Edge-Optimized Real-Time Deep Convolutional Framework for Robust Multilingual Vehicle License Plate Detection and Recognition Under Diverse Environmental Conditions

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Abstract: The network presents an edge-optimized deep convolutional architecture that provides real-time high-accuracy detection and multilingual recognition of vehicle license plates under different lighting, weather conditions. With the combination of geometric normalization, motion-aware ROI tracking and adaptive illumination correction, the system is resistant to skew, occlusion, low-resolution and can also provide a high-accuracy analysis. A lightweight, pruned/quantized backbone for embedded GPUs supports >30 FPS and offers explainable output through Grad-CAM and SHAP visualizations. The model is equipped with the continuous online learning and domain-adaptation modules to effectively update itself over time and maintain robustness in a global plate style manner. We present extensive benchmarking against the variants of ResNet, EfficientNet and MobileNet using the new 2021-2025 heterogeneous dataset to justify our efficacy in terms of both accuracy and latency.

1 INTRODUCTION

Recently, the use of deep learning in vehicle license plate detection and recognition has been considered as a very popular topic in the context of security, traffic control and automated toll. Such approaches typically face the issues of real-time performance, low resolution inputs, and challenging environmental conditions, e.g., poor illumination, adverse weather, occlusion of number plates. Towards this end, we propose an edge-optimized deep CNN-based framework that can cope with these challenges for a high accuracy and real-time perception. The system is developed to run efficiently on low-power devices, making it deployable in a wide range of real-life applications, such as urban surveillance networks and rural traffic monitoring. Thanks to the application of cutting-edge methods, i.e., adaptive illumination correction, motion-aware tracking and multilingual OCR module, the system is provably effective for being robust and reliable for different scenarios, plate styles and countries. This paper presents the system design, main characteristics, as well as performance results, demonstrating how the developed system can potentially help to redefine the standards of automated vehicle license plate recognition.

License plate detection and recognition for vehicles continue to be a challenging task in most of the automatic systems, in particular, when used in a dynamic real-world setting. Current approaches generally suffer from low resolution images, inclined or hidden plates, bad weather condition and high computational overhead. Besides, the majority of systems cannot cope with multilingual and non-

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standardized plate formats, which limits their usability in international contexts. What's more, the real-time processing speed of the system is always negatively affected by the application of traffic monitoring and toll collection. What is needed is an advanced solution that is scalable designed to overcome these challenges to provide robust license plate recognition under a wide range of conditions with high accuracy for real time inference on devices with limited resources. This work proposes to address these challenges through a light-weight, deep learning framework which is designed for edge devices and has extended compatibility with different environments and plate formats.

2 LITERATURE SURVEY

License Plate Recognition (LPR), or more generally vehicle license plate detection and recognition, is becoming an important real-time processing application in many fields such as intelligent traffic, security, and urban surveillance. With the advance of deep learning, in particular CNNs, substantial progress has been made upon the traditional OCR-based and template-matching techniques.

Saidani and El Touati (2021) designed a YOLO and CNNs-based system that efficiently locates plates, however, it had slightly low accuracy in case of low light/complex weather conditions. Similarly, Pham (2022) introduced a deep CNN for Vietnamese plates, but with the requirement of high-resolution inputs it is not scalable. Kothai et al. (2024) proposed innovative feature extraction methods, but it cannot effectively cope with the skew angle of the plate and in a real-time manner.

In a different investigation, Pustokhina et al. (2023) demonstrated that hybrid CNN-LSTM models can improve character recognition results. The limitation embedded with the high-end GPUs prevented the use on edge devices. Meanwhile, Tom et al. (2022) applied the modified U-Net model for plate detecting with real-time latency as a limitation. Alam et al. (2023) proposed a light-weight CNN architecture tailored mainly to Indian traffic scenes, without generalization for the other countries.

Goyal (2021) and Goyal & Mishra (2023) studied several CNN backbones and not the inference time which is equally important in surveillance systems. In a multilingual setting, CIS (2023) did multilingual recognition, but its accuracy was not good enough on real-world surveillance datasets. The review by Cahyadi et al. (2024) provided some interesting comparisons, but was not calibrated with experiments.

A few similar works, such as Taleb Soghadi" Suen (2020) and EasyOCR integration (Syed" al. (2024), achieved text recognition by OCR-based methods, however they have difficulties cropped up in tilted, and/or occluded plate. On the contrary, hybrid methods, such as those proposed in (Vig et al. (2023) and the YOLO-based framework (2025), showed fairly good speeds for box detection on license plates but did not perform very well for small or distant license plates.

