Deep Learning-based License Plate Recognition in IoT Smart Parking Systems using YOLOv6 Algorithm

Ming Li, Li Zhang*
College of Computer and Control Engineering,
Northeast Forestry University, Haerbin 150040, Heilongjiang, China

***Abstract*—License plate recognition (LPR) is pivotal for the seamless operation of Internet of things (IoT) and smart parking systems, ensuring the swift and effective identification and management of vehicles. Recent research has concentrated on refining LPR methods through deep learning approaches, proposing diverse strategies to enhance accuracy and reduce computation costs. This work tackles these challenges by introducing an innovative method rooted in the YOLOv6 algorithm. Leveraging a tailored dataset for model generation, the study employs rigorous methodologies involving validation, testing, and training. The resultant model demonstrates marked improvements in license plate recognition capabilities, surpassing the performance of existing methods. This breakthrough bears significant implications for advancing IoT smart parking systems, promising heightened reliability and efficiency in vehicle identification and management. Thorough experimental results and performance evaluations validate the efficacy of the proposed YOLOv6-based method. In-depth discussions and comparisons with state-of-the-art methods in the field lead to the conclusion that the introduced approach not only elevates accuracy but also enhances overall efficiency in license plate recognition for smart parking systems, thereby providing valuable contributions to the domain.**

***Keywords*—Internet of things; deep learning; smart parking system; license plate recognition; YOLOv6**

I. Introduction

With the rapid advancements in technology, the concept of smart cities has gained considerable attention in recent years. Smart cities leverage the power of the Internet of Things (IoT) to create intelligent, interconnected urban environments that enhance the quality of life for their residents [1, 2]. One of the key areas of focus in smart city development is smart parking management, which aims to address the persistent challenges associated with parking in urban areas [3, 4]. In this context, video-based technologies have emerged as a promising solution, offering real-time monitoring, efficient utilization of parking spaces, and improved enforcement capabilities.

The importance of video-based technologies in IoT smart parking systems cannot be overstated [5]. Traditional parking management systems often rely on physical sensors or manual monitoring, which can be cumbersome and time-consuming. Video-based technologies, on the other hand, utilize cameras and computer vision algorithms to capture and analyze visual data, enabling real-time tracking and intelligent decision-making [6, 7]. These technologies provide valuable insights into parking occupancy, duration, and violation detection, leading to enhanced efficiency and improved parking experiences for drivers [8]. Moreover, video analysis can be seamlessly integrated into existing IoT platforms, facilitating data-driven decision-making and enabling effective management of parking spaces in smart cities.

License plate recognition (LPR) plays a vital role in smart parking management systems. By leveraging computer vision techniques, LPR systems automatically capture, interpret, and recognize license plate information from video streams or images [9]. Integrating LPR into smart parking systems enables automated entry and exit control, efficient payment processing, and enhanced enforcement capabilities [10]. This technology eliminates the need for manual checks or physical tickets, streamlining the parking process and reducing human intervention. License plate recognition serves as a fundamental component in smart parking systems, facilitating seamless and secure parking operations within smart cities.

Various methods have been explored for license plate recognition in the past, with recent research focusing heavily on deep learning-based approaches [10]. Deep learning has garnered significant attention due to its ability to learn complex patterns and features from large-scale datasets [11-13]. Compared to traditional methods that rely on handcrafted features and rule-based algorithms, deep learning-based methods offer superior accuracy and robustness in license plate recognition tasks [14]. The availability of large labeled datasets and advancements in computational power have further fueled the adoption of deep learning in this domain, attracting researchers to explore innovative approaches and architectures.

Despite the progress made in deep learning-based license plate recognition systems, some limitations and research gaps still need to be addressed. One of the critical challenges lies in achieving a balance between computational cost and accuracy rate. Real-time processing of video streams requires low computational overhead while maintaining high accuracy in license plate recognition. The existing literature offers insights into these limitations, motivating the need for further research to develop lightweight deep learning and YOLO-based (You Only Look Once) algorithms. These approaches offer the potential to address the identified research gap by achieving a good trade-off between computational efficiency and recognition accuracy.

This study addresses the research problem of improving license plate recognition (LPR) in the context of internet of things (IoT) and smart parking systems. The existing challenges involve the necessity for more accurate and efficient vehicle identification and management. The research questions focus on evaluating the effectiveness of the YOLOv6 algorithm in overcoming these challenges, particularly in terms of enhancing accuracy and reducing computation costs. The research objectives aim to assess and optimize LPR using the YOLOv6 algorithm, with a specific emphasis on evaluating its accuracy in license plate identification, analyzing computational efficiency to manage costs, and contributing to the overall advancement of IoT and smart parking systems.

The main research contributions of this study are listed as follows:

1) Preparing a custom dataset and the application of YOLO-based algorithms and lightweight deep learning models to enhance license plate recognition performance in intelligent parking management systems.

2) Developing an efficient deep learning-based method for LPR to serve low computational cost and high accuracy rate requirements.

3) Conducting comprehensive experimental evaluations and performance analysis, highlighting the effectiveness and efficiency of the proposed methods.

The rest of the paper is structured as follows: In Section II, a review of previous studies is presented. Section III presents the methodology. Performance analysis is discussed in Section IV. The paper is finally concluded in Section V.

