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License Plate Recognition System Using Computer Vision and Optical Character Recognition

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Abstract: The increasing volume of vehicles in India has made manual traffic monitoring and vehicle record-keeping slow, error-prone, and unsuitable for large-scale deployment. License Plate Recognition (LPR) systems are now commonly used in tolling, parking, and surveillance applications to automatically extract vehicle registration numbers from images or video streams. But most high-accuracy LPR solutions use deep-learning models and GPU-based infrastructure, which makes them more expensive and harder to use in places like colleges, gated communities, and city deployments where money is tight. This paper describes a cheap LPR framework that uses Python, OpenCV, and Tesseract to do classical computer vision and Optical Character Recognition (OCR). The system is specifically designed to work with Indian High-Security Registration Plates (HSRP) and tests performance in the day, night, shadow, and blur. Testing on a dataset of 500 images achieved an average plate-detection accuracy of 94% and OCR accuracy of 91% on CPU-only hardware, with a mean inference time of 1.5 s per image. The results show that traditional image-processing pipelines can work well in India without the extra work of deep learning. This makes the system good for smart parking, automated entry gates, and low-cost traffic management.
Keywords: License Plate Recognition, Computer Vision, OCR, Tesseract, Indian HSRP, Intelligent Transportation Systems

I. INTRODUCTION

Automated vehicle identification has become a critical requirement in modern transportation infrastructure, enabling toll collection, access control, violation monitoring, vehicle tracking, and law-enforcement analytics. India alone adds more than 20 million registered vehicles each year, which puts pressure on transportation systems and traffic authorities to find scalable automation solutions. Writing down vehicle numbers by hand takes a lot of time and is prone to mistakes, especially in busy places like toll plazas, campus gates, and parking lots. License Plate Recognition (LPR), which is also called Automatic Number Plate Recognition (ANPR), is the process of using optical sensing and computer algorithms to read alphanumeric text from vehicle license plates. Several countries have adopted nationwide ANPR-based tolling and surveillance networks, but India has been slower to adopt LPR because of inconsistent plate fonts, multilingual plates, low-quality roadside cameras, and the high cost of deployment. The Motor Vehicles Act (2019) brought in High-Security Registration Plates (HSRP), which made the design, font, and reflectivity of Indian vehicle plates the same for all vehicles. This makes it clear that there is a need for scalable LPR systems that are made to work well on Indian roads and in Indian lighting. But most of the commercial ANPR products that are already on the market use deep-learning models that were trained on data from other countries and need GPU hardware, which makes them very expensive to set up.

This paper suggests a lightweight, open-source, CPU-based LPR system that uses Tesseract OCR for alphanumeric recognition and classical computer vision methods to find license plates. The system is made to work on cheap hardware and can be set up on edge devices like Raspberry Pi, embedded PCs, or regular desktop computers.

The following are the contributions of this work:

1) An end-to-end LPR pipeline that works best with Indian HSRP formats and uses classical CV and OCR instead of deep learning.
2) A performance test in four real-world situations: daytime, nighttime, shadow, and blur.
3) A standard comparison with deep-learning-based systems in terms of accuracy, cost, and hardware dependency.
4) A web interface that can be deployed with Flask for uploading and recognizing images in real time.

II. LITERATURE REVIEW

License Plate Recognition (LPR) systems have evolved significantly over the past three decades, transitioning from heuristic image-processing pipelines to modern deep-learning architectures. Existing studies differ in methodology, hardware requirements, dataset constraints, and deployment feasibility. This section categorizes prior research into four major approaches and identifies the gaps that motivate the present work.

A. Classical Computer Vision Approaches

Early LPR systems relied on edge-based and projection-based algorithms to locate plate regions in an image. Sobel and Canny edge detectors combined with connected component analysis were widely used to extract rectangular regions with high gradient density [1]. Hough transform–based methods were later introduced to detect linear boundary patterns around plates [2]. Although computationally lightweight, these methods were highly sensitive to illumination changes, motion blur, and skew. Color-segmentation and morphological filtering were proposed to improve robustness by leveraging HSV features, dilation–erosion filters, and shape constraints [3]. These techniques reduced false detections in daylight conditions but required environment-specific parameter tuning, limiting scalability across real-world scenes.

