

Automatic Cambodian License Plate Recognition Using Deep Learning With Robust Skew Handling

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Abstract

This study addresses the challenges of Automatic License Plate Recognition (ALPR) in Cambodia, with a specific focus on accurately detecting and recognizing license plates at varying skew angles. While recent advances in deep learning have improved ALPR systems, the unique characteristics of Cambodian license plates including dual script formats and distinct layout types combined with skewed orientations present significant technical challenges that current solutions do not adequately address. The research employs YOLOv8 instance segmentation for license plate detection, segmentation and type classification, followed by perspective correction using Canny Edge Detection, Douglas-Peucker algorithm, and Homography Transformation to rectify plate skew. Text zone detection utilizes separate YOLOv8 models for Type 1 and Type 2 plates to localize Latin script and plate number, with EasyOCR performing final character recognition enhanced through preprocessing and post-processing optimization. The study utilizes a purpose-built dataset of 1,200 real-world Cambodian license plate images systematically distributed across four skew angle categories ranging from 0° to 60° and two plate types. Performance evaluation demonstrates exceptional results with YOLOv8m-seg achieving 99.5% mAP@70 for detection, a 26.9% improvement over previous benchmarks, while maintaining 100% recall across all skew categories. The perspective correction and EasyOCR integration delivered substantial recognition improvements, with character recall exceeding the previous study by margins ranging from 1.2% to 32.6%, particularly achieving 30% exact match rate improvements for severely skewed plates (45-60°). The findings establish the first systematic skew-handling methodology for Cambodian license plates and demonstrate robust performance across varying skew conditions, providing a methodological foundation for advancing Cambodian ALPR research beyond previous limitations in handling skewed plates.

Keywords: Automatic License Plate Recognition, YOLOv8, EasyOCR

Introduction

Automatic License Plate Recognition (ALPR) systems are essential for modern transportation infrastructure, enabling applications from traffic monitoring to automated toll collection (Etomi & Onyishi, 2021). However, Cambodia faces unique implementation challenges due to distinct license plate characteristics featuring dual Khmer and Latin scripts, with Type 1 and Type 2 formats being most common for private vehicles (Prum et al., 2023; Thourn, 2013). A critical limitation in current Cambodian ALPR research is the inadequate handling of skewed plate orientations (Prum et al., 2023; Tang & Chhea, 2020; Thourn, 2013). This represents a significant practical problem, as skewed license plates dramatically degrade recognition performance, with recall rates dropping from over 90% at 0-15° angles to less than 30% above 60° (Lin & Li, 2019). Such challenging orientations frequently occur



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in real-world scenarios due to road conditions, vehicle movements, and varying camera angles (Li et al., 2018).

To address these limitations, this research develops a comprehensive deep learning pipeline that combines YOLOv8 for robust detection and segmentation with perspective correction and optimized EasyOCR for character recognition. We investigate two key research questions: (1) To what extent can YOLOv8 achieve robust detection, segmentation, and classification across varying skew angles? (2) How effective is the combination of perspective correction and EasyOCR in recognizing Latin script and numerical elements on Cambodian license plates? The specific objectives include creating a comprehensive dataset, training a robust YOLOv8 model, and implementing optimized EasyOCR processing.

Our study focuses on Type 1 and Type 2 plates across skew angles from 0° to 60°, utilizing a purpose-built dataset of 1,200 images. The recognition targets Latin script and plate numbers exclusively, as both Khmer and Latin scripts convey identical provincial information. The dataset follows a systematic 70% training, 20% validation, and 10% testing distribution (Bichri et al., 2024). This work advances both computer vision research and provides technical methodologies applicable to Cambodian license plate recognition challenges.

Literature Review

This literature review examines Cambodian license plate recognition systems and related studies. Cambodian plates, implemented since 2004, feature Khmer and Latin provincial identifiers in three formats (shown in Table 1): Type 1 and Type 2 for private vehicles (compact three-row versus wider two-column layouts), and Type 3 for official vehicles (Prum et al., 2023). With 413,067 registered vehicles in 2024, Type 1 and Type 2 represent the majority (The Khmer Today, 2024). License plate detection has evolved from traditional methods to deep learning approaches, with YOLO algorithms proving superior for speed and accuracy. YOLOv8 demonstrates 83% accuracy, outperforming other YOLO versions (Shyaa & Hashim, 2024). However, skewed plates remain challenging, with recognition accuracy dropping dramatically beyond 30-45° angles (Lin & Li, 2019). For OCR, EasyOCR achieves 95% accuracy versus Tesseract's 88% using Convolutional Recurrent Neural Networks (Vedhaviyassh et al., 2022).

Cambodian ALPR research shows significant limitations. Early work (2013) achieved 98.57% localization on 70 images but lacked skew handling and depended on camera angle and image size configurations (Thourn, 2013). Recent implementations include Faster R-CNN using a hybrid dataset (only 473 of 3,197 images were Cambodian) achieving 72.6% mAP detection and 47% recognition accuracy while identifying plate tilt as a challenge (Tang & Chhea, 2020), and YOLOv8 with Tesseract trained on 200 Cambodian images achieving 86% recognition rate without comprehensive skew handling and evaluation (Prum et al., 2023).

