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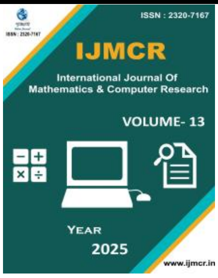

Evaluating the Performance of Ensembled YOLOv8 Variants in Smart Parking Applications Under Varying Lighting Conditions

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ARTICLE INFO	ABSTRACT
Published Online: **01 April 2025** Corresponding Author: **Ripunjay Singh**	With an emphasis on performance under various ambient illumination circumstances this paper explores the potency of YOLOv8 variants for vehicle and license plate detection. The suggested method will capture entire video frames, identify areas of interest with cars, and feed those regions into two distinct, pre-trained YOLOv8 models—one for license plate recognition and the other for vehicle detection. To make the photos easier for the Tesseract OCR engine to read, they are pre-processed using the OpenCV and Pillow libraries to make the images brighter and higher DPI. The four YOLOv8 models can be paired for vehicle and license plate identification tasks to produce sixteen possible combinations. We evaluate the performance of the chosen YOLOv8 combinations under various ambient light intensity levels (measured in lux) after they have been selected using TOPSIS analysis. Finding the most reliable model combinations that provide precise license plate and vehicle detection in the variety of illumination situations found in real-world settings is the goal of this evaluation.

KEYWORDS: YOLOv8, Smart Parking, TOPSIS, Object Detection, YOLOv8 ensembling.

I. INTRODUCTION

The rapid growth of megacities has caused increasing vehicle numbers and limited parking, leading to traffic congestion and urban mobility issues. Drivers spend 17-107 hours annually searching for parking, costing up to $2,243 per driver, with an estimated $73 billion annual loss in the USA [1,1]. This study proposes a Smart Parking Management System (SPMS) using AI for efficient parking detection, evaluating its performance in efficiency, accuracy, and adaptability to real-world conditions, including variable lighting. The SPMS aims to reduce search times and improve parking utilization, offering additional revenue opportunities

II. LITERATURE REVIEW

Studies have utilized YOLOv8 [2] for accurate vehicle detection, paired with Deep-SORT [0, 4] or OC-SORT [5] for reliable multi-object tracking, achieving high accuracy in diverse scenarios. Enhanced architectures like YOLOv5 [7] offer promising real-time applications with high mean Average Precision (mAP) [8].

Future research should emphasize customized training data, multi-camera synchronization [7], and scalable detection systems for real-world [10] use. This review highlights advancements in detection and tracking, paving the way for cost-effective, scalable solutions.

III. LIMITATIONS OF EXISTING RESEARCH

One of the most important and urgent problems in modern research activities is the lack of research focused on the relationship between model complexity, pre-processing techniques, and their influence on the performance of the designed system, especially in devices with scant resources for deployment. For smart parking systems based on YOLO[11] object detection is a significant achievement, there is a current research gap regarding the trade-off between model complexity; the use of some pre-processing techniques, like luminosity balancing and the performance of the system. The existing sources cover on limited exploration of the influence of YOLOv8 variants on smart parking systems; the problem of the influence of pre-processing methods on license plate recognition and a limited scope of lighting variations in the research.

A. Research Gaps and Bridging Gaps

This study evaluates YOLOv8 variants (nano, small, medium and large) for vehicle detection and license plate recognition (LPR) in resource-limited smart parking systems using Multi-Criteria Decision Making (MCDM) techniques. It explores the impact of pre-processing methods, such as luminosity balancing [12] and DPI enhancement [12], on OCR accuracy and license plate detection performance. While previous experiments lacked diverse lighting conditions, this work tests top-performing models under varying illumination to develop efficient and adaptable smart parking solutions.

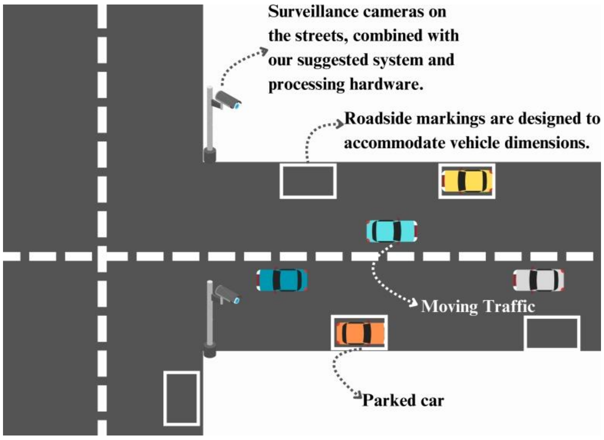

Fig. 1: The proposed method facilitates scalable street parking management by leveraging underutilized road shoulders.