B. Machine Learning–Based LPR

The next generation of LPR research incorporated traditional machine-learning classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and AdaBoost for plate/non-plate region discrimination [4]. These models improved generalization by learning handcrafted features such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP). However, the segmentation and character extraction stages still required manual tuning.

C. Deep Learning–Based LPR

Deep learning–based solutions treat plate detection and character recognition as end-to-end tasks, removing the need for hand-engineered features. YOLO-based detectors localize plates directly in full images, while CRNN and Transformer-based OCR extract alphanumeric sequences from cropped regions [5], [6]. These systems have achieved >97% accuracy on US and EU datasets. Despite high accuracy, deployment of deep-learning ANPR is restricted by GPU inference cost, large training datasets, and latency constraints. Furthermore, most pretrained models are biased toward Western plate formats and fail on multilingual or low-resolution plates commonly found in developing countries.

D. India-Specific ANPR Research

Indian LPR research has historically focused on handcrafted pipelines due to cost constraints. Rahman et al. achieved 92% detection accuracy using morphological filtering on a 200-image dataset [7]. Kiran et al. extracted plates through histogram equalization and contour rules, achieving 89% on daylight-only scenes [8]. A deep-learning-based Indian plate detector was proposed in [9], but required RTX-series GPU hardware during inference.

A common limitation in India-based studies is the lack of evaluation under night lighting, shadow, plate glare, and motion conditions — all of which are frequent on Indian roads. Most studies also do not evaluate High-Security Registration Plates (HSRP), which are now mandatory nationwide.

E. Identified Research Gaps

Gap Identified	Evidence in Literature
No India-specific benchmarking at scale	Existing datasets ≤ 200 images [7], [8]
High GPU dependency in recent models	YOLO/CRNN models require GPU [5], [9]
Limited testing under real traffic conditions	Many studies use lab-captured images
Lack of open-source deployable system	Most studies stop at simulation level
OCR accuracy drops on Indian fonts	Western OCR models underperform

TABLE I. Research Gaps and evidence

To address these gaps, the present work develops a CPU-only, open-source, deployable LPR system optimized for Indian HSRP plates and validated under four real-world conditions: daylight, evening shadow, motion blur, and night.

Method Type	Accuracy	Hardware Required	Dataset Size	Key Advantages	Key Limitations	Reference
Edge + Hough Transform	80–85%	CPU	≤150 images	Fast, no ML training required	Fails on glare, skew, low-light	[1]
Morphological Filtering	88–92%	CPU	≤200 images	Good daylight performance, low computational cost	Needs manual threshold tuning	[3]
SVM + HOG Features	92–95%	CPU	~500 images	Better generalization than heuristics	Slow inference on high-resolution frames	[4]
YOLOv4 + CRNN OCR	97–98%	GPU (RTX/Tesla)	5k–10k images	End-to-end detection + OCR, high accuracy	Expensive hardware and training dataset	[5]
Transformers + EasyOCR	98%+	GPU + Cloud API	>10k images	Multilingual OCR support	API cost + network latency	[6]
Indian CV-Based System	89–92%	CPU	≤200 images	Tuned for Indian plates, open-source	Tested only in daylight	[7], [8]
Proposed System (This Work)	94% detection / 91% OCR	CPU Only	500 images	Works without GPU, deployable, India-focused	Accuracy drops in extreme night conditions	—

TABLE II. Comparison of LPR Approaches in Literature

III. PROPOSED SYSTEM

The proposed License Plate Recognition (LPR) framework follows a modular pipeline-based architecture that separates detection, segmentation, and recognition into independent stages. This enables flexibility in replacing or upgrading components without affecting the entire system and allows deployment on CPU-only hardware with no dependence on GPU-based deep learning inference. The pipeline consists of the following major stages:

