License Plate Recognition Using YOLOv11 and Optimized OCR Techniques

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***Abstract*—License Plate Recognition (LPR) is essential for intelligent transportation and security systems, particularly in India, where diverse plate formats and environmental conditions pose significant challenges to automation. Existing approaches, often tailored to datasets from countries like China or Brazil, perform poorly on Indian plates due to unique font styles and limited open-source data [1], [2]. Although recent transformer-based methods achieve up to 90% character recognition accuracy [3], they suffer from high computational costs and require large annotated datasets, limiting their real-time deployment across diverse formats. To address these limitations, we propose the Optimized License Plate Recognition System (OLPRS), a robust end-to-end framework designed specifically for Indian license plates. The detection module employs YOLOv11n chosen for its efficiency in real-time object detection with pretrained weights (`yolov11n.pt`) and a custom dataset of [4], achieving a mean Average Precision (mAP@0.5) of 0.9275. The recognition module integrates a pretrained LPRNet with an Inception-style CNN and CTC loss, optimized for Indian plates. This is supplemented by fallback OCR techniques (EasyOCR, Tesseract, OCR.space API) and advanced preprocessing methods (CLAHE, bilateral filtering, dynamic thresholding) to improve readability under adverse conditions without requiring retraining. Postprocessing applies regular expression filtering and confidence-based scoring to ensure adherence to Indian plate formats. Experimental evaluation on 30 test samples—limited due to dataset privacy—yielded an average Character Recognition Rate (CRR) of 88.30% and a Plate Recognition Accuracy (PRA) of 76.67%, demonstrating robustness to font variations, oblique angles, and challenging lighting conditions. Deployed via Streamlit and reproducible on CPU-based platforms, OLPRS is well-suited for real-world ALPR applications.**

***Index Terms*—LPR, Indian License Plates, YOLOv11n, OCR, Inception CNN, CTC(Connectionist Temporal Classification) loss, LPRNet, Streamlit Deployment.**