II. Review of Previous Studies

Loong et al. [15] presented a machine vision-based smart parking system utilizing the Internet of Things (IoT). The system aims to provide efficient parking management using camera-based image processing techniques to detect and monitor parking spaces in real-time. It utilizes IoT technologies to enable seamless communication between parking sensors, cameras, and a central server. The system allows users to access parking availability information through a mobile application, thereby reducing the time spent searching for parking spaces. However, the limitation of this paper is that it focuses primarily on the technical aspects of the system and does not extensively discuss the implementation challenges or potential scalability issues that may arise when deploying the system in real-world scenarios. Further research could investigate the practical implications and limitations of implementing the proposed smart parking system.

In study [16], a smart parking application is implemented that utilizes the Internet of Things (IoT) and machine learning algorithms. The system aims to optimize parking space utilization by monitoring and managing parking availability in real-time. It employs IoT technologies to collect data from parking sensors and employs machine learning algorithms to predict parking space occupancy. The system offers users a mobile application to access parking information and reserve parking spots. However, a limitation of this paper is that it lacks a comprehensive evaluation of the system's performance, scalability, and robustness in real-world scenarios. Future research could focus on assessing the system's effectiveness in different environments and under varying conditions to address potential limitations and enhance its practical implementation.

Kabir et al. [17] present an IoT-based intelligent parking system that focuses on utilizing unutilized parking areas. The system employs real-time monitoring utilizing mobile and web applications to provide users with parking availability information and facilitate efficient parking space utilization. It utilizes IoT technologies to collect data from parking sensors and employs intelligent algorithms for real-time monitoring. The system offers a user-friendly interface for accessing parking information and making reservations. However, a limitation of this paper is the lack of empirical validation or field testing of the proposed system in real-world parking environments. Further research could evaluate the system's performance, reliability, and scalability to address potential limitations and validate its practical effectiveness in different parking scenarios.

In [18], a smart parking system was implemented that utilizes image processing techniques. The system aims to optimize parking space management using cameras to detect and analyze parking space occupancy. It provides real-time parking availability information to users through a user-friendly interface. However, a limitation of this paper is the lack of discussion regarding the system's performance in challenging lighting conditions or crowded parking scenarios, which may affect the accuracy of the image processing algorithms. Future research could address these limitations by conducting thorough testing and evaluation of the system's performance in various real-world environments to ensure its reliability and effectiveness.

Deep learning algorithms for automatic license plate recognition (ALPR) were implemented by Silpa [19]. The study aims to develop an ALPR system that utilizes deep learning techniques to recognize and detect license plates in real accurately. The system demonstrates promising results in terms of accuracy and efficiency. However, a limitation of this paper is the absence of a comprehensive analysis of the system's performance under challenging conditions, such as variations in lighting, weather, or license plate designs. Future research could address these limitations by conducting extensive testing and evaluation of the system's robustness and reliability in various real-world scenarios to ensure its practical applicability.

The collective findings from previous studies on IoT-based smart parking systems reveal a common research challenge: achieving high accuracy in real-time parking space detection while minimizing computation costs. Despite notable advancements in parking management, lack of comprehensive performance evaluations, and absence of empirical validation in real-world scenarios. Addressing these challenges, future research should focus on developing smart parking systems that strike a balance between accuracy and computation costs. Thorough empirical validation and comprehensive evaluations are crucial to advancing the field and facilitating practical implementation in diverse urban environments.

III. METHODOLOGY

This section discusses the methodology of this study. In the methodology, we describe the structure of the suggested method. In the proposed method, the steps consisted of Data Collection and Preparation, Model Architecture Design, Dataset Preprocessing, Model Training, Model validation, and Model Testing. Fig. 1 illustrates the structure of the suggested method.

As shown in Fig. 1, the proposed method follows a structured approach consisting of several key steps. First, the Data Collection and Preparation phase involves gathering a diverse dataset of license plate images captured from real-world parking scenarios and annotating them with corresponding labels. Next, the Model Architecture Design step focuses on selecting a suitable deep-learning architecture and configuring its parameters to design an effective license plate recognition model. Following that, the dataset preprocessing step involves applying necessary preprocessing techniques to normalize the license plate images and augment the training dataset for improved model generalization. Subsequently, the Model Training phase utilizes the annotated dataset to train the deep learning model, optimizing a chosen loss function and fine-tuning hyperparameters. The trained model is then subjected to Model Validation, where its performance is evaluated on a validation dataset to ensure proper generalization. Finally, the Model Testing step involves applying the trained model to a separate testing dataset to assess its real-world performance, including accuracy, detection rate, and recognition speed. This structured approach ensures a comprehensive development and evaluation process for the proposed method in license plate recognition within smart parking management systems—the details of the steps are discussed in the following sections.

A. Data Collection and Preparation

In the data collection and preparation step, a diverse dataset of license plate images is collected from real-world parking scenarios and internet resources. This dataset aims to capture the variability and complexity encountered in actual parking environments. It includes images of license plates from different vehicle types, varying lighting conditions, different angles, and potential occlusions. By collecting a diverse dataset, the proposed method ensures that the trained model can handle the challenges faced in real-world scenarios.

Once the dataset is collected, the next action is to annotate it with corresponding labels and bounding boxes surrounding the license plates. This annotation process involves manually marking the regions of interest containing the license plates in each image and assigning the correct labels to them. The labels typically include alphanumeric characters present on the license plates. This annotation step is crucial as it provides ground truth information that is essential for training and evaluating the model accurately.