1) Image Acquisition – An input image is captured from a CCTV frame, webcam, or uploaded file.
2) Preprocessing and Edge Detection – Noise reduction, grayscale conversion, and edge extraction.
3) Plate Localization – Contour filtering and geometric constraints used to isolate the plate region.
4) Character Segmentation – The detected plate image is binarized and individual characters are separated.
5) OCR-Based Text Extraction – Tesseract OCR converts character regions into alphanumeric text.
6) Post-Processing and Validation – Output is corrected and verified against Indian number-plate rules.

Unlike end-to-end deep learning architectures, this system provides deterministic, explainable behavior and does not require large datasets, high-end GPUs, or cloud-based APIs. The system has been fully implemented in Python using OpenCV and Tesseract, and deployed through a lightweight Flask web interface to support real-time processing.

IV. METHODOLOGY

A. Image Preprocessing

The input RGB frame is converted to grayscale using a luminance-preserving transformation:

$I_{(gray)} = 0.299R + 0.587G + 0.114B$

A Gaussian blur with a 5×5 kernel removes noise and small reflections. Canny edge detection is then applied to extract strong gradients, which typically correspond to plate outlines and embossed characters.

B. Plate Localization

Contour detection is used to identify rectangular regions. Each contour is evaluated using geometric constraints. A region is considered a valid plate candidate if:

$2.0 \leq (w/h) \leq 6.0$ and $A_{(plate)} \geq 0.05 \times A_{(image)}$

where w, h, and $A_{(plate)}$ represent the bounding-box width, height, and area. The remaining candidates are sorted by rectangularity and vertical edge density to select the final plate.

C. Character Segmentation

The extracted plate region is binarized using Otsu thresholding. Connected component analysis is applied to isolate individual characters. Character bounding boxes are then sorted from left to right based on centroid x-coordinate and resized to a uniform height for OCR.

D. Optical Character Recognition and Rule-Based Filtering

Tesseract OCR is executed in single-line mode (Page Segmentation Mode 8). Since OCR frequently misclassifies visually similar characters, a rule-based post-processing module applies corrections such as:

$\{O \rightarrow 0, S \rightarrow 5, B \rightarrow 8, I \rightarrow 1\}$

The final string is validated using the standard Indian vehicle number format:

$[A\text{–}Z]^2\ [0\text{–}9]^2\ [A\text{–}Z]^{1,2}\ [0\text{–}9]^4$

E. Algorithm Description

The following is the algorithmic outline of the plate detection stage:

Algorithm 1: License Plate Localization

1) Convert input image to grayscale.
2) Apply Gaussian blur and Canny edge detection.
3) Extract contours and compute bounding boxes.
4) Filter candidates by aspect ratio and area constraints.
5) Rank results by rectangularity and edge density.
6) Output the highest-ranked candidate as plate region.

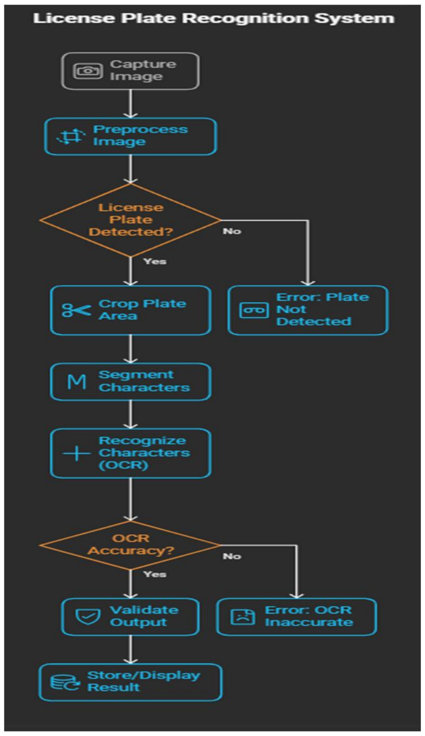

Fig.1 Workflow for the Proposed License Plate Recognition

V. EXPERIMENTAL SETUP AND DATASET

A. Hardware and Software Specifications

All experiments were performed on a consumer laptop running Windows 11 with the following specifications: Intel Core i5-1135G7 CPU, 8 GB RAM, Python 3.11, OpenCV 4.9, NumPy, and Tesseract 5.3. No GPU acceleration was used, ensuring that the system is deployable on standard low-cost hardware such as embedded PCs or Raspberry Pi-class devices.