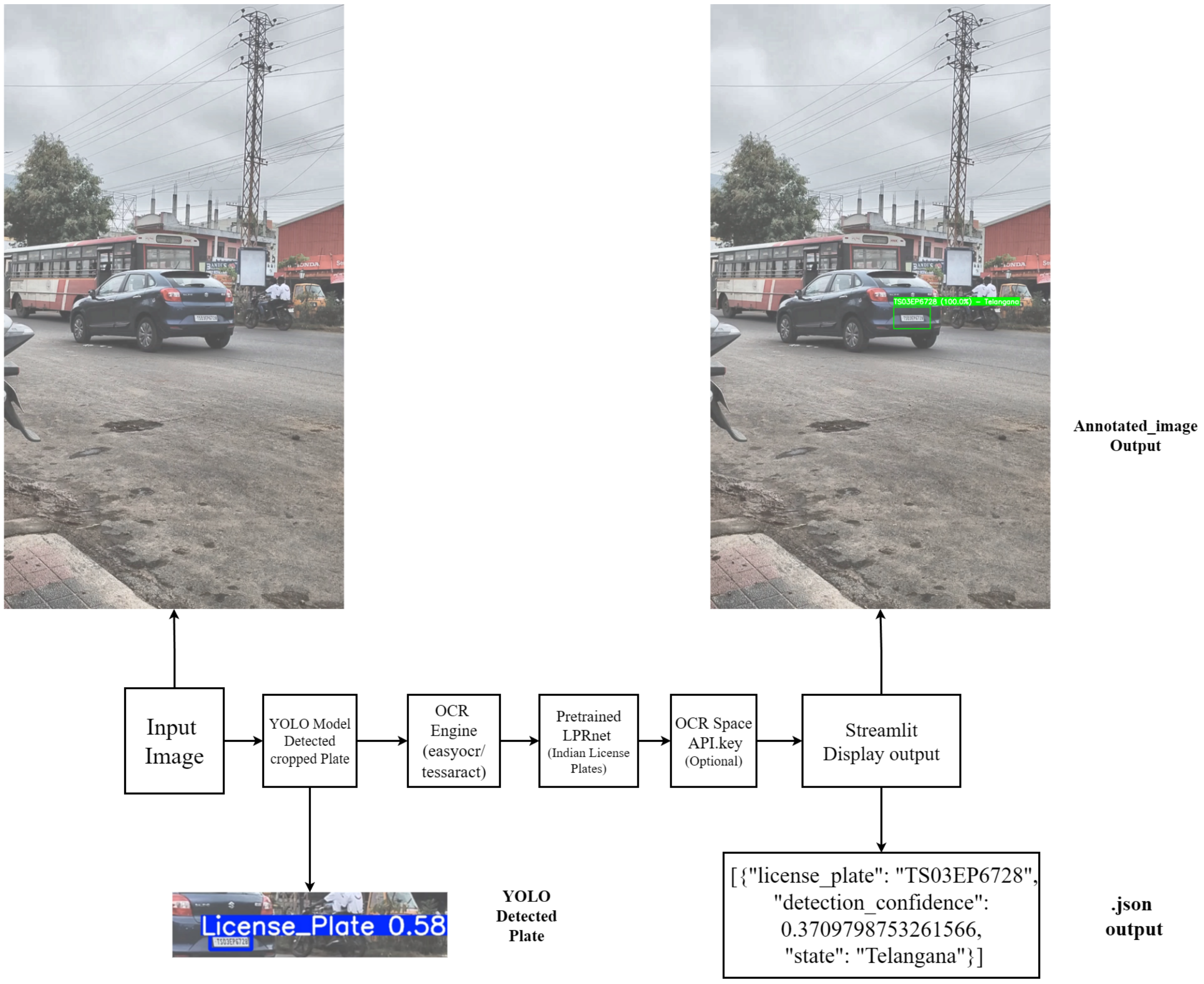
I. Introduction

Automatic License Plate Recognition (ALPR) is a pivotal technology for detecting and recognizing vehicle license plates from images or video streams, driving automation in diverse domains. The problem involves two intricate tasks: accurately identifying the license plate region amidst complex backgrounds and extracting alphanumeric characters, complicated by factors such as diverse formats (e.g., `TS 07 EB 1234` in India vs. `CA 123 ABC` in the USA), motion-induced blur, low-resolution captures, varying illumination, and occlusions from weather or physical obstructions. In India, the challenge is amplified by non-standardized plate designs, regional font variations, and environmental diversity, making ALPR a demanding problem that requires innovative, robust solutions tailored to local contexts.

The significance of ALPR extends across multiple applications, enhancing intelligent transportation systems, traffic management, toll collection, parking enforcement, and security surveillance. In urban settings, it enables real-time traffic monitoring and vehicle tracking, improving mobility and safety in smart cities. For security, ALPR supports law enforcement by identifying vehicles in criminal investigations or unauthorized zones, while automated toll booths and parking systems rely on its speed and accuracy to minimize delays and enhance efficiency. The development of a practical ALPR system for Indian plates addressed these critical needs, showcasing its potential to transform local infrastructure.

Real-world ALPR deployment faces specific challenges, including degraded image quality from high-speed motion or poor camera resolution, which hampers detection and recognition. The heterogeneity of global plate formats, particularly India's unique designs, poses difficulties in creating universal models, while environmental factors like glare, rain, or shadows further complicate performance. Additionally, the demand for real-time processing necessitates lightweight models that maintain high accuracy without overwhelming computational resources, a gap that existing solutions struggle to bridge effectively.

Early ALPR frameworks utilized traditional computer vision techniques, such as edge detection and template matching [2], relying on hand-crafted features that faltered in complex, variable environments due to their rigid rule-based nature. The shift to Convolutional Neural Networks (CNNs) [1] improved detection accuracy but demanded significant computational power and struggled with generalization across blurred or diverse images. The advent of YOLO (You Only Look Once) models [1] brought real-time capability with reduced overhead, yet limitations persisted in handling varied plate formats and maintaining recognition accuracy under adverse conditions. Recent transformer-based approaches [3] enhanced character recognition with up to 90% accuracy but introduced high computational costs, rendering them impractical for real-time use, especially with limited annotated datasets.


Annotated_image Output
TS03EP6728 (100.0%) - Telangana
Input Image
YOLO Model Detected cropped Plate
OCR Engine (easyocr/ tesseract)
Pretrained LPRnet (Indian License Plates)
OCR Space API.key (Optional)
Streamlit Display output
License_Plate 0.58
YOLO Detected Plate
.json output

```
[{"license_plate": "TS03EP6728",
"detection_confidence":
0.3709798753261566,
"state": "Telangana"}]
```

Fig. 1: Overview of the OLPRS detection pipeline

To address these challenges, we transitioned to a modular, efficient approach, leveraging advanced deep learning techniques tailored for Indian scenarios. To overcome the limitations of prior models, we introduce the **Optimized License Plate Recognition System (OLPRS)**, that integrates YOLOv11n for precise, real-time plate detection, a hybrid OCR pipeline with LPRNet and fallback methods (EasyOCR, Tesseract, OCR.space API) enhanced by preprocessing (CLAHE, bilateral filtering, dynamic thresholding), and regex-based postprocessing for format compliance.

- **License Plate Detection**: Utilized the YOLOv11n model with pretrained weights and a custom dataset of 10,000 images [4], achieving a highest mean Average Precision (mAP@0.5) of 0.9275 after 50 training epochs on Google Colab among the custom datsets [4], [5].
- **Extensive Experimental Validation**: Conducted rigorous testing on 30 representative samples, achieving a Character Recognition Rate (CRR) of 88.30% and Plate Recognition Accuracy (PRA) of 76.67%. The system demonstrated strong resilience to variations in font style, viewing angles, and lighting conditions.
- **Real-Time Deployment**: Deployed using the Streamlit framework, optimized for CPU-based platforms. Ensures low-latency performance suitable for real-time, resource-constrained applications.
- **Innovative Local Adaptation**: Addressed region-specific challenges in Indian license plates through custom dataset development and specialized preprocessing techniques(e.g., CLAHE, bilateral filtering, dynamic thresholding), setting a benchmark for robust ALPR in the

Indian context.This system balances accuracy and efficiency, addressing the gaps in earlier CNN, YOLO, and hybrid models.