International approaches demonstrate more advanced skew handling solutions. Traditional methods using Mask R-CNN achieved 97% character accuracy for Arabic plates (Hefnawy et al., 2024). Deep learning solutions include YOLOv2 with Mask R-CNN achieving 91% mAP across 0-60° angles, with performance varying from 97.9-99.9% recall at 0-15° to 13.1-22.1% at 60-75° (Lin & Li, 2019). Hybrid approaches achieved 99.6% recognition accuracy with 8.3ms processing speed (Nguyen, 2023).

This analysis reveals critical gaps in Cambodian research: limited datasets, absent comprehensive skew evaluation, heavy manual preprocessing reliance, and lack of dedicated skew handling solutions (Prum et al., 2023; Tang & Chhea, 2020; Thourn, 2013).

Table 1: Cambodian License Plate Types and Examples

License Plate Type	License Plate Example(s)
Type 1	
Type 2	
Type 3	Royal Palace  Supreme Institutions  State Property  Royal Cambodian Armed Force  National Police Force  National Election Committee  Diplomatics  UN, IO, and NGOs  Temporary Import or Duty Suspension Status 

Methodology

The proposed method employs a multi-stage pipeline for Cambodian license plate recognition with robust skew handling, utilizing three datasets: one full-car view dataset (1,200 images) for license plate detection (shown in Table 2) and two cropped plate datasets (400 images each) for text zone localization, with data collected from public vehicle sales posts in Telegram groups and then annotated using Roboflow, where rotation augmentation was also applied to triple the training dataset size. The pipeline begins with YOLOv8m-seg instance segmentation model for license plate detection, segmentation, and type classification (Type 1 vs Type 2) (Ultralytics, 2025), with training utilizing Optuna Bayesian optimization for hyperparameter tuning and shear augmentation applied during training for improved skew robustness in Google Colab with T4 GPU. Detailed hyperparameter configurations for YOLOv8m-seg (shown in Table 3), YOLOv8s Type-1 (shown in Table 4), and YOLOv8s Type-2 (shown in Table 5) models are systematically optimized and documented to ensure reproducible training processes.

Table 2: Dataset Distribution by License Plate Type and Skew Angle Categories

Plate Type	Skew Angle				Total
	0-15°	15-30°	30-45°	45-60°	
Type 1	150	150	150	150	600
Type 2	150	150	150	150	600
Total	300	300	300	300	1200

Table 3: Optimized Hyperparameters for YOLOv8m Instance Segmentation

Hyperparameter	Optimized Configuration
Optimizer	SGD
Image Size (pixels)	960
Initial Learning Rate (lr0)	0.00347
Final Learning Rate Ratio (lrf)	0.00344
Momentum	0.919
Weight Decay	0.000183

Table 4: Optimized Hyperparameters for YOLOv8s Type-1 Detection

Hyperparameter	Optimized Configuration
Optimizer	SGD
Image Size (pixels)	640
Initial Learning Rate (lr0)	0.008695
Final Learning Rate Ratio (lrf)	0.008492
Momentum	0.9380
Weight Decay	0.00473

Table 5: Optimized Hyperparameters for YOLOv8s Type-2 Detection

Hyperparameter	Optimized Configuration
Optimizer	SGD
Image Size (pixels)	640
Initial Learning Rate (lr0)	0.005990
Final Learning Rate Ratio (lrf)	0.018885
Momentum	0.9036
Weight Decay	0.00102

Following detection, perspective correction implements a three-step process: Canny Edge Detection for edge identification (Agrawal & Desai, 2024), Douglas-Peucker Algorithm for corner detection (OpenCV, 2025a), and Homography Transformation for skew correction (Alhussein et al., 2019), with statistical corner refinement using Mahalanobis distance (Hefnawy et al., 2024) and subpixel corner refinement (OpenCV, 2025b) to enhance corner detection accuracy. Text zone localization employs two separate YOLOv8s object detection models handling Type 1 and Type 2 plates respectively, accommodating different spatial arrangements while maintaining computational efficiency. Character recognition utilizes EasyOCR for Latin script and plate number recognition (JaidedAI, 2025), focusing on Latin script while excluding Khmer script due to redundancy (both scripts

convey identical provincial information), enabling resource optimization for improved Latin recognition accuracy, with structured output formatting based on plate type.

Performance evaluation uses mAP@50, mAP@70, and mAP@50-95 for detection and segmentation, and Levenshtein Distance, Character Error Rate (CER), precision, and recall for recognition, with benchmark comparisons following study (Tang & Chhea, 2020) for detection (mAP@70) and study (Lin & Li, 2019) for recognition across angle categories (0-15°, 15-30°, 30-45°, 45-60°). The complete pipeline is demonstrated through a Streamlit web application providing user-friendly interface for image upload and processing results display.