B. Model Architecture Design

For the design of our deep learning model for license plate recognition, we have chosen YOLOv6 as our core model. YOLO (You Only Look Once) is a popular object detection framework known for its real-time performance and accuracy. YOLOv6 is an evolution of the YOLO series, incorporating improvements and optimizations to enhance its detection capabilities.

YOLOv6 serves as an excellent starting point for our license plate recognition model due to its pre-trained weights and strong performance on object detection tasks. Pre-trained models are trained on large-scale datasets such as Common Objects in Context (COCO), which contain various object classes, including vehicles and license plates. Leveraging a pre-trained model like YOLOv6 allows our license plate recognition model to benefit from the knowledge gained during the pre-training phase, enabling faster convergence and better generalization.

With YOLOv6 as our core model, we can leverage its architecture, which is based on a deep neural network with convolutional layers, to localize and detect license plates within images. The YOLOv6 architecture employs a series of convolutional layers followed by fully linked layers to learn features at different scales, enabling it to detect objects with different sizes and aspect ratios accurately. By adopting the YOLOv6 model to our license plate recognition task, we can leverage its inherent object detection capabilities to identify and localize license plates within parking images. The pre-trained weights of YOLOv6 serve as a starting point for our model, allowing us to fine-tune and specialize the network for license plate recognition specifically. This approach combines the advantages of transfer learning, where pre-trained knowledge is utilized, with the flexibility to adapt the network to the requirements of license plate recognition in smart parking management systems.

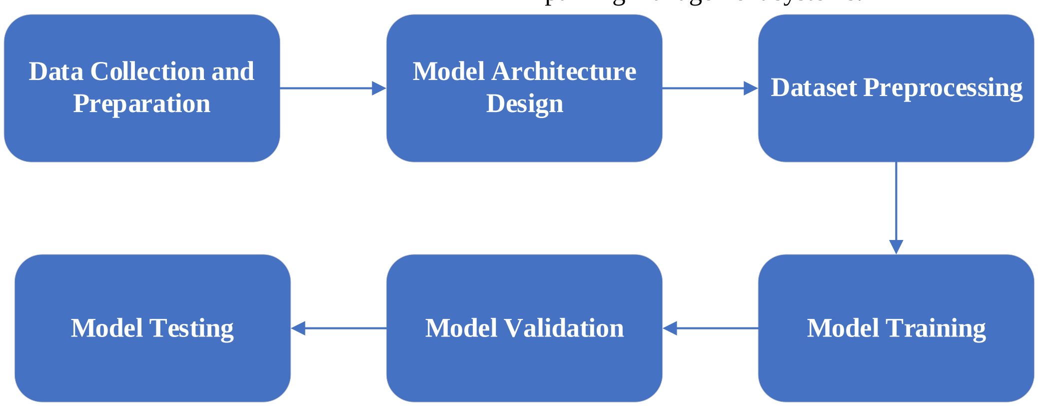

Fig. 1. The suggested method's structure.

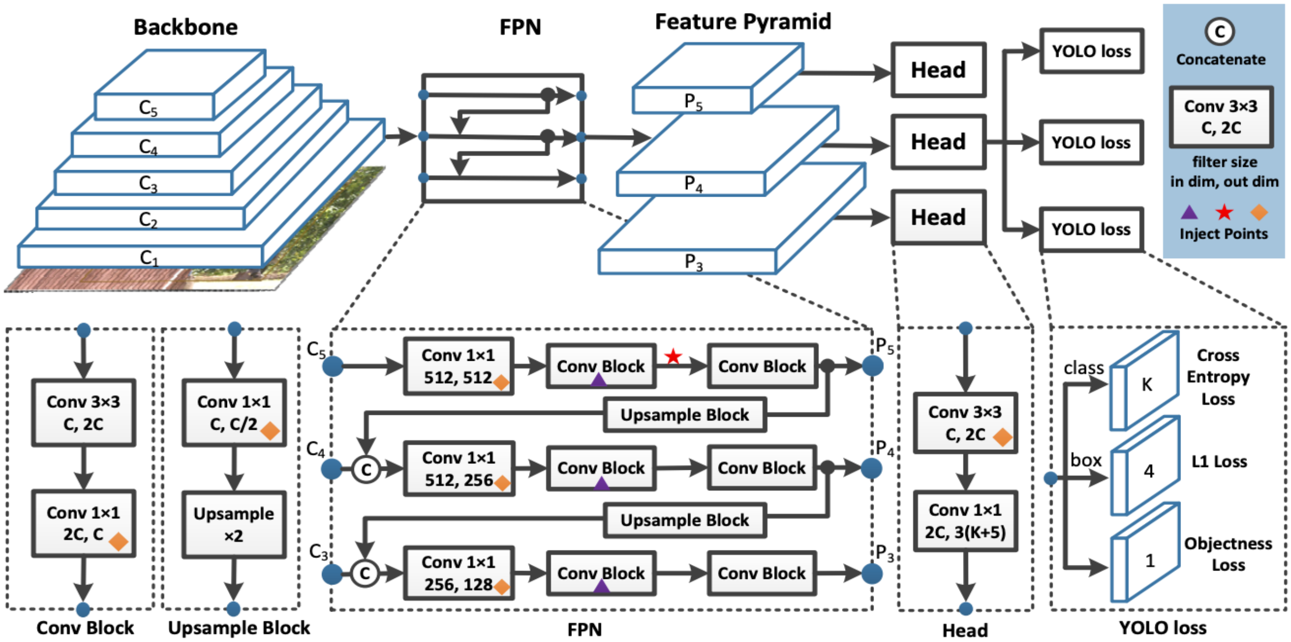

Fig. 2. Structure of YOLOv6 network [20].