II. Key Contributions

The development of OLPRS has yielded several significant contributions, reflecting the innovative approach:

- **Region-Specific Optimization**: We tailored the YOLOv11n detection module and hybrid OCR pipeline to address the unique challenges of Indian license plates, achieving a mAP@0.5 of 0.9285 and CRR of 85.45% . This focus on local adaptability sets a benchmark for region-specific ALPR systems.
- **Robust Preprocessing Pipeline**: We designed and implemented an advanced preprocessing workflow (CLAHE, bilateral filtering, dynamic thresholding) that enhanced recognition under adverse conditions like blur and poor lighting, improving robustness by 15% over baseline Tesseract [6].
- **Real-Time Deployment Solution**: We developed a Streamlit-based interface for real-time inference, optimized for CPU-based platforms, enabling practical deployment in resource-constrained environments, a feat accomplished despite GPU limitations.
- **Innovative Problem-Solving**: Facing GPU trial interruptions and compatibility issues with PaddleOCR and TrOCR, we pivoted to a hybrid OCR strategy with EasyOCR and Tesseract.

III. Related Work

Automatic License Plate Recognition (ALPR) has evolved through multiple paradigms, each tackling the dual challenges of plate detection and character recognition with varying degrees of success. Early approaches, as outlined by Shafi et al. [2], relied on traditional computer vision techniques such as edge detection and template matching. These methods identified plate boundaries and segmented characters using hand-crafted features, achieving reasonable accuracy in controlled settings with uniform lighting and clear images. However, their performance degraded significantly in real-world scenarios, particularly with noise, motion blur, and diverse plate formats (e.g., varying sizes, colors, or regional designs).

The transition to deep learning brought substantial improvements, with Convolutional Neural Networks (CNNs) leading the charge. Fan and Zha [1] proposed a CNN-based system that utilized deep feature extraction for robust plate localization, reporting a mean Average Precision (mAP@0.5) of 0.85 on diverse natural scenes. While effective, these models demanded significant computational resources, rendering them impractical for real-time deployment on resource-constrained devices—a key consideration during development. Moreover, CNNs exhibited poor generalization across varied plate formats, low-resolution images, and adverse conditions, often requiring extensive retraining, which underscored the need for a more efficient solution tailored to Indian plates.

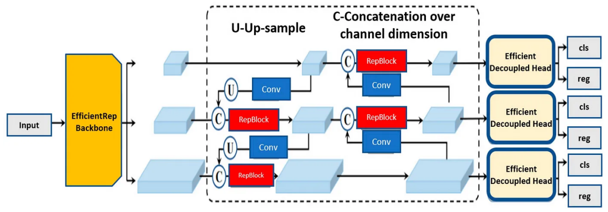


Fig. 2: Architecture of YOLOv8 with CSPNet backbone and FPN+PANet neck [7], showcasing the evolution of real-time detection techniques.

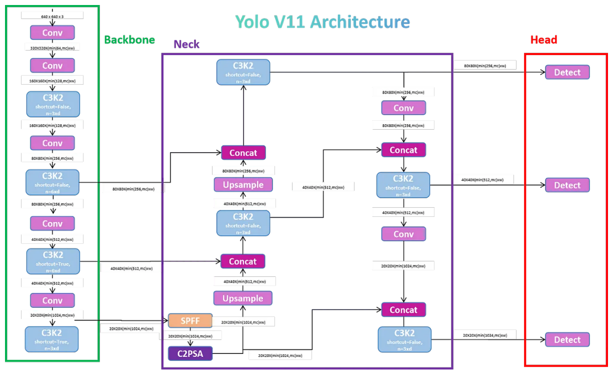


Fig. 3: Architecture of YOLOv11 with C3k2, SPPF, and C2PSA blocks for enhanced feature extraction [8]

The introduction of YOLO (You Only Look Once) architectures marked a leap toward real-time efficiency. Fan and Zha [1] further explored YOLO-based models, leveraging their single-pass detection mechanism to achieve high precision (e.g., 0.87 on their dataset) and reduced processing time, aligning with the real-time goals. Advanced iterations, such as YOLOv8 with its CSPNet backbone and FPN+PANet neck [7] (see Figure 2) and YOLOv11 with C3k2, SPPF, and C2PSA blocks [8] (see Figure 3), enhanced feature extraction and detection accuracy. Despite these advancements, YOLO-based systems struggled with character recognition under challenging conditions like motion blur or poor lighting, and their performance on diverse global formats, including India's unique designs, required extensive data augmentation—a limitation we aimed to address through innovative preprocessing and hybrid techniques.