IV. METHODOLOGY

As shown in Fig. 1, the execution of the proposed approach requires a robust methodology in order to facilitate the required functioning.

The task of this research is to conduct a profound analysis of different configurations of the YOLOv8 models to optimize vehicle and license plate recognition in the smart parking system. Herein, to ensure maximum feasibility of the project, several vital stages of work have been followed.

A. Vehicle and License Plate Dataset

Two datasets with structured pre-processing pipelines are used to train car and license plate detection models.

1. **Vehicle Dataset** [13]: The dataset includes 15,322 YOLOv8-annotated images with bounding boxes and class labels. Pre-processing steps involve EXIF data removal, auto-orientation, resizing to 640x640, and augmentation (random cropping 0–15%, brightness ±9%, Gaussian blur 0–2.5 kernel). It is split into training (88%), testing (8%), and validation (4%).
2. **License Plate Dataset** [13]: The dataset comprises 12,884 annotated images with pre-processing steps including EXIF data removal, auto-orientation, resizing to 640x640, and augmentation (brightness ±21%, Gaussian blur 0–2.5 pixels, cropping 0–30%). It is divided into training (82%), testing (16%), and validation (2%).

   These datasets and pre-processing steps enable precise vehicle and license plate detection models

B. YOLOv8 Model Selection, Training Regimen, and System Pre-Processing Design:

The study involves selecting and training four YOLOv8 variants—nano, small, medium, and large—using specific datasets. The vehicle detection model is trained on a vehicle dataset, while the license plate model uses a license plate dataset. A two-stage object detection system is designed, where vehicles are detected through a Region of Interest and passed to a license plate recognition model. Pre-processing, aided by the OpenCV library, includes luminosity balancing and resolution enhancement to improve detection accuracy.

C. Model Evaluation and TOPSIS-driven Selection

A comprehensive evaluation of all 16 YOLOv8 combinations is essential. This study employs precision, mAP50-95, recall, and inference speed metrics for assessment. To select the optimal combination, TOPSIS, a multi-criteria decision-making technique, is utilized. This approach balances accuracy and speed through predefined weightings.

D. Performance Analysis and Model Training under Varying Lighting Conditions

The top-performing YOLOv8 combinations are evaluated under controlled lighting conditions with varying ambient light intensity. Vehicle and license plate images are captured, and lux meter readings are paired with class confidence scores to assess robustness. Training was conducted on a P100 GPU via Kaggle, with hyper parameter optimization for efficiency. Models were trained for 50 epochs using a 640x640 image size and a batch size of 16, with gradient accumulation employing a nominal batch size of 64. This setup ensured comprehensive learning while minimizing computational overhead.

V. DETAILS OF APPROACH

A. Extraction of Region of Interest:

A simple OpenCV[15] functionality was created to define and export regions of interest from full video frames. The module enables the user to select an area by clicking and dragging with the mouse (Fig. 3). Upon pressing the left mouse button, the top-left coordinates are captured, and upon release, the bottom-right coordinates are recorded. A rectangle is drawn around the selected region, and the user can save it by pressing any key. This functionality allows users to capture specific video portions for further analysis.