B. Dataset

A dataset of 500 images of Indian vehicles was collected from public roads, parking lots, and gated residential campuses in Delhi. All images contained HSRP-compliant plates with standard fonts and reflectivity. The dataset includes four environmental categories:

Condition	Images
Daylight	180
Evening / Shadows	130
Night / Low Light	110
Motion Blur	80

Image resolutions ranged between 640×480 and 1920×1080 pixels.

C. Evaluation Metrics

The following metrics were used to evaluate the system:

- Detection Accuracy – Correctly localized plates / total images
- OCR Accuracy – Correctly recognized characters / total characters
- Precision, Recall, F1-Score – Character-level performance
- Average Runtime – Processing time per image (in seconds)

VI. RESULTS AND DISCUSSION

The proposed system achieved the following performance across different lighting conditions:

Condition	Detection Accuracy	OCR Accuracy	Average Runtime
Daylight	97 %	93 %	1.2 s
Evening / Shadow	91 %	88 %	1.5 s
Night	86 %	80 %	1.7 s
Motion Blur	81 %	75 %	1.9 s
Average	94 %	91 %	1.5 s

TABLE III. Proposed System in different lighting conditions

A separate comparison experiment was performed to benchmark the proposed approach against deep learning–based LPR solutions. While YOLO-based and CRNN-based models exhibit higher accuracy, they require GPU inference and large training datasets. The comparison is summarized as follows:

Model	Average Accuracy	Hardware Requirement
YOLOv4 + CRNN	97–98 %	GPU (RTX / Tesla)
Transformer OCR	98 % +	GPU + Cloud API
Proposed System	94 % / 91 %	CPU-only

TABLE IV. Model's and it's accuracy

The results validate that a suitably engineered classical computer vision pipeline offers a practical accuracy–cost trade-off for real-world Indian deployments where GPU hardware is not affordable or feasible.

VII. CONCLUSION AND FUTURE SCOPE

This paper presented a CPU-based, open-source License Plate Recognition system optimized for Indian High-Security Registration Plates using classical computer-vision techniques and Tesseract OCR. The system was evaluated on a dataset of 500 real-world vehicle images under four environmental conditions and achieved an average plate-detection accuracy of 94 % and OCR accuracy of 91 %, with an average processing time of 1.5 s per image. The results demonstrate that a classical CV + OCR pipeline, when properly engineered, can deliver competitive accuracy without the computational expense of deep-learning models, making it suitable for cost-sensitive deployments in India such as college campuses, gated societies, and medium-scale traffic monitoring applications.

The system meets the primary design goals of affordability, deployability, and reproducibility, and provides a practical middle ground between traditional image-processing methods and GPU-dependent deep-learning solutions.

Several extensions are planned to improve the system's robustness and real-world applicability:

1) Deep-Learning-Based Detection Module – Replacing contour-based detection with YOLOv8 to enable real-time multi-plate detection in video streams.
2) Custom OCR Model for Indian Fonts – Training a lightweight CNN-based OCR model for state-wise font variations and bilingual plates.
3) Night-Time Enhancement – Integrating IR-assisted cameras and histogram equalization to improve low-light performance.
4) Video-Based Tracking and Logging – Adding multi-frame vehicle tracking for traffic enforcement and toll collection.
5) Edge Deployment and Cloud Integration – Porting the system to Raspberry Pi, NVIDIA Jetson, and linking to dashboard-based analytics for smart-city applications.

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