Results

The study created a balanced dataset of 1,200 Cambodian license plate images (600 Type 1, 600 Type 2) distributed equally across four skew angle categories (0-15°, 15-30°, 30-45°, 45-60°), representing the largest Cambodian license plate dataset in research to date. The optimized YOLOv8m-seg model achieved exceptional performance with 99.5% mAP@70, 99.8% precision, and 100% recall for detection across all skew categories, representing a 26.9% detection improvement over the previous Cambodian study (shown in Table 6). Segmentation performance unexpectedly improved with increasing skew angles, rising from 94.9% at 0-15° to 97.3% at 45-60°, possibly due to shear augmentation training effects optimizing the model for non-frontal angles. The perspective correction pipeline achieved 96.375% success rate which significantly enhanced OCR performance at higher skew angles, with exact match rates improving by 30% for 45-60° plates.

Table 6: Performance Comparison with Previous Cambodian License Plate Detection Study

Study	Model	Dataset Composition	Test Set Size	mAP@70 (Detection)
Tang & Chhea, 2020	Faster R-CNN	473 Cambodian plates (mixed with 2,724 international plates)	500 images	72.6%
Current Study	YOLOv8m-seg	1,200 Cambodian plates	120 images	99.5%

EasyOCR achieved 71.1% overall exact match rate with 96.9% precision, 96.2% character recall, and 96.5% F1 score, with character recall outperforming the previous study by 1.2-32.6% across angle categories (shown in Table 7). However, 28.86% of cases experienced recognition failures, primarily due to character misclassification (62.99%) such as M/I and 1/4 confusions, incomplete text recognition (27.56%), and text zone detection errors (9.45%) in low-quality images. Figure 1 demonstrates the complete pipeline, showing license plate detection with segmentation and classification, perspective correction of skewed plates, and final character recognition results with the corresponding confidence scores.

Table 7: OCR Character Recall Rate Comparison with Previous Study

Angle Category (°)	Current Study Average Character Recall Rate	Previous Study Average Character Recall Rate	Remark
0-15°	97.4%	96.2%	Beat the Benchmark by 1.2%
15-30°	99.0%	93.0%	Beat the Benchmark by 6.0%
30-45°	94.7%	85.4%	Beat the Benchmark by 9.3%
45-60°	93.6%	61.0%	Beat the Benchmark by 32.6%

License Plate Detection & Recognition

Image Requirements for Best Results:

- Only Type 1 and Type 2 Cambodian License Plates
- Full view of the car/vehicle (not just the cropped license plate)
- Clear, well-lit, and non-blurry image

See Supported Plate Types

Drop an image here or click to browse



Drag and drop file here

Limit 20MB per file • JPG, JPEG, PNG

Browse files



PHNOM_PENH_2AC-6317.jpg 214.9KB



Detected License Plate

Plate Type: Type 1

Detection Confidence: 0.95



Original Plate



Corrected Plate

Recognized Text:

PHNOM PENH 2AC-6317

OCR Confidence: 0.20

Figure 1: Illustration of the complete license plate detection and recognition pipeline.

The key findings demonstrate that all research questions and objectives were successfully addressed. The comprehensive dataset creation achieved the first objective, while YOLOv8's robust performance across all skew angles fulfilled the second objective and definitively answered the first research question regarding its capability across varying angles. The combination of perspective correction and EasyOCR, demonstrated through significant performance improvements at higher skew angles with optimal effectiveness in the 15-30° range, answered the second research question and achieved the third objective of implementing optimized OCR processing. The results validate the implementation-focused approach while revealing fundamental limitations stemming from using pre-trained models rather than domain-specific training, highlighting both the achievements and constraints of external optimization strategies for Cambodian license plate recognition.

Conclusion

In this paper, we presented the first comprehensive pipeline for automatic Cambodian license plate recognition with robust skew handling. Our primary contribution is a hybrid deep learning and computer vision approach that successfully integrates YOLOv8m-seg for high-accuracy detection with Douglas-Peucker-based perspective correction to handle skewed orientations. The proposed pipeline definitively addresses a critical, previously unsolved challenge in Cambodian ALPR research. Performance evaluation demonstrates a new state of the art in detection, achieving 99.5% mAP@70, a 26.9% improvement over the previous benchmark, while maintaining 100% recall across all skew angles. Furthermore, our perspective correction and optimized EasyOCR implementation proved highly effective, boosting character recall by up to 32.6% for severely skewed plates (45-60°) compared to the prior study. These findings establish a validated, high-performance methodological foundation for future APLR research in Cambodia and similar regional contexts. While this study focused on skew handling with 1,200 images representing the largest Cambodian license plate dataset to date, future work should expand dataset diversity (weather conditions, lighting variations, etc.) and fine-tune OCR models on domain-specific data to further reduce character misclassification errors.

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