Comparative Study of Various Techniques for Automatic Number Plate Recognition Using Generative Adversarial Networks

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***Abstract*—This paper conducts a comparative analysis of various models for Automatic Number Plate Recognition (ANPR) technology. The central focus is on evaluating and contrasting the performance of different ANPR models in accurately capturing and identifying license plates during vehicle entry and exit in parking areas. The study aims to provide insights into the strengths and weaknesses of these models, shedding light on their efficacy in real-world scenarios. The comparative assessment aims to contribute valuable information for selecting the most suitable ANPR model for applications requiring efficient and reliable license plate recognition.**

***Index Terms*—ANPR, Deep Learning, Data analysis, Computer Vision, YOLO algorithm, TFOD Algorithm**

I. INTRODUCTION

In the ever-changing realm of city transportation, technological progress has ushered in a new era for vehicle movement and parking control. Leading this transformation is Automatic Number Plate Recognition (ANPR) technology—a sophisticated system that combines cameras and Optical Character Recognition (OCR) to decipher vehicle license plates. This innovative technology goes beyond the limitations of manual inspection, providing exceptional efficiency and accuracy, even in difficult conditions like low visibility and adverse weather.

This research paper provides an in-depth analysis of the pivotal technologies shaping the performance of Automatic Number Plate Recognition (ANPR). ANPR's proficiency in capturing, processing, and analyzing real-time datasets has redefined its applications beyond parking facilities. It seamlessly records license plates, utilizing Optical Character Recognition (OCR) to extract textual information. The extracted data is then intelligently cross-referenced with databases, enabling diverse applications, such as issuing citations and supporting law enforcement agencies.

The paper centrally examines the automated processes driven by ANPR in capturing and analyzing vehicle movements. Deployed strategically at entry and exit points, ANPR systems have the power to revolutionize vehicle tracking, ensuring precise revenue collection and efficient ticket issuance. Beyond parking applications, these systems play a pivotal role in enhancing operational efficiency. ANPR technology identifies vehicles exceeding allotted parking durations, triggering real-time notifications for immediate responses, whether it involves issuing citations or coordinating timely towing services.

Nevertheless, ANPR's influence goes beyond efficient parking management; it extends to the robust enforcement of parking regulations. Rapidly identifying unauthorized vehicles and those infringing upon restricted zones, ANPR generates alerts, empowering parking lot staff to enforce regulations promptly and effectively.

This paper thoroughly examines different ANPR systems, shedding light on their advantages and limitations. Furthermore, it meticulously dissects the challenges associated with implementing ANPR technology. In response to these challenges, the paper provides insightful recommendations, serving as a valuable resource for urban planners, policymakers, and technologists. It outlines a roadmap for the seamless integration and optimal utilization of ANPR technology in the dynamic field of urban parking management. This research not only acknowledges the transformative potential of ANPR but also establishes the foundation for its enhanced effectiveness and widespread adoption in urban environments.

In summary, ANPR technology stands as a noteworthy advancement in urban transportation and parking management. Its influence extends beyond parking facilities, providing prospects for improved security, traffic management, and integration into smart city initiatives. As cities grapple with growth and transportation challenges, ANPR technology is poised to play an increasingly crucial role in shaping the future of urban mobility and safety. This research paper aims to illuminate these possibilities and offer

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guidance for realizing the full potential of ANPR in urban environments.

II. LITERATURE SURVEY

In the fast-evolving field of urban surveillance and vehicular management, the incorporation of deep learning techniques has instigated a paradigm shift in Automatic Number Plate Recognition (ANPR) systems. A thorough examination of extensive academic literature reveals a range of pioneering methodologies and innovative approaches embraced by researchers, emphasizing their continuous efforts to achieve precision and efficiency in ANPR technology.