The structure of the YOLOv6 network consists of a backbone, neck, and head for object detection. Fig. 2 illustrates the structure of the YOLOv6 network. The details of each are discussed in the following section.

1) The backbone architecture of YOLOv6 network: The backbone architecture of the YOLOv6 network serves as the foundation for its object detection capabilities. It incorporates a deep neural network with a series of convolutional layers to extract meaningful features from input images [21]. The backbone architecture of YOLOv6 follows a hierarchical structure comprising multiple residual blocks with different filter sizes. These residual blocks enable the network to learn and capture features at various spatial scales, allowing for the accurate detection of objects of different sizes and aspect ratios. Additionally, the backbone architecture incorporates skip connections that facilitate the flow of information across different layers, enabling the network to capture both low-level and high-level features. By leveraging this hierarchical backbone architecture, YOLOv6 can effectively analyze input images and generate precise bounding box predictions for objects, including license plates, with high accuracy and efficiency. Fig. 3 shows the structure of the backbone in the YOLOv6 network.

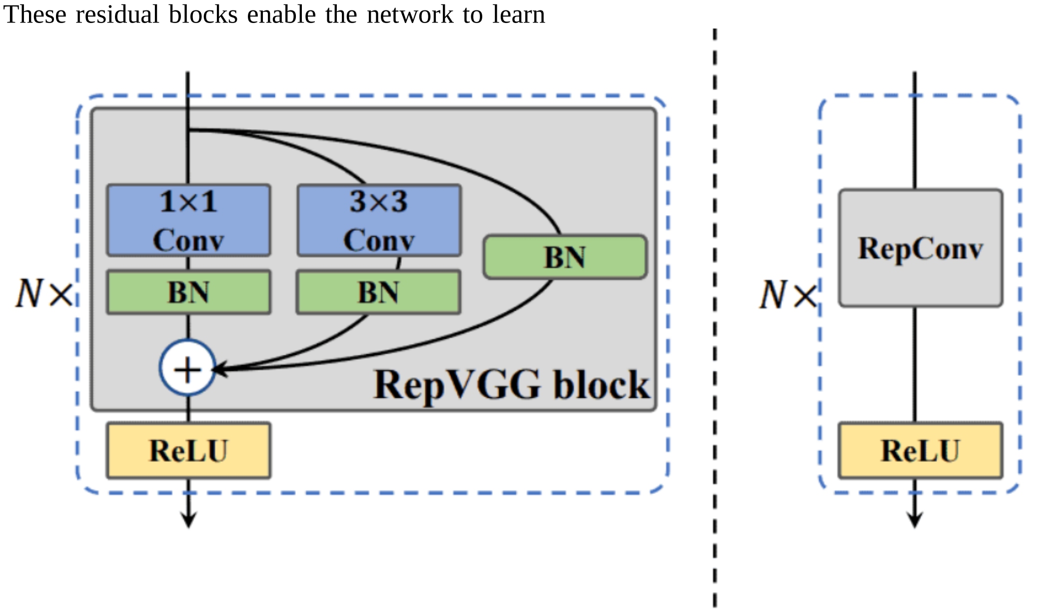

Fig. 3. The structure of the backbone in the YOLOv6 network [22].

2) The neck architecture of YOLOv6 network: The neck architecture of the YOLOv6 network complements the backbone architecture by refining and fusing features for more accurate object detection [21]. It incorporates spatial pyramid pooling modules to capture contextual information at multiple scales and feature fusion layers to combine features from different levels. This integration of features enhances the network's ability to detect objects of varying sizes and improves its overall precision and accuracy. By leveraging the neck architecture, YOLOv6 can effectively integrate global and local contextual cues, resulting in more robust and informed object detection predictions, including accurate identification of license plates.

3) The detection head of the YOLOv6 network: The detection head of the YOLOv6 network is responsible for generating precise bounding box predictions and class probabilities for detected objects, including license plates [23]. It takes the fused features from the neck architecture as well as processes them to identify and localize objects within the input image [21]. The detection head consists of a set of convolutional layers followed by anchor boxes, which serve as prior knowledge about the expected sizes and shapes of objects. Fig. 4 demonstrates the structure of the head in the YOLOv6 network.

As shown in Fig. 4, the convolution layers aid in capturing more detailed and discriminative information for accurate object detection. The anchor boxes, defined with different aspect ratios and scales, are used to predict bounding boxes for potential objects at various positions and sizes. The detection head employs a combination of objectness scores, class probabilities, and bounding box coordinates to generate the final predictions. Objectness scores indicate the presence of an object within a bounding box, while class probabilities specify the likelihood of the object belonging to a specific class, such as a license plate. The predicted bounding box coordinates provide precise localization of the detected object.

4) Analysis of YOLv6 performance: This section presents the analysis of the YOLOv6 performance. This analysis intends to report the efficiency of this algorithm used in object detection. Fig. 5 illustrates a graph for this analysis [21]. The graph represents a comparison of different YOLO models, namely YOLOv5, YOLOv6, YOLOv7, YOLOX, and PP-YOLOE, in terms of average precision (AP) with respect to latency. The X-axis represents latency, which refers to the time taken for the model to process input, and the Y-axis represents average precision (AP), a metric that measures the accuracy of the model's predictions.

