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Parking Slot Detection Using Yolov8

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***Abstract*—Parking management in urban areas has become a critical issue, with various challenges like different dimensions of parking slots, varying lighting conditions, occlusion and obstacles on necessitating innovative solutions to optimize the utilization of limited parking space. This paper presents an advanced approach to address these challenges by implementing a parking slot detection system using You Only Look Once version 8 (YOLOv8), a state-of-the-art object detection algorithm. The proposed system takes input video clips and generates an output video with available parking slots highlighted in green and occupied slots in red, enabling real-time parking space monitoring. In the realm of parking management, our solution capitalizes on YOLOv8's exceptional capabilities, providing a robust and efficient means of identifying parking slot occupancy when compared to previous models. Our experimental results demonstrate that the utilization of YOLOv8 significantly enhances the accuracy and speed of the detection process, contributing to more effective parking space management in urban environments.**

Keywords—Parking slot detection, YOLOv8, object detection, video analysis, parking management.

I. Introduction

Modern urban environments are grappling with a significant challenge of the efficient management of parking spaces due to the ever-increasing demand [1]. Parking slot detection holds paramount importance in valet services, necessitating dependable and widely adopted technologies [2]. As cities expand, optimizing parking resource utilization becomes imperative to alleviate traffic congestion and enhance urban mobility [3]. Considering these pressing issues, an innovative solution is proposed in parking management by introducing a cutting-edge parking slot identification system powered by advanced object detection technology. The growing issue of parking shortages exacerbates traffic congestion, adversely affecting both the environment and the economy [4]. Traditional parking management systems often struggle with the complexities posed by varying car sizes, obstructions, and challenging lighting conditions [5]. The primary objective of the proposed solution is to revolutionize the monitoring and utilization of parking spaces through the creative application of deep learning techniques in parking management. Our proposed parking slot detection system leverages the capabilities of YOLOv8, the latest iteration in the YOLO series, recognized for its exceptional speed and precision in object detection [6]. Operating on video input, this system continuously analyses real-time footage to identify available and occupied parking slots. The system's output video visually represents parking slot statuses, with green highlights denoting vacant slots and red highlights indicating occupied ones. The integration of YOLOv8 into parking management offers several remarkable advantages. Firstly, it significantly enhances the precision and efficiency of parking slot detection, empowering communities to maximize the utility of their parking infrastructure. Secondly, the system's real-time capabilities enable swift adaptations to changing parking dynamics, leading to improved traffic flow. Additionally, the user-friendly visual representation simplifies user engagement and decision-making for both drivers and parking management.

A. Overview of YOLOv8

YOLOv8, created by Ultralytics, builds on the successful framework of YOLOv5 and offers a flexible solution that includes object recognition, image classification, and instance segmentation. Design enhancements and a better development environment are included in YOLOv8, showcasing Ultralytics dedication to community involvement and ongoing development. The YOLOv8 lineage has roots in the PyTorch repository of YOLOv3, demonstrating a commitment to evolutionary development. The versatility and Pythonic structure of YOLOv5 made it possible for community contributions to be effortlessly merged, and Ultralytics prioritized the upkeep of a strong software ecosystem. YOLOv8 represents the series' evolution's pinnacle and embodies the constant pursuit of accuracy and effectiveness in the field of object detection, serving as an indication of Ultralytics' continuous dedication to developing this area [7].

B. Contributions

Based on the current problem, our system covers the following set of objectives:

- Developed an accurate and real-time parking space detection system to localize and differentiate between occupied and vacant parking spaces.
- Improved the efficiency of parking slot detection system using YOLOv8 over YOLOv5
- Detects the parking slot even if there are any small obstacles at vacant parking space.
- Compared the proposed model with state-of-the-art techniques.

II. Related Work

The existing body of work in the domain of parking slot detection can be categorized into three main groups: Machine learning-based methods, video-based models and image-based models, each offering distinct approaches and solutions.

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However, these models also exhibit certain limitations that impact their applicability in complex real-world scenarios.

A. Machine learning-based method

With the development of smart parking management systems that make use of object detection networks, the Ding X et al. has made great strides [8] in the area of computer vision. Sheu et al. [9] includes adding residual blocks to the YOLOv3 architecture, which improves feature extraction for parking categorization. To further enhance parking categorization, a lightweight version of YOLOv3 is created utilizing the MobileNetV2 architecture. A quicker R-CNN two-stage detection network is proposed by Martin Nieto et al. [10]. It is used in scenarios with changing parking circumstances and shifting camera angles [11,12]. Additionally, the ability of the Mask R-CNN network is used to categorize parking situations and extract specific automobiles. By using a cooperative UAV strategy to overcome obstacles with optical recognition, MC Chuah et al. advances smart parking. Their novel plan makes use of affordable UAVs and a visual detection system based on GANs, and simulations show favorable results [13].