Research Jawale et al. [4] leads the way in this transformative wave by introducing a novel Automatic Number Plate Recognition (ANPR) system with a comprehensive methodology. This system revolutionizes the traditional ANPR process by seamlessly integrating various phases, such as license plate extraction, image pre-processing, character segmentation, and recognition. The system involves the collaborative synergy of convolutional neural networks (CNN), MobileNet, Inception V3, and ResNet 50, pushing the boundaries of recognition accuracy and system robustness. In their groundbreaking work, the researchers have not only enhanced the recognition accuracy of ANPR systems but also streamlined the entire process. The fusion of CNN, MobileNet, Inception V3, and ResNet 50 highlights the effectiveness of collaboration between deep learning techniques, establishing a high standard for system robustness and precision.

Expanding on this groundwork, M. G. Khan et al. [3] delves into the intricacies of smart vehicle access control, unlocking the potential of YOLOv4 for vehicle detection. Their pioneering work goes beyond the limitations of uniform number plates, addressing the complexity of diverse plates. This deep learning-based Automatic Number Plate Recognition (ANPR) pipeline not only highlights the effectiveness of YOLOv4 but also establishes the framework for a more adaptable and versatile ANPR system. This work emphasises on smart vehicle access control using YOLOv4 showcases a forward-thinking approach. Their capacity to handle diverse number plates broadens the scope of ANPR, enhancing its adaptability and flexibility in various real-world scenarios.

Simultaneously, Y. Zou et al. [6] engineers a robust Automatic Number Plate Recognition (ANPR) model strengthened by Bi-LSTM and 1-D attention layers. Their system remains resilient even under the most challenging and unrestricted conditions, emphasizing the importance of robust feature extraction and character localization. This effort illuminates a

crucial path toward ANPR systems that surpass the limitations imposed by environmental variables.

In scholarly research, J. Shashirangana et al. [7] conducts a comprehensive survey, meticulously analyzing various Automatic Number Plate Recognition (ANPR) methods. Their examination serves as a guiding beacon, helping researchers navigate the intricacies and challenges in the field. It reflects the collective intelligence of the research community, promoting a spirit of collaboration and shared knowledge. This collaborative effort advances the understanding and development of effective ANPR methodologies.

I. H. El-Shal et al.[8] explores uncharted territories by leveraging the potential of Generative Adversarial Networks (GANs) for the super-resolution of license plates. This innovative approach improves recognition accuracy by enhancing image quality, a vital effort in scenarios where image clarity is compromised. Their contribution broadens the horizons of Automatic Number Plate Recognition (ANPR) technology, introducing a new dimension of image enhancement and refinement.

Concurrently, H. Shi and D. Zhao [10] combines multiple deep learning methodologies, resulting in an end-toend Automatic Number Plate Recognition (ANPR) model that combines YOLOv5 with an enhanced channel attention mechanism and GRU + CTC for character recognition. This elegant fusion of techniques attains unprecedented levels of recognition precision, marking the onset of a new era in the realm of ANPR systems.

C. Henry et al. [2] charts an international course, developing a multinational Automatic Number Plate Recognition (ANPR) system proficient in deciphering license plates from diverse countries. Their use of YOLOv3-SPP for detection and recognition highlights the adaptability of their system, addressing the complexities of international license plate formats. This effort bridges geographical divides, paving the way for standardized ANPR solutions on a global scale.

Moreover, Khan et al. [11] tackles the challenge of plate localization in challenging environments by introducing a twostep approach involving Faster R-CNN and morphological operations. This innovative method emphasizes resilience, ensuring accurate plate localization even in adverse conditions. Their work highlights the crucial role of careful localization techniques in addressing real-world challenges.

In challenging scenarios, Khan et al. [9] introduces a clever method based on enhanced YOLOv5m and LPRNet. Their approach attains impressive recognition accuracy under various challenging conditions, establishing a new standard for ANPR systems. This achievement underscores the adaptability and robustness of their methodology, showcasing its effectiveness across a wide range of real-world challenges.