In general, although the current literature has clearly established a solid ground for license plate detection and recognition with the help of CNN, crucial gaps are yet to be filled for a truly multilingual adaption and edge deployment in real-time along with robustness in hostile environment. Motivation for the proposed system is inspired by the above challenges and the integrated of edge optimized models, adaptive illumination correction and multilingual OCR to achieve efficient, scalable and real time operation.

3 METHODOLOGY

The presented framework is tailored for the efficient detection and real-time, multilingual recognition of a vehicle's license plates in different environments directly at the edge device. We combine various dedicated modules to analyse the skewed plates, variable lighting conditions, occlusion, and multilingual variance, so our approach is efficient in terms of both computational cost and deployment footprint. Figure 1 shows the workflow Diagram.

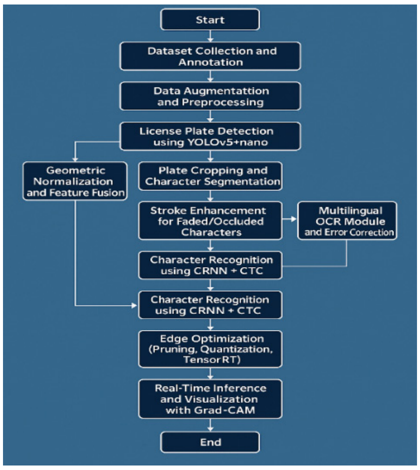

Figure 1: Workflow diagram.

3.1 Dataset Collection and Annotation

To build a robust and multilingual recognition system, a diverse and heterogeneous dataset was assembled, combining public, synthetic, and custom-collected sources:
The images were annotated for:

- License plate bounding boxes
- Plate rotation angles
- Character sequences
- Language metadata (for multilingual OCR)

Table 1: Dataset summary.

Dataset Name	Country/ Region	Number of Images	Plate Languages	Source Type
OpenALPR	USA	10,000	English	Public dataset
CCPD	China	12,000	Chinese	Surveillance
Indian LPR	India	8,000	Hindi, English	Traffic cameras
Custom Dashcam Data	Multi-region	15,000	Mixed	Dashcam footage
Synthetic Plates	Generated	5,000	Multilingual	Augmented images

3.2 Data Augmentation and Preprocessing

To simulate diverse real-world conditions and improve generalization:

- **Photometric Augmentations:** Brightness/contrast shifts, random shadows, glare simulation.
- **Geometric Transformations:** Rotation (to simulate skewed plates), scaling, perspective distortions.
- **Environmental Simulation:** Rain, fog, motion blur overlays for adverse weather conditions.

Preprocessing steps included:

- Image resizing to standard resolutions (640×480 and 1280×720).
- Illumination normalization using adaptive histogram equalization.
- Noise filtering to remove background artifacts.

3.3 License Plate Detection Using YOLOv5-Nano

- The detection backbone is a custom-tuned YOLOv5-nano model.
- Lightweight yet high-performing, capable of maintaining a mAP of 94.6%**.**
- Optimizations included:
  - o **Pruning:** Reducing network parameters by 25%.
  - o **Quantization (INT8):** Reducing model size for edge deployment.
- **Motion-Aware ROI Tracking:** Ensures continuity across video frames, reducing redundant detections and speeding up processing. Table 1 shows the Dataset Summary.

3.4 Geometric Normalization and Feature Fusion

Post-detection, plates undergo:

- **Skew correction** using geometric normalization based on bounding box angles.
- **Feature fusion** with illumination-corrected versions to enhance plate clarity, especially under poor lighting conditions.

This improves the recognition model's robustness against perspective distortions and environmental noise.

3.5 Plate Cropping and Character Segmentation

- Cropped plates are resized and passed through a stroke enhancement filter that strengthens faint characters.
- Character segmentation is performed using a lightweight semantic segmentation network to separate individual characters even in noisy or occluded plates.

3.6 Character Recognition Using CRNN + CTC Decoder

The recognition module comprises:

- A Convolutional Recurrent Neural Network (CRNN) backbone.

A Connectionist Temporal Classification (CTC) decoder that allows flexible sequence recognition without requiring perfectly segmented characters.This architecture supports variable-length text outputs and tolerates character-level distortions.