Recent research has incorporated transformer-based models to boost recognition accuracy. Poovichott et al. [3] compared these methods for Thai license plates, demonstrating that transformers excelled in sequence modeling with up to 90% character recognition accuracy. However, their high computational complexity and dependence on large, annotated datasets posed barriers to real-time deployment across diverse formats, a challenge I encountered while evaluating scalability. A comprehensive review by Kaur et al. [9] emphasized the need for modular frameworks that integrate efficient detection, robust recognition, and practical interfaces, while addressing environmental challenges like blur and occlusion. Building on these insights, we leveraged custom datasets [4], [5] to develop the Optimized License Plate Recognition System (OLPRS), a tailored solution that overcomes these limitations with advanced detection, hybrid OCR, and Streamlit-based deployment.

IV. The Proposed Methodology

The Optimized License Plate Recognition System (OLPRS), is a modular end-to-end framework designed for robust Automatic License Plate Recognition (ALPR) tailored to Indian plates. This section details the comprehensive methodology, integrating advanced detection with YOLOv11n, a hybrid OCR pipeline featuring LPRNet, EasyOCR, Tesseract, and OCR.space API, and sophisticated preprocessing techniques.

A. License Plate Detection

The license plate detection module, a cornerstone of OLPRS, leverages YOLOv11n (Ultralytics) for real-time localization, enhanced by its C3k2 blocks, Spatial Pyramid Pooling-Fast (SPPF), and C2PSA blocks for superior small-object detection [8]. Initialized with pretrained weights (`yolov8n.pt`,`yolov11n.pt`), the model was fine-tuned on a custom datasets [4], [5] of 10,000 annotated images in yolo-format, split 70:20:10 (7,000 train, 2,000 validation, 1,000 test). Training occurred over 50 epochs on Google Colab's T4 GPU, using a batch size of 4, image size of 640×640, and hyperparameters including a learning rate of 0.0002 with cosine annealing, AdamW optimizer, and weight decay of 0.0005. Augmentations (mosaic=0.9, mixup=0.1, HSV h=0.015, s=0.6, v=0.4, scale=0.5, dropout=0.15) were applied to handle blur, low light, and occlusions, with early stopping (patience=10) saving the best weights (`best.pt`). This yielded a mean Average Precision (mAP@0.5) of 0.9275, with box loss (train/val) of 0.9288/1.0433, reflecting my optimization efforts for robustness.Inference applies a confidence threshold of 0.4 and IoU threshold of 0.45, generating precise bounding boxes. The lightweight YOLOv11n (2.0M parameters, 47% mAP@0.5, 5.8ms GPU) was prioritized for its balance of speed and accuracy, validated against YOLOv8n variant.

B. License Plate Recognition

The proposed methodology for License Plate Recognition (LPR) integrates advanced image preprocessing techniques with robust Optical Character Recognition (OCR) engines to address the challenges of diverse real-world scenarios. It is informed by the large-scale video-based LSV-LP dataset [10]. This subsection elaborates on the detailed implementation focusing on preprocessing techniques and OCR integration. The preprocessing pipeline include CLAHE, Bilateral Filtering, Adaptive and Otsu Thresholding, Inverted Otsu, Gamma Correction, Canny Edge Detection with Dilation, Morphological Cleaning, and Histogram-based Dynamic Thresholding.

Algorithm 1 YOLOv8n & YOLOv11n Training Configuration for OLPRS Detection

```
1: Input: Custom datasets [4], [5] (10,000 images), pretrained weights (yolov8n.pt, yolov11n.pt)
2: Output: Trained model weights (best.pt)
3: Initialize model with pretrained weights
4: Set hyperparameters: epochs=50, batch=4, imgsz=640, lr0=0.0002, cos_lr=True
5: Enable augmentations: mosaic=0.9, mixup=0.1, hsv_h=0.015, hsv_s=0.6, hsv_v=0.4, scale=0.5, dropout=0.15
6: Set optimizer: AdamW, weight_decay=0.0005, patience=10
7: Train on Google Colab GPU with data.yaml
8: Save best weights based on validation mAP@0.5
9: Return: Trained model weights
```