Moreover, Shafi et al. [5] sheds light on the journey toward precise detection and recognition mechanisms for nonstandard, transitional vehicle license plates. Their inventive use of YOLOv3-based CNN architecture instills

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confidence in plate detection and character recognition, even in situations where traditional methods struggle. This groundbreaking work lays the foundation for ANPR solutions designed for unconventional license plate formats.

Together, these groundbreaking studies highlight the transformative influence of deep learning on shaping the realm of Automatic Number Plate Recognition (ANPR) systems. They are an example of innovation, resilience, and adaptability, acting as guiding lights towards more precise, efficient, and versatile ANPR technologies. As these efforts come together, they propel the field into a new era where ANPR systems adeptly handle the intricacies of real-world conditions, fundamentally changing how we understand and manage vehicular movements in urban environments.

III. PROPOSED METHODOLOGY

Figure 1 illustrates the research approach in the current study, with detailed descriptions of each stage presented in the following sections. The methodology recommends utilizing big data and big science studies, incorporating data science. This involves comparative analyses of existing processes in data mining, along with their classification based on localization and segmentations.

A. Data acquisition

Images of vehicles are sourced from Google's Open Images Dataset V7, and a custom dataset is created for individual characters in the initial phase of the methodology. Similar to many other developing nations, India's license plate vendors do not follow a standardized format for letter size, color, etc. Additionally, individuals design their license plates based on personal preferences. Some also engrave names, images, and statements near or around the license plate number. After collecting data, the Roboflow API is used to annotate labels and license plates. The study employs two types of datasets: one for vehicles and license plates, and another for numbers and characters.

1) Vehicle license plate dataset: The Roboflow License Plates dataset is an object detection dataset containing diverse vehicles' license plates, including cars and vans. It includes annotations for both "vehicle" and "license-plate." The dataset is split into training, validation, and test sets with proportions of 245, 70, and 35, respectively.

2) Character dataset: The character dataset comprises 571 number plate character images organized into two folders with comments. In the annotation folder, coordinates (x-min, ymin, x-max, and y-max) represent the labels obtained during segmentation. The image folder contains license plates. The dataset employs 37 labels in total, covering letters A to Z, numbers 0 to 9, and (N/A), representing not attempted.

B. Preprocessing

Pre-processing is employed to improve crucial image functionalities or reduce unnecessary distortions, enhancing the quality of image data for subsequent processing. Deformed pixels often revert to the average of their neighboring pixels during this process. The image pixel values are converted into grayscale images sized at 416 x 416 and then input into the neural networks. To avoid excessive complexity in neural networks, the following procedures are adopted for image preprocessing:

1) Read images: In this stage, we initially read the image. Images can be in various formats such as jpg, png, and mpeg.

2) Resize images: With the OpenCV library, the images are resized in this stage. Reducing the size helps decrease the computational complexity of neural networks and the feature vector.

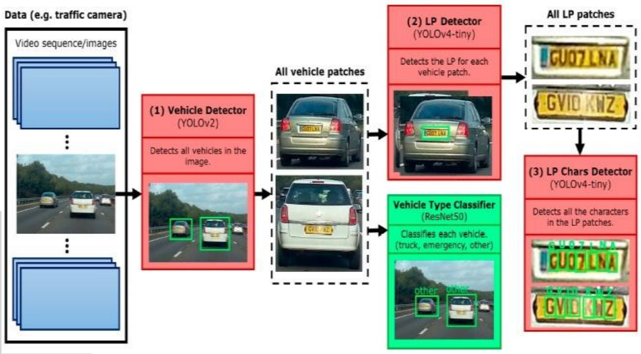

Fig. 1. A flow diagram for the computer vision tasks

3) Convert BGR2RGB: BGR (Blue, Green, Red) color images in the datasets are converted to RGB (Red, Green, Blue). While OpenCV reads images in BGR format, our model performs better with RGB. Hence, the images are adjusted accordingly.