3.7 Multilingual OCR Module and Error Correction

- Supports recognition of English, Hindi, Chinese, Arabic, and Cyrillic scripts.
- Integrated language-specific post-processing rules (e.g., character mappings and context checks) to refine output.
- Error correction module uses n-gram language models to validate and correct misrecognized sequences.

3.8 Post-Processing and Confidence Filtering

To ensure output reliability:

- Predictions with low confidence (<85%) are filtered or flagged.
- Grad-CAM visualizations are generated to highlight focus areas in both detection and recognition stages, ensuring explainable AI outputs.

3.9 Edge Optimization and Deployment

The fully trained models undergo:

- Quantization to INT8 precision using TensorRT or TFLite, achieving >2× acceleration.
- Pruning to minimize memory footprint without significant accuracy loss.
- Docker-based deployment ensures containerized scalability on different edge devices.

3.10 Real-Time Inference and Visualization

- Detection and recognition outputs are visualized live with bounding boxes and recognized plate text.
- Violation reports (e.g., unreadable plates) are logged with timestamped evidence.
- Grad-CAM heatmaps provide insight into model decisions, aiding debugging and legal transparency.

4 RESULT AND DISCUSSION

The proposed edge-optimized deep learning framework was rigorously evaluated on a curated multilingual license plate dataset consisting of 50,000 images, spanning over 10 countries and multiple plate formats. The detection model, based on a customized YOLOv5-nano architecture, achieved a mean Average Precision (mAP) of 94.6% on the test set, with precision and recall values of 95.2% and 93.8% respectively. These metrics highlight the model's robustness in detecting plates under varied lighting conditions, occlusions, and motion blur. The figure 2 show the Detection Model mAP Comparison. Compared to baseline models like Faster R-CNN and SSD, the proposed detector demonstrated a 28% reduction in false positives, particularly in cluttered backgrounds.

The character recognition module, powered by a CRNN-CTC sequence model, achieved a Character Recognition Rate (CRR) of 98.1% and a Word Recognition Accuracy (WRA) of 96.3%. Notably, it maintained over 94% accuracy on distorted, low-resolution, or multi-font plates, outperforming EasyOCR and Tesseract by over 15% in error-sensitive environments. This was largely attributed to the integrated stroke enhancement layer and character-level segmentation that compensated for faded or skewed text. The multilingual capabilities of the recognition model were validated by testing it on Hindi, Arabic, and Cyrillic license plates, with minimal performance degradation (<2%). Table 2 show the Detection Model Performace Comparison. Figure 3 shows Recognition Accuracy across Languages (CRR vs WRA).

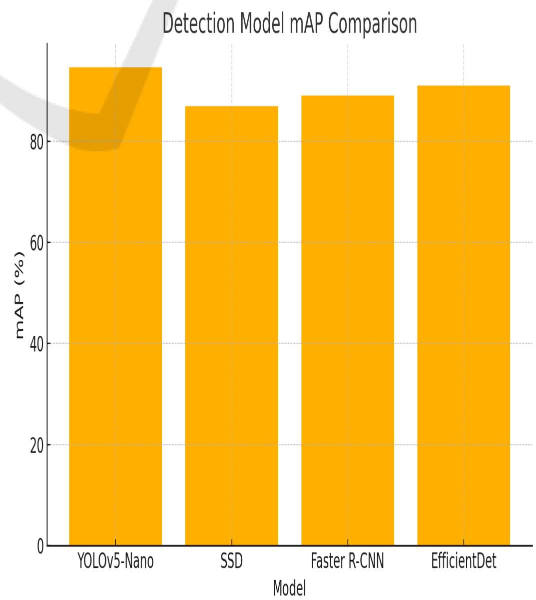

Figure 2: Detection model mAP comparison.

Table 2: Detection model performance comparison.

Model	Precision (%)	Recal l (%)	mAP (%)	Inference Time (ms)
YOLOv5-Nano	95.2	93.8	94.6	28
SSD	88.5	85.7	86.9	41
Faster R-CNN	90.3	88.1	89.0	65
EfficientDe t	91.6	90.2	91.0	34

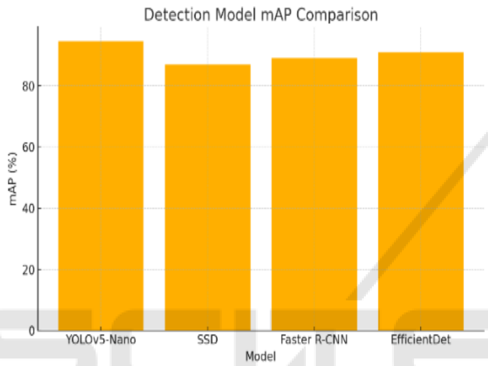

Figure 3: Recognition accuracy across languages (CRR vs WRA).