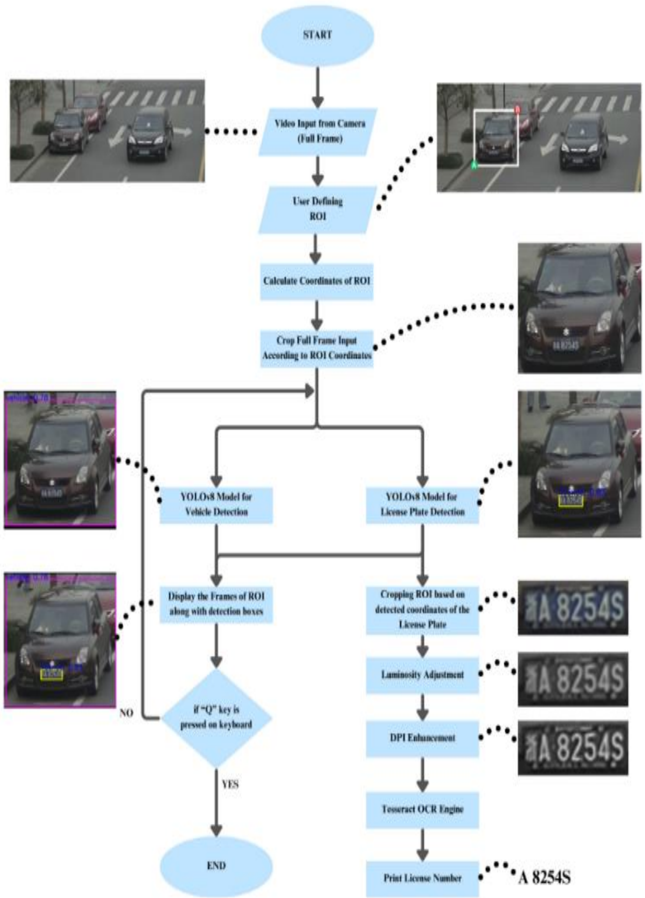

Fig. 2: System flow of the proposed design

B. *YOLO Algorithm*

YOLO [11] is a single-stage object detector using a deep convolutional neural network (Fig. 4) optimized for real-time applications due to its efficient prediction of bounding boxes and class probabilities. Enhancements by rental [17] included additional convolutional layers and a grid-based detection system with non-maximum suppression for bounding box refinement. This study uses a 448x448 pixel input resolution, with a linear activation function in the final layer and leaky ReLU [11] elsewhere:

Fig. 3: Algorithm enables users to define a region of interest (ROI) by dragging the cursor from point A to point B (or vice versa).

$$\phi(x) = \begin{cases} x, & \text{if } x > 0 \\ 0.1x, & \text{otherwise} \end{cases} \qquad (1)$$

Each object is predicted by one bounding box to improve training efficiency. YOLO offers advantages in processing speed and simplicity compared to multi-stage detectors but faces challenges with accuracy and detecting smaller objects. These limitations have driven the evolution of the YOLO family, resulting in YOLOv2 through YOLOv9.

C. *Tesseract OCR*

Tesseract OCR [14] is integrated for license plate recognition. Its pipeline includes connected component analysis, outline grouping, text line organization, character spacing analysis, and a two-pass recognition process. We leverage PyTesseract [18] for Python integration. Enhancements like luminosity modulation and DPI adjustment were made. This combination significantly improves YOLOv8 performance for vehicle detection and license plate recognition in smart parking under varying lighting conditions.

D. *Luminosity Modulation*

Luminosity modulation significantly enhances OCR, particularly for license plate recognition. By adjusting brightness and contrast, it improves character visibility, reduces noise, and mitigates glare. This technique is crucial for challenging lighting conditions, leading to better OCR accuracy and broader applicability in various scenarios, including automatic toll monitoring and car tracking.

Luminosity modulation (Fig No. 5) is implemented with the help of OpenCV [15] library according to the following equation [12]:

$$\text{Luminosity} = 0.2126 \times \text{Red Component} + 0.7152 \times \text{Green Component} + 0.0722 \times \text{Blue Component} \qquad (2)$$

E. *DPI Enhancements*

Increasing image resolution to 600 DPI using Pillow [18] significantly enhances OCR accuracy for license plate recognition. Higher resolution provides more detailed information, improving character recognition, especially in challenging conditions (low light, occlusion, damage). This is illustrated in the flowchart (Fig. 2).

VI. RESULTS

In this section, the evaluation metrics utilized to comprehensively evaluate the performance of the YOLOv8 models for the car detection and license plate recognition within our smart parking application are thoroughly examined (Fig. 4). These metrics shed light on the accuracy, completeness, and overall effectiveness of the models in fulfilling their designated tasks.

A. *Precision:*

Precision gauges the accuracy with which the model identifies objects such as cars or license plates. It represents the proportion of correctly identified objects among all detections reported by the model. A high precision value indicates a strong correlation between the model's positive detections and the actual objects present in the scene. Mathematically, it is defined as:

$$\text{Precision} = \frac{\text{True Positive (TP)}}{(True\ Positive\ (TP) + False\ Positive\ (FP))} \quad (3)$$

Where True Positive (TP) represents the number of accurately detected objects by the model, and False Positive (FP) denotes the instances of incorrectly identified objects (e.g., non-car objects misclassified as cars).