4) Image normalization: Image normalization aims to distribute pixel values across all images based on a common statistical distribution, enhancing data preparation. Achieving this involves dividing the picture array by 255, effectively normalizing the image. The term "intensity normalization" is synonymous with this process of normalizing pixel values in an image.

5) Noise removal: Gaussian noise, a prevalent form of image blur, arises when a Gaussian function brightens an image, resulting in what is known as Gaussian noise or Gaussian blurring. Graphic applications frequently use this effect to reduce visual noise, creating a visual outcome resembling a translucent screen with a slightly altered buoyancy effect. In computer vision algorithms, the pre-processing stage referred to as Gaussian optimization enhances image textures in various areas.

C. License plate localization

Character segmentation (CS) and license plate localization (LPL) are vital elements of the license plate (LP) recognition system. For the examination of this process, LPL employs histogram equalization. Another technique for character division is the hybrid binarization method. Algorithmic proposals are put forth to achieve effective localization and

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segmentation. An M x M grid divides the provided image, where each grid cell is responsible for predicting the centered object. The model outputs a vector for each M x M grid cell, represented as B x 5 + C, where B defines the bounding box and grid cell confidence score, and C is the class probability of the predicted bounding box. Each bounding box comprises five parts: the confidence score (boxC), bbx, bby, bbw, and bbh.

The (bbx, bby) coordinates indicate the center of the object relative to the grid cell position, while the (bbw, bbh) coordinates represent the bounding box width and height relative to the image dimension. YOLO-based models predict multiple bounding boxes for each grid cell, selecting the one with the highest Intersection over Union (IOU) overlap with the true ground, a process known as non-maximum suppression.

D. OCR text extraction

The subsequent step involves utilizing Optical Character Recognition (OCR) to extract text after isolating the license plate region of interest (ROI) as shown in Figure 2. This process precisely identifies and extracts alphanumeric characters from the isolated license plate region using OCR techniques, recognizing the text on the license plate. OCR algorithms separate individual characters on the plate, identify their shapes and patterns, and then create machine-readable text. Our entire license plate recognition system depends on this text extraction technique to accurately recognize and decipher alphanumeric characters, making it a fundamental component of the system.

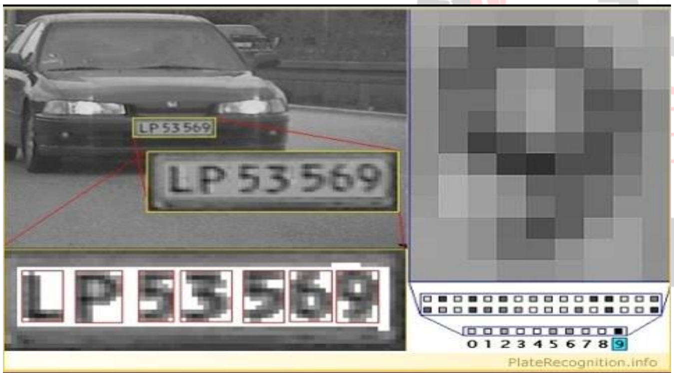

Fig. 2. Working of OCR (Optical Character Recognition)

E. Image super resolution

We are committed to achieving excellent results in our research framework, emphasizing both accuracy and visual clarity. To enhance the quality of originally extracted license plate photos, we incorporate the use of Super-Resolution Generative Adversarial Networks (SRGAN). SRGAN, a cuttingedge deep learning method, enhances visual output by upscaling and improving image resolution, resulting in crisper and more detailed images.

Our objective is to significantly improve the visual quality of retrieved license plate photos by applying SRGAN. This enhancement is particularly valuable in scenarios with poorquality or partially occluded license plate photos, such as dimly lit areas or camera constraints. By leveraging SRGAN, our system demonstrates enhanced resilience and efficacy, providing better and more readable license plate images. This not only benefits administrators and end-users relying on the system for license plate identification but also aids downstream analytics by ensuring input data is of the highest quality, leading to more precise and insightful analysis.