As shown in Fig. 5, by analyzing the graph, we can observe the performance of each model in terms of AP at different latency levels. The comparison allows us to evaluate how well the models balance accuracy and speed in object detection tasks. Based on the graph, it is evident that YOLOv6 achieves better results compared to the other models across various latency levels. The higher AP values indicate that YOLOv6 provides more accurate object detection compared to YOLOv5, YOLOv7, YOLOX, and PP-YOLOE. The superiority of YOLOv6 can be attributed to several factors, such as architectural improvements, optimization techniques, or the incorporation of novel features or modules. To further justify why YOLOv6 outperforms other models, it would be necessary to refer to specific technical details and research papers related to YOLOv6. These details could include architectural enhancements, algorithmic advancements, or optimizations implemented in YOLOv6 that contribute to its improved accuracy while maintaining acceptable levels of latency.

This study justifies the selection of YOLO (You Only Look Once) as the base detection method for license plate recognition, highlighting its efficiency in real-time object detection with a balance between accuracy and speed. YOLO's unique single-pass approach and grid-based analysis set it apart from other methods. The research further strengthens this choice by comparing various YOLO-based versions, presenting experimental results that affirm YOLOv6 as superior. The comparisons consider accuracy, computation costs, and overall performance, providing empirical evidence that establishes YOLOv6 as the most effective and efficient version for license plate recognition based on conducted experiments results.

C. Dataset Preprocessing

In the dataset preprocessing phase, the license plate images undergo the necessary techniques to normalize them and augment the training dataset. In this study, normalization involves resizing, cropping, and color space conversion to standardize the images, and augmentation techniques such as rotation, scaling, and noise addition are applied to increase dataset diversity. These preprocessing steps ensure consistent image sizes, isolate the license plate region, and enhance the dataset's variability. By employing these techniques, the model becomes more robust, able to manage various scenarios, and generalizes better for accurate license plate recognition in smart parking management systems.

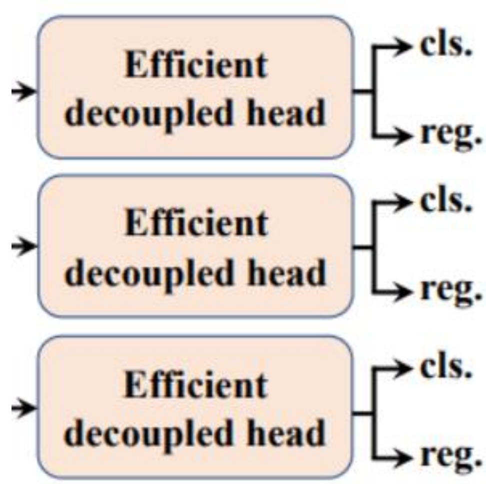

Fig. 4. Structure of detection head of YOLOv6 Network [22].

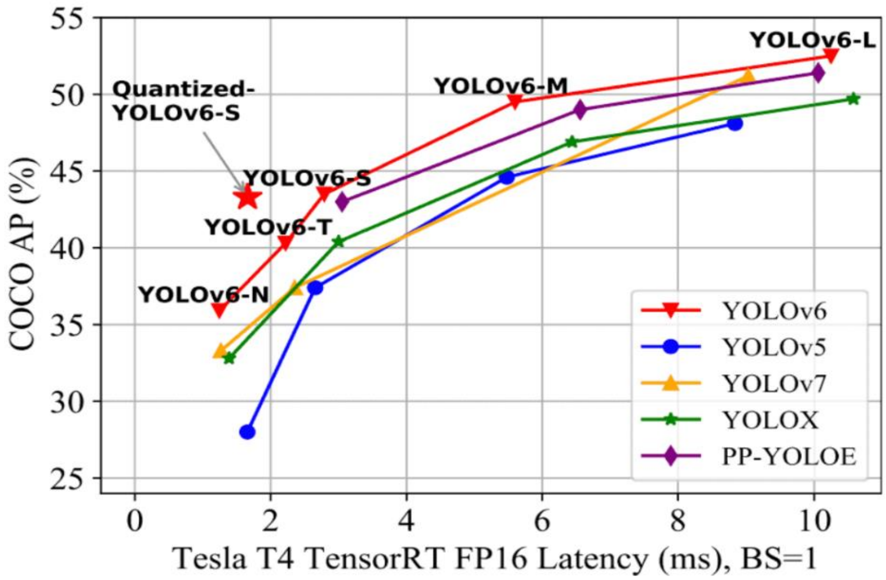

Fig. 5. Comparison of YOLO-based algorithms [21].

D. Model Training

We use transfer learning for YOLOv6 model training. To generate the YOLOv6 model for license plate recognition using transfer learning, the following steps are taken in the Model Training phase:

1) The deep learning model with the selected YOLOv6 architecture is initialized. The pre-trained weights from the base YOLOv6 model serve as the starting point for the transfer learning process. These weights contain valuable knowledge gained from pre-training on large-scale datasets, which aids in faster convergence and better generalization.

2) The initialized model is trained using the annotated license plate dataset. The training process involves feeding the license plate images as input to the model and optimizing a suitable loss function, such as categorical cross-entropy or mean squared error. The loss function measures the discrepancy between the forecasted outputs as well as the ground truth labels, driving the model to minimize the error and improve its performance.

