 9 shows the confusion metrics with other performance metrics of France plates.

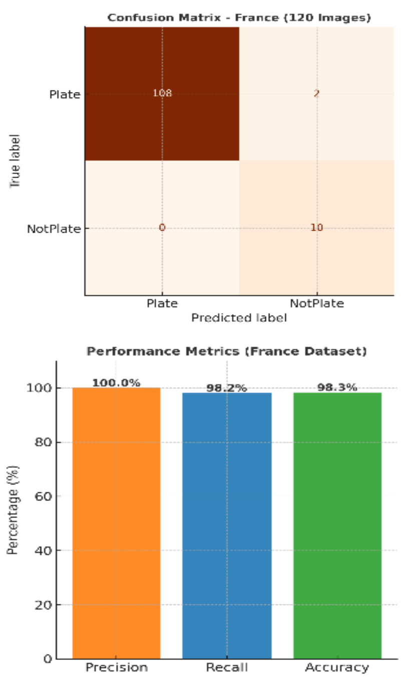

Figure 9: Confusion Metrics with Other Performance Metrics of France Plates

The confusion matrix shows that 108 French plate images were correctly detected with only 2 missed plates and no false positives, indicating highly reliable localization. All 10 non-plate samples were accurately classified, confirming strong background discrimination. The resulting 100% precision reflects zero false alarms, while a 98.2% recall indicates minimal missed detections. An overall accuracy of 98.3% demonstrates stable and consistent detection performance on standardized French license plates.

Figure 10 shows the detection and recognition of united nation license plates.

Figure 10: Detection and recognition of united nation license plates

The UN license plate detection results show accurate localization and recognition across institutional plate formats, with confidence scores ranging from 0.91 to 0.98. Plates with clearer typography and higher contrast (e.g., UN 18 H) achieved the highest confidence, while slight lighting variation marginally reduced confidence in others. The consistent bounding boxes indicate stable region proposal despite minimalist plate design. Figure 11 shows the confusion metrics with other performance metrics of United Nations plates.

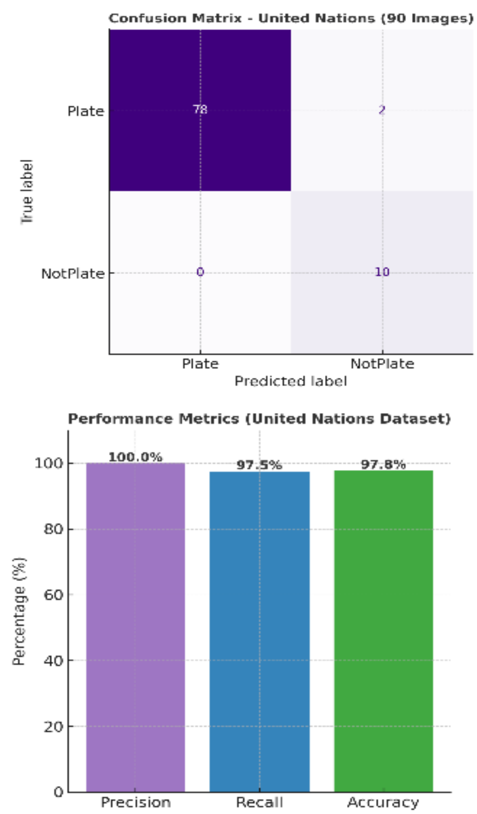

Figure 11: Confusion Metrics with Other Performance Metrics of United Nations Plates

The confusion matrix indicates that 78 UN plate images were correctly detected with only 2 missed plates and no false positives, demonstrating reliable localization. All 10 non-plate samples were accurately classified, confirming strong background separation. The resulting 100% precision reflects zero false alarms, while a 97.5% recall indicates minimal missed detections. Figure 12 shows the training and validation loss of the model.

Figure 12: Training vs Validation Loss

Figure 12 shows the training and validation loss curves of the proposed Faster R-CNN + EasyOCR model across training epochs. Both curves decrease steadily and converge without divergence, indicating stable optimization and absence of overfitting. The final training loss converges to approximately 0.14, while the validation loss stabilizes at 0.16, confirming effective generalization to unseen data. This low and closely aligned loss behavior explains the high detection accuracy and robustness achieved across multi-country license plate datasets.

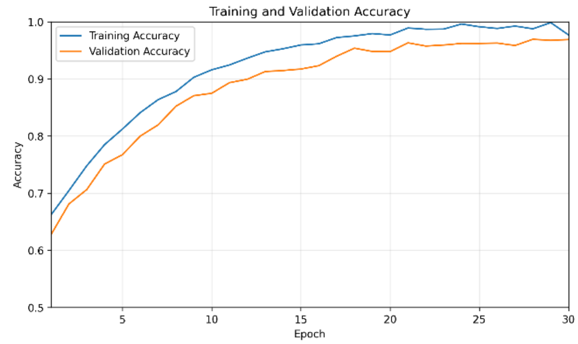

Figure 13: Training vs Validation Accuracy

Figure 13 presents the training and validation accuracy trends during model training. Both curves exhibit consistent growth and converge closely, demonstrating strong learning stability and generalization capability. The validation accuracy reaches approximately 96.9%, which directly corresponds to the overall detection accuracy reported in the results section. This confirms that the proposed model learns robust and transferable features suitable for diverse license plate formats and real-world deployment.