Through the improvement of license plate picture quality, we aim to address challenges arising from diverse environmental conditions and image quality issues. This state-of-theart image processing method adds a layer of sophistication to our system, ensuring that retrieved license plate photos remain readable and clear even in less-than-ideal circumstances.

F. Training and testing

The dataset is divided into three sets—training, validation, and testing—using the default technique. The training dataset for the modeled convolutional neural network comprises learning examples paired with the intended target. The trained model is then validated using 70 images. The pre-processing approach for training data involves converting BGR to RGB, scaling photos, extracting features, and conducting the training process. Subsequently, the validation dataset is employed to assess the trained model, extending its application to realworld data as well.

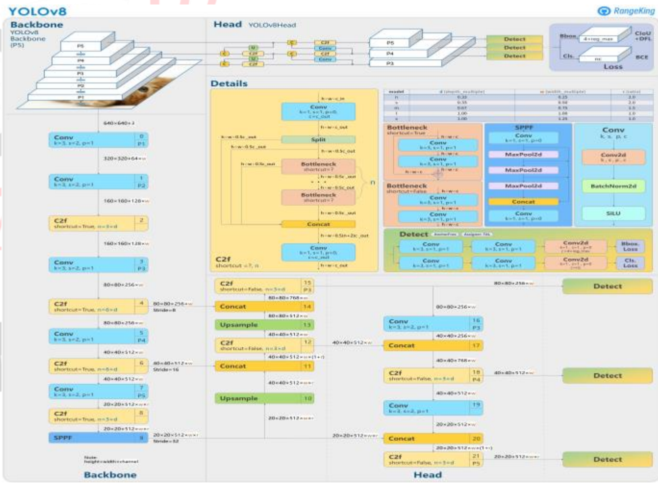

Fig. 3. YOLO V8 architecture

G. Real world working

In real-time scenarios, this paper introduces an integrated system for efficient vehicle control at entry and exit points. The solution relies on a meticulously trained object detection model applied to real-time license plate detection through CCTV cameras at entry gates. This robust combination enables swift identification and recording of license plate data as vehicles pass through the gate. Optical Character Recognition (OCR) is then employed to precisely extract and interpret the alphanumeric text from the identified license plates.

Once the license plate data is extracted, an entry record is generated, including crucial details such as the date, time,

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and the corresponding city or state. This information is stored in a centralized database. The system also monitors departing vehicles using the same process, capturing departure times and updating the relevant database records. Our analytical capabilities are grounded in comprehensive entry and exit data collection. By scrutinizing entry and exit timestamps and correlating them with geographical data, insightful analytics are derived.

These analytics, presenting a comprehensive overview of vehicle travel patterns, are displayed on a user-friendly admin page. The paper specifically delves into entry and exit trends at various times of the day, providing in-depth insights for peak hour analysis. This information is crucial for managing traffic, enhancing security, and optimizing logistics. Moreover, the system generates reports highlighting the cities and states most frequently visited by cars, aiding regional traffic monitoring and resource allocation.

In our real-time working methodology as shown in Figure 4, we prioritize system efficiency and scalability by employing Docker to containerize our backend infrastructure. By encapsulating different parts of our system—such as the database, image processing modules, and analytics engines—inside distinct Docker containers, we create a highly modular and portable environment. This containerization not only expedites maintenance and upgrades but also simplifies deployment across diverse hardware configurations.