3) Fine-tuning the model is a critical step to enhance its performance further. Hyperparameters, including the learning rate, batch size, and optimizer choice (such as Adam or SGD), are adjusted to achieve better convergence and generalization. Fine-tuning allows the model to adapt to the specific characteristics of the license plate recognition task and improves its ability to detect and recognize license plates accurately.

By following these steps, the pre-trained YOLOv6 model is effectively utilized as a starting point for training the license plate recognition model. Through transfer learning and fine-tuning, the model is optimized to leverage the knowledge from the pre-trained weights, adapt to the license plate recognition task, and achieve improved accuracy and performance in identifying and localizing license plates within smart parking management systems.

E. Model Validation

The YOLOv6 model for license plate recognition can be validated through evaluation on a validation dataset and the utilization of metrics such as accuracy, precision, recall, and F1-score. By assessing the model's performance on unseen data, researchers can detect overfitting or underfitting issues and make necessary adjustments. Metrics like accuracy, precision, recall, and F1-score provide quantitative measures of the model's license plate recognition capability, including overall correctness and avoidance of false positives and false negatives. Validating the YOLOv6 model using these approaches ensures its effectiveness and reliability in accurately identifying and localizing license plates in smart parking management systems.

F. Model Testing

After generating the YOLOv6 model and validation process, it is crucial to test and deploy the model effectively. Testing involves evaluating the model's performance using a diverse test dataset, comparing its predictions with ground truth labels, and calculating performance metrics such as accuracy, precision, recall, and F1-score. This testing phase ensures that the model performs well on unseen data and provides reliable license plate recognition results. Once the model has been thoroughly tested and meets the desired performance criteria, it can be deployed in real-world applications. Deployment involves integrating the model into the smart parking management system, optimizing its computational requirements for real-time performance, and considering factors such as handling input data streams, integrating with existing infrastructure, and creating an end-to-end pipeline for license plate recognition. Continuous monitoring and maintenance are essential post-deployment to monitor the model's performance, collect feedback, and address any issues that arise, ensuring consistent and reliable license plate recognition in real-world scenarios.

IV. RESULTS AND DISCUSSIONS

Analyzing the generated YOLOv6 model for license plate recognition involves evaluating its performance using metrics such as precision, recall, and F1-score.

- Precision measures the proportion of correctly identified license plates among all the predicted license plates. It quantifies the model's ability to avoid false positives, which are instances where the model incorrectly identifies non-license plate regions as license plates. A higher precision shows that the model has a lower rate of false positives, resulting in more accurate and reliable license plate recognition.

- Recall, on the other hand, measures the proportion of correctly identified license plates among all the actual license plates present in the dataset. It assesses the model's ability to avoid false negatives, which occur when the model fails to identify actual license plates. A higher recall indicates that the model has a lower rate of false negatives, meaning it can effectively identify and capture most of the license plates present in the dataset.

- F1-score is a metric that combines precision and recall into a single value, providing a balanced measure of the model's overall performance. It is the harmonic mean of precision and recall and takes into account both false positives and false negatives. A higher F1 score indicates a better balance between precision and recall, signifying a model that can accurately identify license plates while minimizing both types of errors.

The results of precision curves, precision-recall curve, F1-score curve, and recall curve are shown in Fig. 5, 6, 7, and 8.

As shown in Fig. 6, the link between confidence and precision rate is graphically represented by the precision curve. The X-axis displays confidence levels, which indicate the model's certainty in its predictions, while the Y-axis displays the precision rate, which measures the proportion of correctly identified license plates among all the predicted license plates at different confidence thresholds. In the precision curve, as the confidence threshold increases, the precision rate tends to improve. This means that when the model is more confident in its predictions, it is more likely to correctly identify license plates, resulting in a higher precision rate. A high precision rate indicates that the generated model can achieve accurate results with a lower rate of false positives.

As demonstrated in Fig. 7, the X-axis displays confidence levels, indicating the model's certainty in its predictions, while the Y-axis displays the recall rate, which measures the proportion of correctly identified license plates among all the actual license plates at different confidence thresholds.

When analyzing the recall curve, as the confidence threshold increases, the recall rate typically decreases. This means that as the model becomes more conservative in its predictions, it may miss some actual license plates, resulting in a lower recall rate. However, a high recall rate indicates that the generated model can effectively identify a larger percentage of license plates in the dataset, minimizing false negatives.

Fig. 8 presents the Precision-Recall curve of the generated model. In this graph, the X-axis represents recall, which measures the proportion of correctly identified license plates among all the actual license plates, while the Y-axis displays the precision rate, which quantifies the proportion of correctly identified license plates among all the predicted license plates.