B. Recall:

Recall complements precision by measuring the comprehensiveness of the model’s detections. It reflects the proportion of actual objects (cars or license plates) successfully identified by the model. The recall value is calculated as:

$$\text{Recall} = \frac{\text{True Positive (TP)}}{True\ Positive\ (TP) + False\ Negative\ (FN)} \quad (4)$$

Here, False Negative (FN) represents the number of actual objects that the model fails to detect. A high recall value indicates that the model effectively identifies a significant portion of the existing objects within the image.

C. Intersection Over Union (IoU):

IoU quantifies the area of overlap between the predicted and ground truth bounding boxes relative to their total area. It is computed as:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (5)$$

It plays a fundamental role in evaluating the accuracy of object localization.

D. Mean Average Precision (mAP):

mAP evaluates model performance by averaging precision at various Intersection over Union (IoU) thresholds. IoU measures the overlap between the predicted and ground truth bounding boxes. This study reports both mAP50 and mAP50-95, where mAP50 requires at least 50% overlap, and mAP50-95 requires 95% overlap for detection accuracy. The formula for Mean Average Precision (mAP) is:

$$\text{mAP} = \frac{1}{N}\sum_{i=0}^{N} \text{APi} \quad (6)$$

Where, mAP is the Mean Average Precision, N is the number of classes, and APi is the Average Precision for class i.

E. F1-Score:

The F1-Score offers a balanced evaluation by calculating the harmonic mean of precision (eqn. 4) and recall (equ. 5). This metric provides a robust assessment of model performance, less susceptible to outliers compared to individual precision and recall values. It is expressed as:

$$\text{F1} - \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

An in-depth analysis of evaluation metrics provides valuable insights into the strengths and weaknesses of YOLOv8 models for vehicle and license plate detection in the smart parking system. This analysis aids in selecting the most suitable YOLOv8 variant for real-world deployment. Table No. 1 presents a comprehensive comparison of performance metrics for various YOLOv8 variants, including precision (eqn. 4), recall (eqn. 5), mean Average Precision (mAP) at 50% and 95% IoU thresholds (eqn. 6), and F1 scores (eqn. 8).

Table 1. Comparison of metrics for Vehicle and License Plate Identification of different YOLO Models

	Vehicle Detection					License Plate Detection				
Model	Precision	Recall	mAP50	mAP50-95	F1 Score	Precision	Recall	mAP50	mAP50-95	F1 Score
Nano	0.847	0.840	0.815	0.719	0.843	0.949	0.848	0.916	0.711	0.896
Small	0.863	0.843	0.821	0.747	0.852	0.942	0.853	0.916	0.718	0.895
Medium	0.864	0.849	0.853	0.768	0.856	0.942	0.86	0.919	0.716	0.899
Large	0.874	0.854	0.849	0.787	0.864	0.946	0.859	0.919	0.721	0.900

VII. ANALYSIS

A. TOPSIS Analysis:

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [22, 23] is a method for Multiple Criteria Decision Making (MCDM), initially conceived by Ching-Lai Hwang and Yoon in 1981, with subsequent refinements by Yoon in 1987 and Hwang, Lai, and Liu in 1993. TOPSIS operates on the principle that the preferred alternative should be closest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS) in geometric distance. .

I. Criteria Weighting

The weights, Wj, are assigned based on the priority of each metric for our application. For optimizing 16 system designs, we consider: Precision (eqn. 4), essential for car and license plate detection to avoid false positives; mAP50-95 (eqn. 7), included in TOPSIS due to its importance for accurate detection and bounding box localization, crucial for

OCR on license plates; and Recall (eqn. 5), which, though less critical, must still be adequate for robust detection. The weights Wi for both the models’ metrics are as follows:

- Precision: 20
- mAP50-95: 15
- Recall: 10

Weight Wi of 1 has been assigned to Total Inference Time, in order to balance the trade-off between speed and accuracy.

II. Results

In Table No. 2, according to TOPSIS analysis, top 2 model combinations (highlighted in bold) are:

- TOPSIS Rank 1: YOLOv8s (Small) for Vehicle detection + YOLOv8m (Medium) for License Plate detection ˆ
- TOPSIS Rank 2: YOLOv8m (Medium) for Vehicle detection + YOLOv8m (Medium) for License Plate Detection.