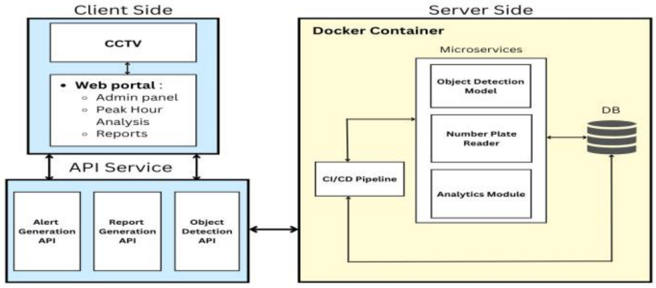

Fig. 4. Real time system architecture

H. Incremental learning

To ensure the long-term resilience and adaptability of our system, we've incorporated incremental learning into our study framework. The continuous evolution of our Object detection model is a key aspect, and incremental learning plays a vital role in this ongoing process. While our initial Object detection model is highly effective at license plate detection, it is imperative to keep it updated and flexible enough to respond to changes in environmental factors, lighting conditions, and license plate patterns.

Incremental learning allows our model to continually learn from new data, adapting its recognition abilities to accommodate emerging license plate variations. This ongoing learning process enhances the model's reliability and accuracy over time, particularly for variations that may not have been present during the initial training phase. The adaptive nature of this learning process not only improves the model's performance but also ensures its continued functionality in real-world scenarios, even amidst changing environmental factors or license plate designs.

Our research aims to establish a system that excels in current settings and possesses the flexibility to adapt to new challenges and changes in the future through the integration of incremental learning. This dynamic approach to model training significantly contributes to maintaining the reliability and accuracy of our license plate identification system, marking it as a noteworthy and cutting-edge advancement in computer vision and intelligent vehicle management.

IV. RESULTS AND DISCUSSION

A. Experiments with YOLO models

YOLOv5 is a very precise object detection model. It has demonstrated state-of-the-art performance on multiple benchmark datasets. YOLOv5 is simple to use and train. This is due to the pre-trained models and user-friendly training and inference scripts offered by YOLOv5.

YOLOv7 is more accurate as compared to its previous versions. It has demonstrated state-of-the-art performance on multiple benchmark datasets. Compared to TFOD and YOLOv5, YOLOv7 is faster. This is a result of YOLOv7's usage of a new, speed-optimized loss function and network design. YOLOv7 is simple to use and train. Pre-trained models and user-friendly training and inference scripts are offered by YOLOv7.

In comparison with YOLOv7, TFOD is observed to be far less flexible. YOLOv7 is made to recognize a particular group of things, including humans, animals, and cars. It is not as effective in identifying different kinds of items, such as scenery. Compared to YOLOv7, TFOD does not have the same level of community support. Less online resources are accessible to assist users in gaining familiarity with TFOD.

YOLOv8 was observed to consistently perform well and have the best metrics out of the other experimented alternatives. On numerous benchmark datasets, it has been demonstrated to produce state-of-the-art results. Out of the four, the YOLOv8 is the fastest. This is due to the fact that YOLOv8 makes use of a new, speed-optimized training pipeline, anchor box selection technique, and attention mechanism. YOLOv8 is simple to use and train. Pre-trained models and user-friendly training and inference scripts are offered by YOLOv8.

TFOD is less flexible than YOLOv8. YOLOv8 is intended to identify a particular class of items, including people, cars, and animals. It is not as effective in identifying different kinds of items, such as scenery.

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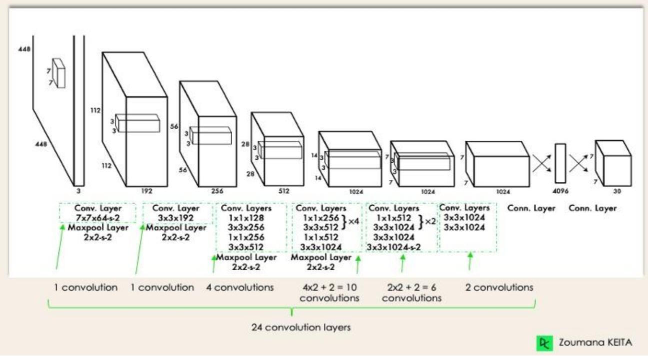

Fig. 6. YOLOv8 Architecture

The backbone of the YOLOv8 architecture is the CSPDarknet53.his modified version of the Darknet53 architecture forms the core feature extractor. It utilizes ”Cross Stage Partial connections” to efficiently reuse feature maps across different stages, improving information flow and accuracy.