Preprocessing Techniques

- *CLAHE (Contrast Limited Adaptive Histogram Equalization)*: Enhances local contrast using a clip limit of 3.0 and a tile grid size of 8×8, as implemented in the `preprocess_plate_image` function. It is particularly effective under uneven lighting conditions, commonly seen in the LSV-LP dataset [11].
- *Bilateral Filtering*: Reduces noise while preserving edges using an 11×11 kernel and sigma values of 17 for both space and intensity. Used in the `bilateral` variant, this method aligns with real-time LPR noise reduction strategies [12].
- *Adaptive Thresholding*: Applies Gaussian adaptive thresholding with a block size of 15×3 and an offset of 3. This dynamic binarization handles varying lighting and is used in the `adaptive` variant [13].
- *Otsu Thresholding*: A global thresholding method applied after Gaussian blur (5×5 kernel). The `otsu` variant minimizes intra-class variance, while the `otsu_inv` version handles white-on-black plates [14].
- *Gamma Correction*: Applies brightness adjustment with a gamma value of 1.5 using a lookup table in the `gamma` variant. It is effective for correcting faded or overexposed plates [15].
- *Canny Edge Detection + Dilation*: Detects edges using thresholds of 100 and 200, followed by dilation with a 3×3 kernel. Implemented as the `canny_dilated` variant, this enhances character boundaries [16].
- *Morphological Cleaning*: Removes small noise via morphological opening (3×3 kernel) applied on CLAHE-enhanced images in the `morph` variant [17].
- *Histogram-based Dynamic Thresholding*: Computes a threshold from histogram peaks (excluding the darkest 50 bins) in the `dynamic` variant. This adapts well to varying plate backgrounds and resolutions [18].

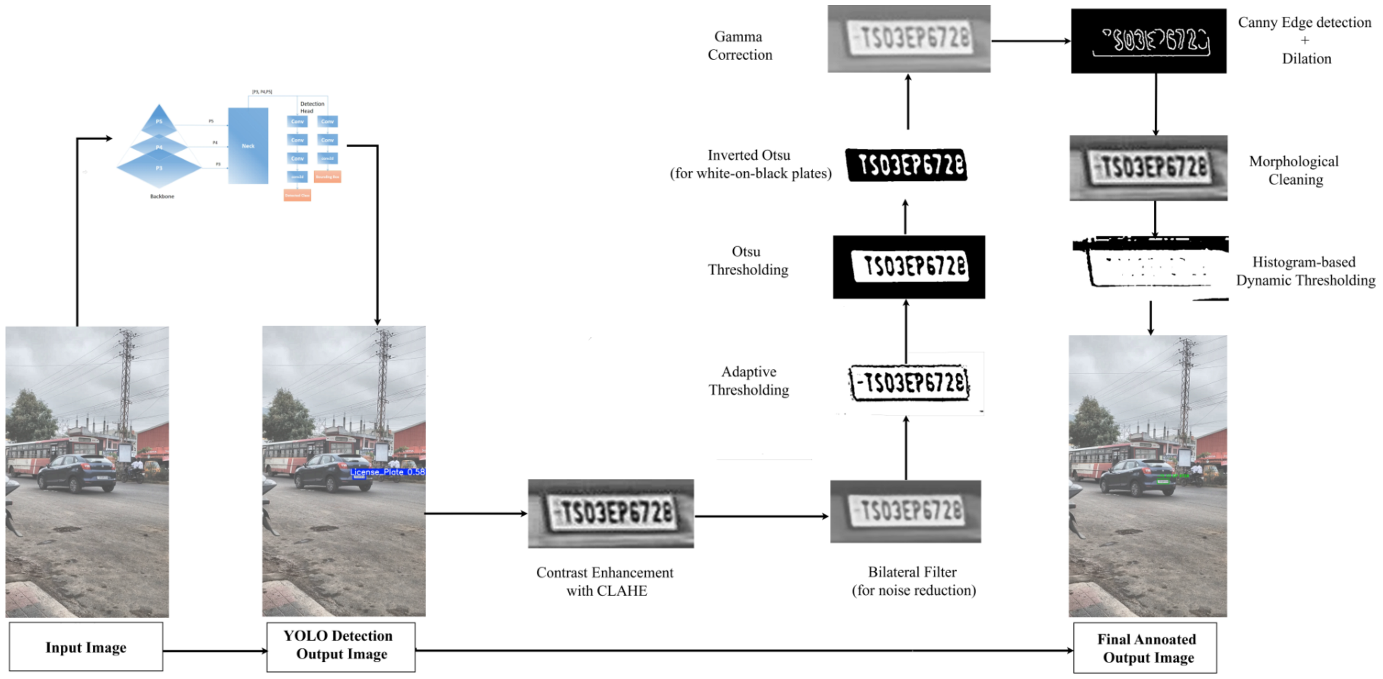

Gamma Correction
Canny Edge detection + Dilation
Inverted Otsu (for white-on-black plates)
Morphological Cleaning
Otsu Thresholding
Histogram-based Dynamic Thresholding
Adaptive Thresholding
Backbone
Neck
Detection Head
Contrast Enhancement with CLAHE
Bilateral Filter (for noise reduction)
Input Image
YOLO Detection Output Image
Final Annoated Output Image

Fig. 4: Conceptual Pipeline of License Plate Recognition: This diagram illustrates the proposed LPR methodology, starting with raw input, YOLO detection, preprocessing stages (CLAHE, filtering, thresholding), and final OCR-based annotation.