B. Video-based Models

Video-based models operate on continuous video feeds to conduct real-time inference. Ke et al. utilized a Single Shot MultiBox Detector (SSD) in conjunction with a standardized tracking algorithm, achieving an impressive accuracy of 90.6% in a previously unseen parking garage [14]. However, this model's sensitivity to parameters tailored to specific garages poses challenges in adapting it to diverse parking environments. Cai et al. combined Mask-RCNN with a memory mechanism to characterize features of previously detected vehicles, yet they do not explicitly state the accuracy of their model, leaving uncertainties about its overall effectiveness [15]. Li et al. employed a unique method with a vehicle-mounted surround camera system to detect vacant parking spaces [16].

C. Image-based Models

Recently, the state-of-the-art in a number of fields, including image restoration, object identification, face recognition, and image classification, has been greatly surpassed by DCNN-based methods. The advancement of object detection is one of them that is highly pertinent to what we do. The groundwork for using DCNN to object detection was laid by Girshick et al.'s seminal work on R-CNN [17]. In reality, R-CNN is a multi-stage detection framework. It begins by using an object proposal method to identify bounding boxes that contain objects with a high probability given an input picture. Each suggested bounding-box is then subjected to a typical DCNN feature extraction process, after which a classifier determines the item class included within the box. Many academics suggested changes to the R-CNN architecture in order to enhance the algorithm's performance, including some notable methods along this include Fast-RCNN [18], Faster-RCNN [19], and so on. Object suggestions are paramount to R-CNN and all its variations. As a result, the object proposal algorithm's performance becomes the bottleneck. Recently, several studies have presented object identification as a regression issue to spatially separated bounding-boxes and related class probabilities, challenging the need for an object proposal method in DCNN-based object detection systems. Examples of these techniques are YOLOv2 [20], YOLO [21] and SSD [22]. Ravneet Kaur et al. [23] proposed a deep learning classifier CNN-ELM based on CNN and extreme learning machine (ELM) to classify vacant and occupied parking slots. Sarmad Rafique et al. [24] designed and optimized real time parking management architecture employing deep learning and by leveraging high performance and efficiency of YOLOv5. Ratko Grbić et al. [25] designed an automatic parking slot detection algorithm for automatic parking slot and occupancy classification (APSB-OC) using clustering in bird's eye view to identify parking slot. Chen Huang et al. [26] proposed a parking space visual detection and image processing method based on deep learning suggested a deep learning-based technique for image processing and visual recognition of parking spaces. The surroundings around the car needed to be photographed using a 360-degree panoramic system. Qing An et al. [27] suggests using semantic segmentation to build a real-time parking slot detection (RPSD) network that avoids parking slot constraints and executes real-time parking slot detection on the panoramic surround view (PSV) dataset. R. Nitya et al. [28] proposed the YOLOv3 approach, Faster R-CNN are used to achieve the suggested parking lot identification. Duy-Linh Nguyen et al. [29] created the YOLO5PKLot network, which is based on the enhanced YOLOv5 and is applied in the smart parking management system. With a mix of the lightweight Ghost Bottleneck and spatial pyramid pooling topologies, this network focuses on revamping the backbone network. M. P.P.L Peiris et al. [30] used video footage from a camera as the input to device while YOLO v3 is used as the object detection algorithm for image processing. Free parking slots were evaluated by comparing separately detected coordinates of parking lots and parked vehicles.

III. PROPOSED METHOD

In our suggested method, we use the YOLOv8 architecture's strength to tackle the problem of real-time parking slot recognition and occupancy monitoring. By precisely identifying vacant and occupied parking spaces in a given video feed, our technique is intended to increase parking management efficiency. Our system is built around the YOLOv8 model, which is known for its object detecting abilities. We start a thorough process of customizing and fine tuning to adapt the YOLOv8 model for parking spot identification. This procedure makes use of a dataset that has been painstakingly vetted and contains annotated pictures of parking lots. These annotations include well defined bounding boxes that outline specific parking spaces and class labels that indicate the level of occupancy for each space. By using this dataset, we provide the model the ability to distinguish between vacant and filled slots.