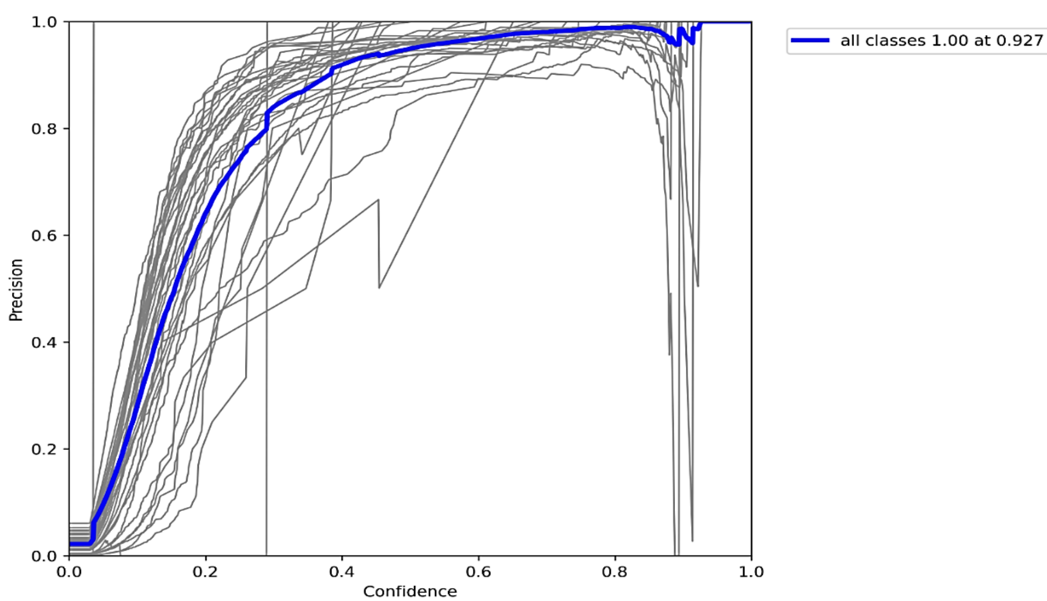

Fig. 6. Precision-confidence curve of the generated model.

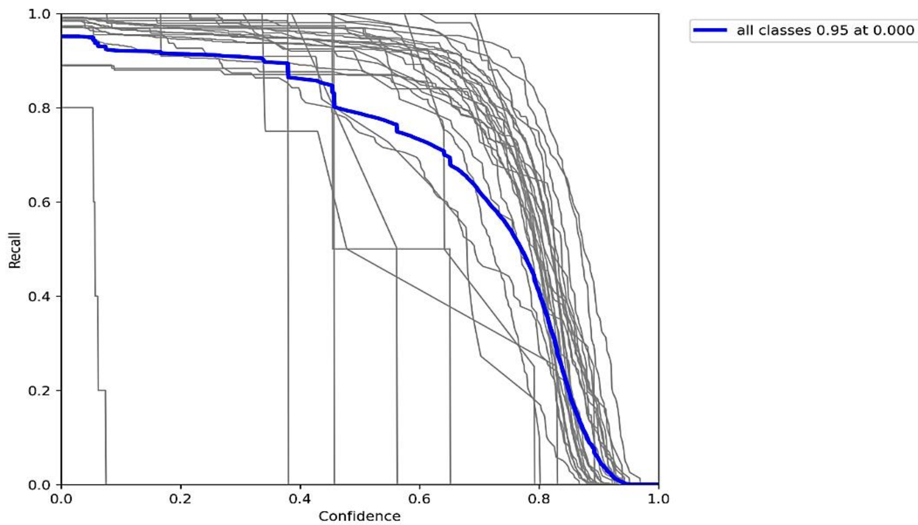

Fig. 7. Recall-confidence curve of the generated model.

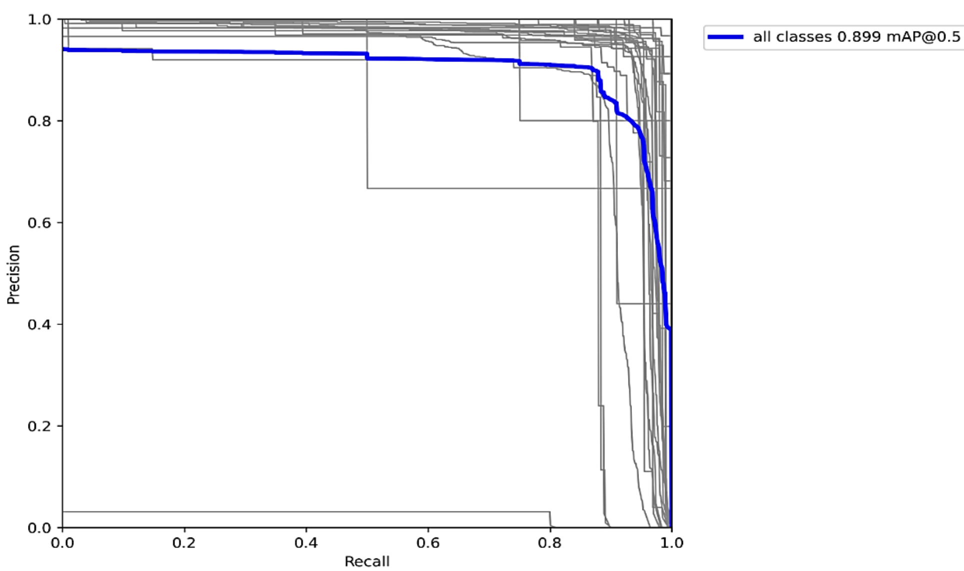

Fig. 8. The precision-recall curve of the generated model.

The precision-recall curve illustrates how changes in the recall threshold impact the precision rate and vice versa. As the recall threshold rises, the model becomes more inclusive and captures a higher percentage of actual license plates, resulting in an increase in recall. However, this may lead to more false positives, causing the precision rate to decrease. On the other hand, raising the precision threshold makes the model more conservative, reducing false positives but potentially missing some actual license plates, which lowers the recall rate. As experimental results show, analyzing the precision-recall rates obtained from the curve provides valuable insights into the accuracy and performance of the generated model in license plate recognition tasks.