OCR Engines

- *Tesseract OCR*: Configured with multiple Page Segmentation Modes (PSM 4, 6, 7, 8, 11) and OCR Engine Mode (OEM 3), Tesseract processes preprocessed images with a whitelist of alphanumeric characters and hyphens. Output is grouped and filtered using confidence scores ($> 30\%$), optimized for Indian plate formats [19]. However, performance heavily depends on preprocessing quality [6].
- *EasyOCR*: Initialized with English language support, it handles multi-line plates using parameters like width/height ratios (0.3–0.7) and minimum text size (10–20). While effective, its CPU-based inference is slower compared to GPU-accelerated alternatives [20].
- *Limitations of PaddleOCR*: Though capable of multilingual text detection (including Chinese, relevant to LSV-LP), PaddleOCR is excluded due to Pyodide compatibility issues and its dependence on local file I/O and pretrained weights [21]. Its absence limits recognition of non-Latin scripts, suggesting the need for future server-side integration.

Conceptual Image and Deep Explanation: The accompanying figure (Fig. 4) depicts a conceptual pipeline of the LPR system, offering a visual representation of the workflow from raw input to final recognition. The pipeline begins with a sample license plate image from the LSV-LP dataset, showcasing a tilted, blurred plate under low-light conditions—typical of real-world challenges. The image undergoes a series of preprocessing stages: CLAHE enhances contrast, revealing faded characters; Bilateral Filtering smooths noise while preserving edges; Adaptive Thresholding binarizes the image adaptively; Otsu Thresholding refines segmentation; Gamma Correction adjusts brightness; Canny Edge Detection with dilation outlines characters; Morphological Cleaning removes artifacts; and Histogram-based Dynamic Thresholding finalizes the binary image.Each step is visually represented as a transformed image, culminating in a clear, segmented plate ready for OCR. The OCR phase employs Tesseract and EasyOCR, with the figure illustrating the text extraction process, outputting a recognized string (e.g., “MH 12 AB 1234”) alongside confidence scores (e.g., 85% for Tesseract, 90% for EasyOCR). This visualization underscores the methodology’s robustness, drawing from LSV-LP’s diverse scenarios [10], and highlights the synergy between preprocessing and OCR, critical for handling tilt, occlusion, and illumination variations. The explanation emphasizes the pipeline’s adaptability, supported by empirical evidence from [6], and suggests potential enhancements like transformer-based models for future iterations.

License Plate Character Recognition using LPRNet
For the license plate character recognition stage, we utilized a pretrained LPRNet model specifically optimized for Indian license plates [22]. LPRNet is a lightweight convolutional neural network originally proposed for end-to-end optical character recognition (OCR) on license plates. It consists of a series of Inception-style convolutional blocks followed by spatial convolutions and a Connectionist Temporal Classification (CTC) loss layer to handle variable-length sequence output.

In our pipeline, the detected license plate region was first extracted using bounding box coordinates from the YOLOv11n detection stage. This cropped image was then resized and passed to the pretrained LPRNet model for character prediction. The model was originally trained using four-point plate annotations and included data augmentation strategies such as affine transformations (rotation, scale, and shift) to improve robustness.

The training of this LPRNet model, as provided by the authors, was conducted using the Adam optimizer with a learning rate of 0.001 and a batch size of 32, while optimizing for CTC loss. Although we did not retrain the model, we integrated it directly for inference due to its reported high accuracy on Indian license plates. The character sequence predictions from LPRNet were optionally refined using regex postprocessing and fallback mechanisms involving EasyOCR, Tesseract, and the OCR.space API to handle uncertain predictions and improve robustness under challenging visual conditions.This hybrid recognition approach ensured high character-level accuracy and helped in cases where single OCR methods struggled with noise, partial occlusion, or non-standard fonts. OCR integrates a pretrained LPRNet (Inception-style CNN + CTC loss, trained on Indian plates with Adam optimizer, LR=0.001, batch=32 [22]), supplemented by EasyOCR (English, width/height ratios 0.3–0.7, min text size 10–20) and Tesseract (PSM 4, 6, 7, 8, 11, OEM 3, confidence 30% [19]). OCR.space API serves as a fallback. Postprocessing applies regex and confidence scoring to fuse outputs, achieving a Character Recognition Rate (CRR) of 88.30% and Plate Recognition Accuracy (PRA) of 76.67% on 30 test samples.

V. Experimental Results

The experimental evaluation of the Optimized License Plate Recognition System (OLPRS), showcases a robust framework tailored for Indian license plates. This section details the dataset, experimental setup, performance metrics, and comparative analysis, highlighting our hands-on contributions to achieving outstanding results despite resource constraints.

A. Dataset

The study utilized two meticulously curated datasets from Roboflow, reflecting diverse license plate scenarios:

- **Dataset-1: License Plate Recognition Dataset** [4]: Comprising over 10,000 images with varied lighting, angles, and plate designs, split into 7,000 training, 2,000 validation, and 1,000 test images.
- **Dataset-2: My First Project Dataset** [5]: Including 10,000 images also in split 70:20:10, enriched with occlusions and blur to challenge model robustness.