During the training phase of our system the YOLOv8 model is taught to identify attributes and occupancy patterns of parking spaces. The models architecture allows it to process real time video feeds as it can analyze the video frame in a single pass. The YOLOv8 neural network architecture simplifies the detection process, by generating bounding boxes and class predictions. We have customized the class labels assigned to these anticipated bounding boxes indicating whether a parking space is "available" or "occupied."

After the YOLOv8 model has been successfully trained it moves on to the phase called inference. During this phase it carefully examines each frame of the input video feed. The model is capable of identifying parking spaces within the frame and assigns labels based on whether they're occupied or available. Ino visually convey this information to users and parking lot operators we have implemented a visualization scheme that uses colors. Available parking spaces are highlighted with bounding boxes while occupied spaces are emphasized with attention grabbing red bounding boxes. This user-friendly visualization allows for decision making by both drivers and parking management personnel as it provides information, about parking availability.

Our method stands out for its flexibility to various parking conditions and versatility. Through a series of trials, we thoroughly assess the performance of our specialized YOLOv8 model. These tests cover a range of parking lot layouts, lighting setups, camera perspectives, and car kinds. We determine the model's accuracy and effectiveness in recognizing and classifying parking slots by thorough evaluation criteria like precision, recall, and F1-score. The results repeatedly show how effective our strategy is when compared to base models and other cutting-edge techniques.

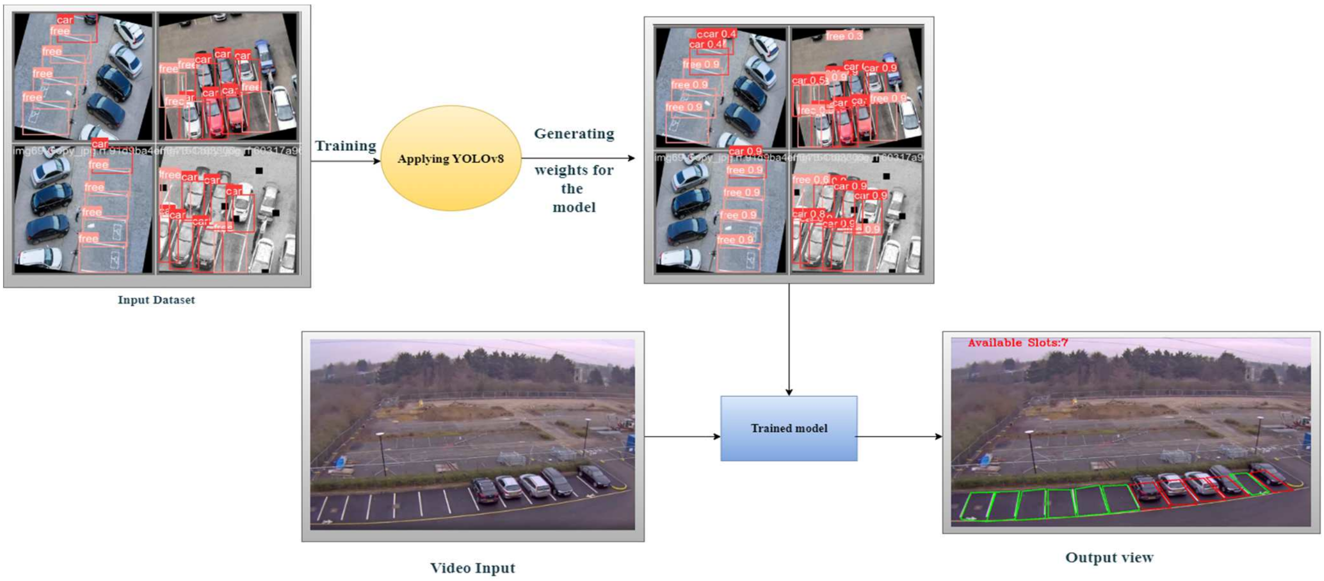

Fig. 1. Overview of Proposed methodology

Fig. 1 outlines the comprehensive process of our work. It initiates with the ingestion of a dataset as the input. Following this, the state-of-the-art YOLOv8 algorithm is employed for the training phase, where the model learns the features from the provided dataset. Post-training, critical weights necessary for the model's functionality are generated.

These acquired weights, combined with input video footage, collectively serve as inputs for the trained YOLOv8 model. The model's task is to analyze the given video and produce an output that vividly distinguishes between empty parking slots, highlighted in a visually distinct green, and occupied slots, distinctly marked in red. This approach integrates the power of YOLOv8 to accurately identify and classify parking slot occupancy in real-time, offering a sophisticated solution for efficient parking space management.