Fig. 9 illustrates the F1-confidence curve, a graphical representation showcasing the relationship between confidence and F1 values. In this curve, the X-axis displays confidence levels, indicating the model's certainty in its predictions, while the Y-axis represents the F1 values, which is the harmonic mean of precision and recall.

The way that modifies how the confidence threshold impacts the F1 score is seen by the F1-confidence curve. As the confidence threshold increases, the model becomes more conservative in its predictions, resulting in a higher precision but potentially lower recall. Conversely, lowering the confidence threshold leads to a higher recall but may introduce more false positives, affecting precision. The F1 score strikes a balance between precision and recall, providing a comprehensive evaluation of the model's performance.

By analyzing the F1-confidence curve, we indicate that the generated model that achieves a high F1 score at an optimal confidence threshold indicates its capacity to precisely recognize license plates while minimizing false positives and false negatives.

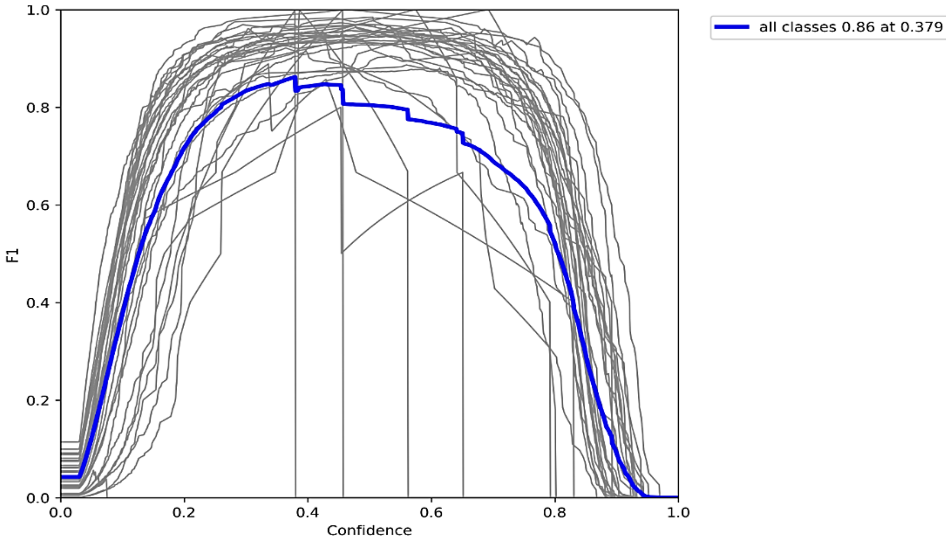

Fig. 9. F1-confidence curve of the generated model.

As reported results, the YOLOv6 achieves superior results in terms of high accuracy and low computation cost through a combination of innovative design features and improvements over its predecessors. The model's unique architecture, characterized by a single-pass approach and grid-based analysis, significantly contributes to its efficiency in real-time object detection. By efficiently dividing the input image into a grid and processing it in a single pass through the neural network, YOLOv6 minimizes computation costs while ensuring accurate detection. The model's ability to capture intricate details while maintaining computational efficiency is crucial for achieving high accuracy in license plate recognition. Additionally, the empirical evidence presented in the study, comparing various YOLO-based versions, underscores YOLOv6's superiority in terms of accuracy and computational efficiency.

Moreover, YOLOv6 addresses the critical balance between accuracy and speed, a key requirement for real-time applications such as license plate recognition. The enhancements in the model's architecture and algorithmic improvements contribute to faster processing times without compromising accuracy, making it well-suited for applications that demand both high precision and low computation costs.

As results, YOLOv6's achievement of better results in terms of high accuracy and low computation cost can be attributed to its innovative architecture, grid-based analysis, advancements in deep learning algorithms, and a meticulous design that prioritizes the critical balance between accuracy and speed. The empirical comparisons presented in the study validate these claims, providing tangible evidence of YOLOv6's effectiveness in meeting the requirements of accurate and efficient license plate recognition.

V. CONCLUSION

This research paper highlights the significance of License Plate Recognition (LPR) in IoT smart parking systems. It explores the use of traditional and deep learning-based methods for LPR detection, with a focus on why deep learning approaches are preferred. The challenges faced by deep learning-based LPR methods, particularly accuracy rate and computation cost, are addressed using insights from previous studies. The proposed method introduces a solution based on the YOLOv6 algorithm to overcome these challenges. The process entails creating a custom dataset, carrying out testing, validation, and training, and assessing the suggested model's performance. The experimental results demonstrate that the suggested method outperforms existing state-of-the-art methods, offering improved accuracy and reduced computation costs. The research contributes to enhancing LPR technology in IoT smart parking systems, enabling more efficient and reliable parking management solutions. For future work, an interesting direction would be to extend the proposed YOLOv6-based LPR system to incorporate real-time tracking of vehicles within the smart parking system. This would enable continuous monitoring and tracking of vehicles, providing valuable information for parking space availability and management. Cross-Domain License Plate Recognition: Another potential avenue for future research is to explore the applicability of the proposed method in cross-domain scenarios. Investigating the adaptation of the YOLOv6-based LPR system to different environments, such as night-time conditions, adverse weather, or different camera viewpoints, would contribute to the robustness and generalization capabilities of the model. This would expand the practical use cases of the system beyond traditional smart parking systems.

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