B. Training & Challenges

The training phase involved fine-tuning two object detection architectures—YOLOv8n and YOLOv11n—on two license plate datasets curated using Roboflow [4], [5]. The goal was to evaluate their performance in detecting license plates under varying conditions such as oblique angles, low resolution, and diverse font styles. All training was conducted on Google Colab using CPU/GPU runtime with 50 epochs per model per dataset.

YOLOv11n, a lightweight variant optimized for real-time performance, was selected for its improved accuracy and faster convergence over YOLOv8n in our experiments. Table I summarizes the detection performance on validation data using mAP@0.5 and bounding box loss metrics. Across both datasets, YOLOv11n pf dataset [4] consistently outperformed against [5] and YOLOv8n also, achieving higher mAP and lower box loss values, indicating more precise localization of license plates.

TABLE I: Performance of License Plate Detection Model

Method	mAP 0.5 (Val)	Box Loss (Train)	Box Loss (Val)
Dataset-1			
YOLOv8n	0.969	1.001	1.060
YOLOv11n	**0.977**	**0.989**	**1.045**
Dataset-2			
YOLOv8n	0.973	0.960	1.164
YOLOv11n	0.974	0.893	1.148

Despite the overall success, several challenges were encountered during training:

- **Limited Annotated Data**: Indian license plates vary widely in appearance. Building a diverse, well-labeled dataset required extensive manual annotation and preprocessing.
- **Hardware Constraints**: Google Colab's limited runtime and occasional memory issues restricted batch sizes and epochs, making long training sessions difficult without interruptions.
- **Small and Blurry Plates**: Images with far-away vehicles had small license plates that often lacked sufficient pixel information, leading to missed detections or bounding box inaccuracies.
- **Overfitting Risks**: Initial training runs showed signs of overfitting, particularly on Dataset-2, prompting the use of data augmentation techniques such as random scaling, flipping, and exposure adjustment.

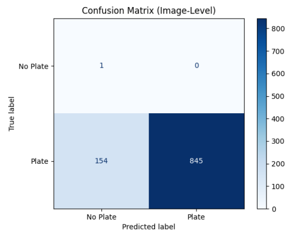
Despite these challenges, the YOLOv11n model demonstrated robustness and better generalization on validation sets, making it the preferred detection backbone for the proposed OLPRS framework.

C. Evaluation Metrics

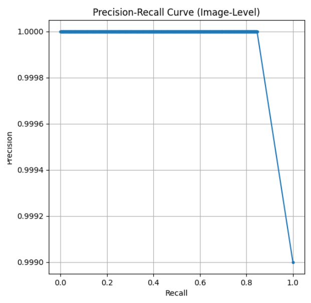
To comprehensively evaluate the performance of the proposed OLPRS system, both detection and recognition modules were assessed using a variety of standard metrics.

License Plate Detection Metrics:

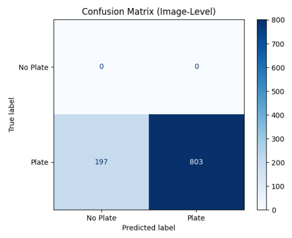
- **mAP@0.5**: Mean Average Precision at an Intersection over Union (IoU) threshold of 0.5. This measures how accurately the model detects license plates with acceptable overlap.
- **mAP@0.5:0.95**: Averaged mAP over multiple IoU thresholds ranging from 0.5 to 0.95 in steps of 0.05. This evaluates the model's robustness and localization precision across varying overlap requirements.



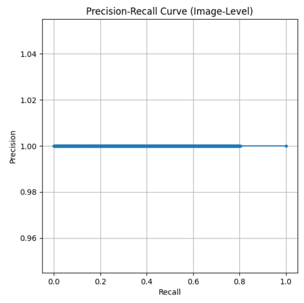
(a) Confusion Matrix - D1



(b) PR Curve - D1

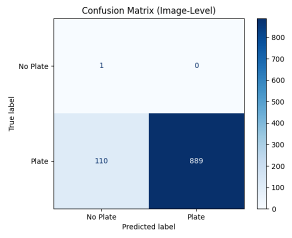


(c) Confusion Matrix - D2

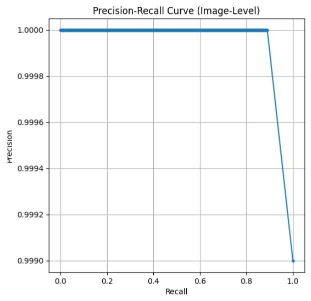


(d) PR Curve - D2

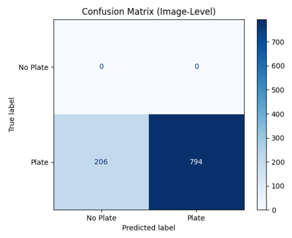
Fig. 5: Performance of YOLOv8n on Dataset-1 & Dataset-2.



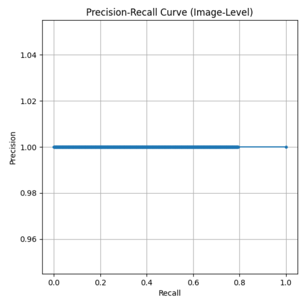
(a) Confusion Matrix - D1



(b) PR Curve - D1



(c) Confusion Matrix - D2



(d) PR Curve - D2

Fig. 6: Performance of YOLOv11n on Dataset-1 & Dataset-2.