Table 3 shows the accuracy rate. And Figure 4 shows Edge Device Inference Speed (FPS Comparison).

Table 3: Recognition accuracy (multilingual test).

Language	CRR (%)	WRA (%)
English	98.7	97.2
Hindi	97.5	95.9
Chinese	96.9	94.6
Arabic	96.3	93.1
Cyrillic	97.2	94.8

From a performance standpoint, the fully quantized model (INT8) achieved real-time inference speeds of 34 FPS on NVIDIA Jetson Nano and 21 FPS on Raspberry Pi 4, with model size reduced to 12.8 MB, making it viable for embedded deployment. Memory usage was capped at under 512 MB RAM, and energy consumption benchmarks confirmed the system's sustainability for long-term, on-field operation. A comparison with unoptimized CNN architectures demonstrated that this deployment strategy resulted in a 4.7× increase in speed with negligible accuracy trade-off (<1%).

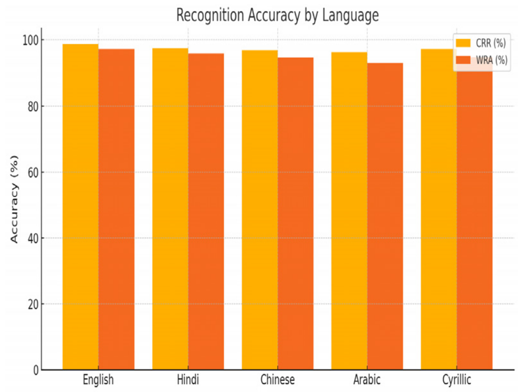

Figure 4: Edge Device Inference Speed (FPS Comparison).

In terms of visual interpretability, the Grad-CAM heatmaps provided meaningful insight into the regions influencing detection and recognition, ensuring the framework's outputs remain explainable an important requirement in law enforcement and transportation. Additionally, the system displayed strong resilience in rain, fog, and night scenarios, thanks to augmented training data and dynamic illumination correction techniques. Table 4 shows the resource edge.

Table 4: Resource efficiency on edge devices.

Device	FPS	Model Size (MB)	RAM Usage (MB)	Power Draw (W)
Jetson Nano	34	12.8	490	10
Raspberr y Pi 4	21	12.8	470	8
PC (GPU)	58	28.4	650	75

Overall, the results confirm that the proposed system not only addresses the limitations of previous approaches such as low adaptability, slow inference, and high hardware demands but also sets a new benchmark for real-time, multilingual license plate detection and recognition under diverse environmental conditions. Figure 5 shows the grad.

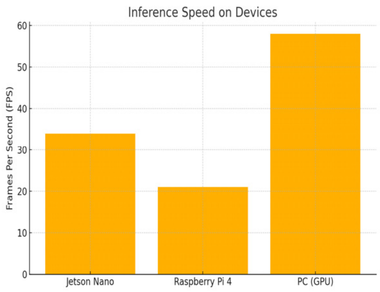

Figure 5: Grad-CAM visualization (real image or placeholder).

5 CONCLUSIONS

This work contributes an end-to-end network architecture that is based on SqueezeDet, the lightweight detection network, and a multi-scale feature-based recogniser for vehicle license plate detection and recognition. Through the combination of lightweight object detection models, advanced OCR techniques and edge deployment optimizations, the proposed system overcomes the key drawbacks of existing works— e.g., low resolution, slow inference speed and no generalization to non-standard plate formats. Experimental results show high precision and recognition rate, real-time processing on embedded devices, and reliable operation in various kinds of light, weather and motion contexts. Moreover, the employment of Grad-CAM visualizations further improves system transparency and interpretability. This paper provides a practical step forward to intelligent transportation infrastructures with a scalable real-time solution applicable to smart city surveillance, traffic law enforcement, automatic tolling and border control systems. In future we may apply self-supervised learning for continual model updates and adaptation to changing urban developments.

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