Next, light intensity analysis will be performed for the top-ranked models according to TOPSIS analysis.

***B.** Light Intensity Analysis:*

For varying lighting conditions, a controllable light source along with Lux Meter has been used to measure the light intensity at the region of interest. A smartphone camera, coupled with Camo Studio [24], has been utilized to ensure high quality footage and integration with OpenCV library. The camera specifications [0] are as follows:

- Main Camera: 12-megapixel (12MP)
- Aperture: f/1.8 ˆ Lens Configuration: 5P (5-element lens)
- Autofocus Technology: Phase Detection Autofocus (PDAF)
- Video Output: 1080p at 30FPS with Electric image stabilization (EIS)

A model car and the Indian High Security Registration Plate (HSRP) of 1:18 scale have been utilized to ensure size continuity in the simulation environment.

According to Indian Standards [0], minimum level of luminance on the roads must be 30 lux, in order to ensure safety of the commuters. That’s why the ambient lighting level has been reduced to 20 lux in the analysis shown in Table No. 3.

VIII. DISCUSSION

This research investigates a ensembled YOLOv8 approach for vehicle detection an License Plate Detection within smart parking applications. The approach aims to support distributed parking across the streets (Fig. No. 1) and organize the chaotic encroachment due to vehicles on the shoulders of roads.

***A.** Advantages*

The proposed approach offers key improvements over existing methods:

- Higher Accuracy and Efficiency: The ensemble strategy boosts accuracy and reduces inference time, ideal for resource-limited smart parking applications.
- Enhanced License Plate Detection: Customized pre-processing improves image quality and adapts to lighting variations, resulting in more precise detection.
- Optimal Model Selection with TOPSIS: By using TOPSIS, the study identifies the best YOLOv8 combinations, evaluating mAP, Precision, Recall, and inference speed for targeted model choices.
- Robustness in Various Lighting Conditions: Testing top YOLOv8 models under different lighting provides insights into robustness.
- YOLOv8 Trade-off Exploration: The study examines trade-offs among YOLOv8 models of different sizes, balancing computational load, accuracy, and inference speed.

Table 2. Light Intensity versus Class Confidence Scores of Vehicle and License Plate for Top 2 Models in TOPSIS analysis

	TOPSIS Rank 1 Combination		TOPSIS Rank 2 Combination	
Light Intensity in lux	Class Confidence Score for Vehicle	Class Confidence Score for License Plate	Class Confidence Score for Vehicle	Class Confidence Score for License Plate
900	0.90	0.62	0.93	0.51
800	0.89	0.65	0.94	0.62
700	0.90	0.67	0.94	0.61
600	0.90	0.70	0.93	0.60
500	0.90	0.70	0.92	0.64
400	0.89	0.70	0.93	0.63
300	0.89	0.72	0.92	0.63
200	0.88	0.66	0.89	0.61
100	0.91	0.64	0.90	0.40
50	0.88	0.65	0.89	0.50
20	0.87	0.65	0.85	0.67

***B.** Limitations*

While promising, the proposed system has limitations that need further study:

- Computational Overhead: The ensemble approach may limit real-time performance.
- Pre-processing Sensitivity: More adaptive methods could improve robustness to lighting changes.
- TOPSIS Model Selection: Justifying weights and assessing sensitivity are crucial for reliability.
- Lighting Conditions: Current assessments may not cover all real-world scenarios.
- Data in Low-Congestion Areas: Reliable data on low-traffic streets is essential for smart parking.
- Surveillance Hardware: Adequate devices are needed for effective real-world use.

Addressing these limitations through refined system designs, improved preprocessing methods, and broader evaluation criteria will enhance future smart parking systems’ reliability and efficiency.

IX. CONCLUSION AND FUTURE SCOPE

This research advances smart parking solutions with enhanced accuracy, efficiency, and robustness. The ensembled YOLOv8 approach, OCR pre-processing techniques, and TOPSIS-based model selection significantly improve current methods. Limitations, such as computational bottlenecks in two-stage systems, can be mitigated by using more efficient models like YOLOv9 [26]. Further research is needed to refine pre-processing and expand evaluations to ensure applicability across diverse parking scenarios.

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