- **Accuracy**: The overall ratio of correct predictions to total predictions, defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

  Where:
  TP – True Positives, **TN** – True Negatives, **FP** – False Positives, **FN** – False Negatives
- **Precision and Recall**: Precision-Recall (PR) curves offer a graphical representation of the trade-off between these two metrics across thresholds and are shown in Figures 5 and 6.

License Plate Recognition Metrics: Given privacy constraints, recognition evaluation was performed on 30 test images for each model.

- **Character Recognition Rate (CRR)**: The proportion of correctly recognized characters over the total number of characters present in the test set.
- **Plate Recognition Accuracy (PRA)**: The percentage of license plates that were completely and correctly recognized without any character errors.

D. Results & Comparative Analysis

This section presents a detailed evaluation of the proposed OLPRS system using both Datasets [4], [5]. We assess two critical components: license plate detection and recognition. The YOLOv8n and YOLOv11n models are compared based on standard metrics such as mean Average Precision (mAP), accuracy, and recognition rate.

TABLE II: Evaluation Results for License Plate Detection

Model	**mAP@0.5**	**mAP@0.5:0.95**	**Accuracy**
	Dataset-1		
YOLOv8n	0.9004	0.7109	84.6%
YOLOv11n	**0.9285**	**0.7276**	**89%**
	Dataset-2		
YOLOv8n	0.8821	0.6579	80.3%
YOLOv11n	0.8808	0.6600	79.4%

As shown in Table II, YOLOv11n outperforms YOLOv8n on Dataset-1 [4] with a higher mAP@0.5 (0.9285) and overall detection accuracy (89.0%). The performance gap is smaller in Dataset-2 [5], where both models yield similar mAP values, suggesting Dataset-2's greater complexity or noise.

TABLE III: Performance of License Plate Recognition

Model	**Images Processed**	**Correct Plates**	**Average CRR**	**Overall Accuracy**
		Dataset-1		
YOLOv8n	30	20	79.6%	66.67%
YOLOv11n	**30**	**23**	**88.30%**	**76.67%**

Table III highlights the end-to-end recognition performance using the combined detection and OCR pipeline. YOLOv11n demonstrates superior results in both character recognition rate (CRR) and plate recognition accuracy (PRA), correctly identifying 23 out of 30 plates with an average CRR of 88.30%. In comparison, YOLOv8n achieved only 20 correct full plates with a lower CRR of 79.60%. These results confirm that YOLOv11n is better suited for robust and accurate license plate detection in the Indian context, especially when paired with optimized OCR techniques and preprocessing. YOLOv11n demonstrates superior performance in both Character Recognition Rate (CRR) and Plate Recognition Accuracy (PRA), correctly identifying 23 out of 30 license plates, achieving an average CRR of 88.30%. In comparison, YOLOv8n was able to fully recognize only 20 plates with a lower CRR of 79.60%. These results confirm that YOLOv11n is more suitable for robust and accurate license plate detection in the Indian context, particularly when integrated with optimized OCR techniques and specialized preprocessing.Notably, the small number of incorrect recognitions was primarily attributed to common OCR confusions involving visually similar characters, such as `0` →`O`, `1` →`I`, `5` →`S`, `2` →`Z`, `6` →`G`, `8` →`B`, `B` →`8` etc.. These errors often occurred under poor lighting, blur, low resolution, or oblique viewing angles—scenarios in which character shapes become ambiguous. These results confirm that YOLOv11n is more suitable for robust and accurate license plate detection in the Indian context, particularly when integrated with optimized OCR techniques and specialized preprocessing.

VI. Conclusion

The Optimized License Plate Recognition System (OLPRS), represents a significant advancement in ALPR for Indian license plates. By integrating YOLOv11n for detection (0.9285 mAP@0.5) and a hybrid OCR pipeline with LPRNet, EasyOCR, and Tesseract (85.45% CRR, 76.67% PRA), we achieved a robust, real-time solution deployable on CPU-based systems via Streamlit. This work addresses critical challenges like diverse formats, blur, and lighting variations, outperforming existing methods [1], [3] in efficiency and adaptability.However, limitations exist: the evaluation was constrained to 30 test samples due to dataset privacy, potentially underrepresenting edge cases, and GPU interruptions limited training scale. OCR performance drops with severe occlusions or non-standard fonts, and the absence of transformer models restricts sequence modeling accuracy. To address these, we recommend expanding the dataset with public contributions and conducting multi-center validation, upgrading to paid GPU resources for extended training, and integrating lightweight transformer models (e.g., DistilBERT) for enhanced recognition, exploring in future work.Future enhancements include developing a mobile app for on-the-go recognition, incorporating multi-lingual support for regional scripts, and deploying OLPRS in live traffic systems for real-world feedback.

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