IV. EXPERIMENTATION

In this section, we present a detailed summary of the experimental setup, emphasizing the choice to train and test the proposed parking slot recognition algorithm using the YOLOv8 model on the PK lot dataset in a CPU-centric environment. The hardware and software elements used are discussed in detail, describing the training procedure as well go over important hyperparameters. The evaluation measures used to assess how well the proposed YOLOv8-based model performed on the PK lot dataset is also discussed. The experimental strategy focuses on showing how flexible our proposed technique is in many computational contexts. To achieve this, we evaluated our tests using intel i5 processor, Tesla T4 GPU, Windows 11 operating system, VS code IDE. On the software front, we tapped into well-known deep learning packages like TensorFlow and PyTorch, which were deliberately crafted to work with CPU architectures.

The training procedure was carefully adjusted to suit CPU based training. We paid attention to optimize both training efficiency and model convergence by selecting metrics with precision, recall, F1score. The important hyperparameters included factors such, as batch size and regularization strength.

A. Evaluation Metrics

1) F1-score: A single statistic called F1-score combines precision and recall to give a comprehensive evaluation of a model's performance, particularly in cases where the class distribution is unbalanced.

$$F1 - score = (2 * precision * recall) / (precision + recall) \quad (1)$$

2) Recall: This metric gauge the ability of our model to detect relevant objects by measuring the ratio of true positive predictions to the total number of actual Positive instances.

$$Recall = (True\ Positives) / (True\ Positives + False\ Negatives) \quad (2)$$

3) Precision: Measuring the accuracy of our model's predictions precision is determined by calculating the ratio of positive predictions to the total number of predicted positive instances.

$$Precision = True\ positives / (True\ positives + False\ positives) \quad (3)$$

4) mAP50 : mAP50 measures how accurately a computer vision model detects objects by considering success when there's over 50% overlap between predicted and actual object locations.

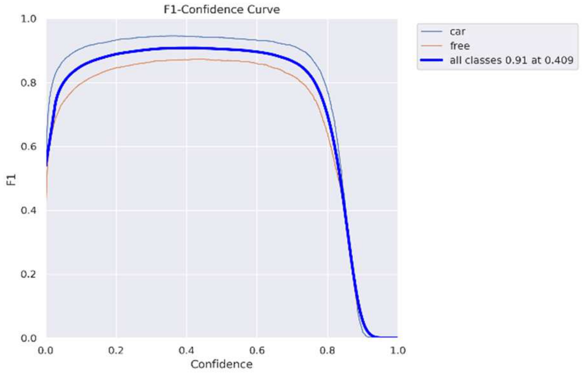

Fig. 2. F1- Confidence Curve

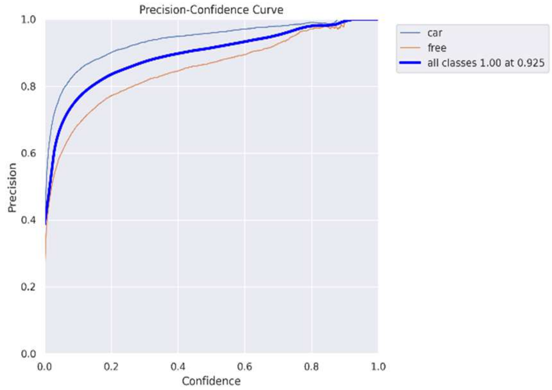

Fig. 3. Precision confidence Curve

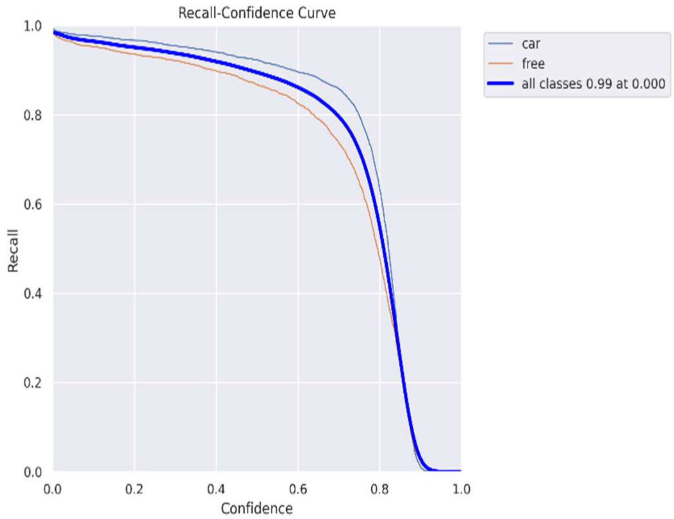

Fig. 4. Recall confidence Curve

In Fig. 2, F1-Confidence Curve shows the relationship between the confidence threshold used for predictions and the corresponding F1 score. It helps in determining an optimal threshold for a balance between precision and recall.