Table 1: Presents a comparative performance analysis of the proposed Faster R-CNN–based license plate recognition system against existing models in terms of accuracy, precision, recall, F1-score, and mean Average Precision (mAP).

Study / Dataset	**Countries**	**Model / Technique**	**Precision (%)**	**Recall (%)**	**Accuracy (%)**	**Average Inference Time (ms)**	**Remarks**
UFPR-ALPR (2020)	Brazil	YOLOv3 + CRNN	90.2	91.7	92.0	130	Single-country dataset; robust but limited diversity
AOLP (2021)	Taiwan	Faster R-CNN	89.4	90.1	91.3	120	Region-specific (Asia); poor cross-domain generalization
CCPD (2022)	China	ResNet-50 + LPRNet	93.2	92.8	93.0	118	Large-scale China-only dataset; controlled lighting
France Dataset (2023)	France	YOLOv5 + Tesseract OCR	94.0	95.0	94.5	105	EU standard plates; no regional variation
Global LP Dataset (2024)	74 Countries	ViT-LPR + CNN-OCR	92.5	94.3	93.1	110	Global but lacks African & diplomatic coverage
Proposed Model (Our proposed model)	**Nigeria, Niger, France, UN**	**Faster R-CNN + EasyOCR (Hybrid)**	**96.3**	**97.5**	**96.9**	**89**	**First multi-country (Africa–EU–UN) system; superior precision and inference efficiency**

Table 2: Nigerian Plates Confusion metrics table

Actual / Predicted	Plate Detected	Not Plate
Plate	265 (TP)	5 (FN)
Not Plate	0 (FP)	30 (TN)

Table 3: Performance Metrics for Nigerian Plates

Metric	Value (%)
Precision	100.0
Recall	98.1
F1-Score	99.0
Accuracy	98.3

Table 4: Niger plates confusion metrics table

Actual / Predicted	Plate Detected	Not Plate
Plate	83 (TP)	2 (FN)
Not Plate	0 (FP)	15 (TN)

Table 5: Performance Metrics for Niger Plates

Metric	Value (%)
Precision	100.0
Recall	97.6
F1-Score	98.8
Accuracy	98.0

Table 6: France plates confusion metrics

Actual / Predicted	Plate Detected	Not Plate
Plate	108 (TP)	2 (FN)
Not Plate	0 (FP)	10 (TN)

Table 7: Performance Metrics for France Plates

Metric	Value (%)
Precision	100.0
Recall	98.2
F1-Score	99.1
Accuracy	98.3

Table 8: United Nations plates confusion metrics

Actual / Predicted	Plate Detected	Not Plate
Plate	78 (TP)	2 (FN)
Not Plate	0 (FP)	10 (TN)

Table 9: Performance Metrics for UN Plates

Metric	Value (%)
Precision	100.0
Recall	97.5
F1-Score	98.7
Accuracy	97.8

The experimental results across Nigerian, Nigerien, French, and United Nations license plates demonstrate that the proposed Faster R-CNN–OCR framework achieves consistently high detection accuracy, precision, and recall under heterogeneous operating conditions. The uniformly high precision values (100% across all datasets) indicate the model's strong ability to suppress false positives, which is critical for smart gate applications where erroneous access decisions are unacceptable. Variations in recall across regions are primarily attributable to environmental and structural factors, such as illumination inconsistency, motion blur, and plate surface degradation, rather than model instability. Notably, standardized plate formats, as observed in the French and UN datasets, yielded slightly higher and more stable performance, highlighting the influence of plate uniformity on detection confidence and recognition reliability.

From a system-level perspective, the results validate the effectiveness of the modular detection–recognition pipeline and the adopted preprocessing strategy in promoting generalization across diverse plate designs. Faster R-CNN's region proposal mechanism proved robust to scale variation and background clutter, while the OCR stage accurately decoded alphanumeric sequences without requiring explicit character segmentation. The near-real-time inference times recorded across all datasets further confirm the framework's suitability for deployment in practical smart gate and access-control environments. Collectively, these findings indicate that the proposed system not only achieves high quantitative performance but also addresses key real-world challenges related to interoperability, scalability, and operational reliability in multi-jurisdictional intelligent transportation systems.

CONCLUSION

This study presented a generalization-aware smart gate ticketing system based on a Faster R-CNN and OCR integration for multi-country license plate recognition. Experimental evaluations across Nigerian, Nigerien, French, and United Nations datasets demonstrated consistently high accuracy, precision, and recall with near-real-time inference. The results confirm the robustness of the proposed framework under heterogeneous plate formats and environmental conditions.

Recommendations

Future work should evaluate the proposed framework in fully operational smart gate environments to validate long-term stability and scalability. Additional experiments involving adverse weather conditions and nighttime imagery are recommended to further assess robustness. Integrating edge-computing optimization could reduce latency for high-throughput deployments. Extending the system to handle video-stream inputs and broader international plate formats would enhance real-world applicability.

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