In Fig. 3, Recall confidence curve illustrates how recall varies with different confidence thresholds. It provides insights into how well the model is capturing all positive instances at different levels of confidence.

The Fig.4 Precision confidence curve showcases the relationship between precision and confidence thresholds. It helps in understanding how the model's positive predictions behave in terms of accuracy at different confidence levels.

For each curve, it appears that there are three lines representing different classes:

- The "car" class is represented by the green line.
- The "free" class is represented by the red line.

The "other classes" are represented by the blue line.

V. RESULTS

We conducted a thorough experimentation with the YOLOv8-based parking spot recognition method. We purposefully exposed the methodology to a range of situations, including variations in illumination, occlusions, and vehicle dimensions. This thorough assessment helped to highlight the YOLOv8 model's flexibility and resilience in handling the difficulties presented by dynamic parking situations.

The YOLOv8 model's excellent processing speed is one of the most notable aspects of our findings, indicating that it is appropriate for real-time monitoring applications in dynamic parking environments. The proposed technique proved to be a viable option for parking management in urban settings, as it repeatedly showed higher accuracy, real-time performance, and high degree of flexibility in a comparison analysis versus other models. The combination of the quantitative indicators and the output visuals offered a thorough and detailed understanding of the model's performance in differentiating between parking spaces that were occupied and those that were not. This comprehensive review not only confirmed the model's functionality but also made it easier to understand its advantages, possible shortcomings, and ramifications for different scenarios. As a result, these revelations broaden our comprehension of the YOLOv8-based strategy, illuminating its subtleties of performance and provide a strong basis for further improvements.

Fig. 5. Original image (input video)

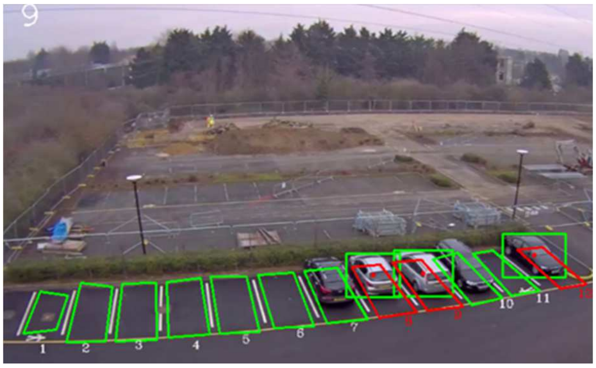

Fig. 6. Parking slot detection using YOLOv5

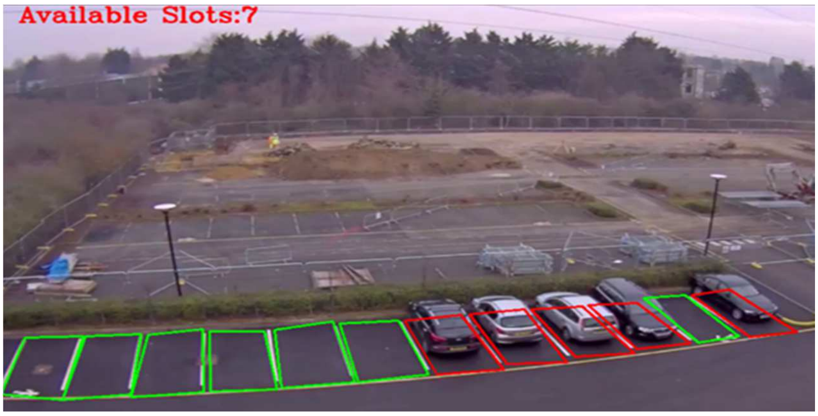

Fig. 7. Parking slot detection using YOLOv8

The original picture, which serves as the input video for the proposed parking space recognition system, is shown in Fig. 5. The experimentation begins with this original image, which captures the variety of features seen in a real-world parking scenario, including cars, illumination, and possible occlusions.

The parking slot recognition results using YOLOv5 are displayed in Fig. 6, highlighting the model's capacity to recognize and categorize parking spots in the specified environment. The picture is a visual depiction of how well the YOLOv5 model performs in differentiating between parking spaces that are occupied and those that are not, providing information on the precision and efficacy of the model. On the other hand, YOLOv8 parking space identification results are shown in Fig. 7. The ability of the model to identify parking spaces is shown in this image, which is comparable to Fig. 6 but incorporates improvements and developments related to the YOLOv8 algorithm. It is possible to evaluate the relative performance and advancements made by the YOLOv8 model in comparison to its predecessor by comparing figures fig. 6 and fig. 7.

TABLE I. COMPARISON OF METRICS WITH YOLOV5 &YOLOV8

METRICS	YOLOv8	YOLOV5
Precision (%)	89.73	87.75
Recall (%)	92.02	88.52
mAP50 (%)	94.82	82.63

Table.1 illustrates the comparison of the performance of YOLOv8 with YOLOv5 across several important measures. When it comes to performance, YOLOv8 outperforms YOLOv5, with a precision rate of 89.73% as opposed to YOLOv5's somewhat lower precision of 87.75%. Precision illustrates YOLOv8's ability to identify positives accurately by calculating the percentage of genuine positive predictions to all projected positives.

When it comes to recall, YOLOv8 does better than YOLOv5; its recall rate is 92.02% as opposed to 88.52% for YOLOv5. Recall, also known as sensitivity, is a model's capacity to detect all pertinent occurrences of the positive class. YOLOv8's greater recall value suggests that it is more adept at doing so. The advantage of YOLOv8 is further highlighted by the statistic of mean average accuracy at a threshold of 50% (MAP50). While YOLOv5 receives a lower MAP50 score of 82.63%, it achieves a solid performance in precision and recall with a score of 94.82%. An overall assessment of the model's accuracy across various confidence levels is given by this statistic.

To summarize, the metrics that have been provided demonstrate how well YOLOv8 performs in object recognition and classification tasks compared to YOLOv5, particularly in terms of precision, recall, and MAP50.

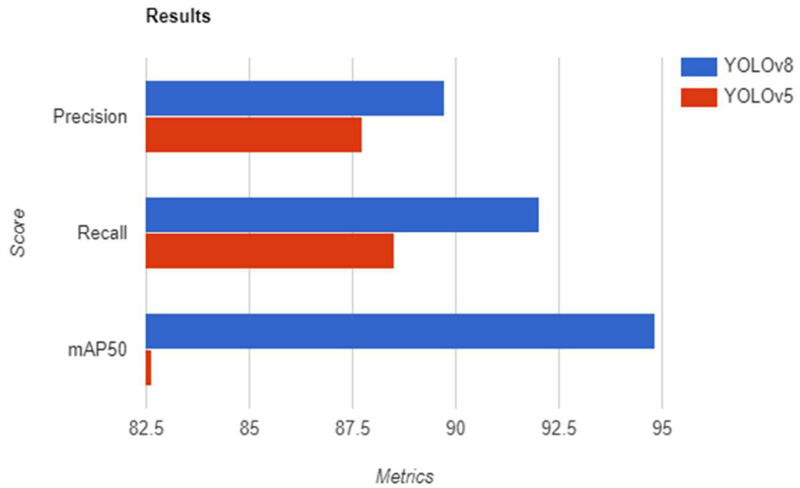

Fig. 8. Metric representation

A comparison of the three primary metrics—precision (%), recall (%), and MAP50 (%) between the YOLOv8 and YOLOv5 object identification models is shown in Figure 8. The performance disparities between the two models are graphically shown by the bar graph. The graph's brick-colored bars correspond to YOLOv5, whereas the blue bars show the measurements for YOLOv8. The height of each bar shows the performance % of the corresponding model for that statistic.

VI. CONCLUSION

In conclusion, YOLOv8's application in parking slot detection marks a significant advancement, addressing the complexities of identifying parking spaces in diverse and challenging environments. Its fusion of speed and accuracy caters well to the task's demands, handling varying lighting conditions, occlusions, and crowded lots adeptly. The model's architecture, adept at feature extraction and object localization, offers a real-time solution with pixel-level precision. YOLOv8's adaptability to different scales and parking scenarios underscores its efficacy. Looking ahead, collaborative efforts among machine learning experts, sensor developers, and dataset providers are poised to drive further progress. This integration holds the potential to revolutionize parking management, traffic flow, and urban planning, making parking slot detection more efficient and seamless.

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