The Spatial Pyramid Pooling Feature (SPPF) layer aggregates features from different spatial resolutions, enhancing contextual understanding of objects. Subsequent convolutional layers further refine and combine extracted features at various scales.

The C2F (Channel to feature) component replaces the traditional YOLO neck architecture. It focuses on ”channel to feature” conversion, efficiently summarizing high-level information and fusing it with lower-level contextual details, leading to more precise object localization.

Modifications to the loss function address issues like anchor box assignment and class imbalance, aiming for improved training stability and convergence.

YOLOv8 eliminates the need for predefined anchor boxes, simplifying the architecture and potentially improving accuracy across object scales. Mosaic data augmentation: This technique artificially expands the dataset by randomly combining image patches, enhancing model generalizability to diverse scenarios.

The decoupled head structure separates prediction tasks into distinct branches, one for bounding box coordinates and another for class probabilities. This decoupling allows for independent optimization and potentially better performance.

In conclusion, YOLOv8 fits the criteria of being the best suited model for the application of Automatic Number Plate Recognition for our dataset.

B. Experiment using TFOD

TFOD is less flexible than YOLOv5. YOLOv5 is intended to identify a certain class of objects, including people, cars, and animals. It is not as effective in identifying different kinds of items, such as scenery.

V. PERFORMANCE ANALYSIS OF VARIOUS MODELS

TABLE I PRECISION, RECALL, AND MAP FOR EACH CLASS FOR YOLOV5

Metric	all	license-plate	vehicle
Precision	0.886	0.924	0.847
Recall	0.775	0.833	0.716
mAP	0.856	0.894	0.818

Precision is a measure of the accuracy of the positive predictions. In this case, for the ”all” class, YOLOV5 achieved a precision of 0.886, indicating that 88.6% of the predicted objects were correct. For the ”license-plate” class, the precision is even higher at 92.4%, and for the ”vehicle” class, it is 84.7%.

Recall measures how well the model captures all the relevant instances of a particular class. The ”all” class has a recall of 77.5%, ”license-plate” has 83.3%, and ”vehicle” has 71.6%. This suggests that the model is better at capturing license plates compared to the overall vehicles.

mAP is an overall measure that combines precision and recall across all classes. YOLOV5 achieved an mAP of 85.6% as shown in Table I, indicating good overall performance across classes.

TABLE II PRECISION, RECALL, AND MAP FOR EACH CLASS FOR YOLOV7

Metric	all	license-plate	vehicle
Precision	0.883	0.916	0.85
Recall	0.794	0.869	0.718
mAP	0.874	0.944	0.803

YOLOV7 shows slightly higher precision and recall values, leading to a higher mAP of 87.4% as shown in Table II.

TABLE III PRECISION, RECALL, AND MAP FOR EACH CLASS FOR YOLOV8

Metric	all	license-plate	vehicle
Precision	0.851	0.881	0.822
Recall	0.861	0.893	0.828
mAP	0.911	0.952	0.869

YOLOV8 shows slightly lower precision values but higher recall and mAP compared to YOLOV5 and YOLOV7 as shown in Table III. This suggests that YOLOV8 is more focused on capturing all instances of a class (higher recall) at the expense of precision.

TABLE IV LOSSES FOR TFOD

Metric	Value
Loss / Classification loss	0.142
Loss / Localization loss	0.077
Loss / Regularization loss	0.030
Loss / Total loss	0.250

Table IV provides information on the different components of the loss function for TensorFlow Object Detection (TFOD). The “Classification loss”, ”Localization

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loss", and "Regularization loss" contribute to the total loss. The values presented indicate the contribution of each component to the overall loss. In this case, "Classification loss" has the highest contribution, followed by "Localization loss" and "Regularization loss."

TABLE V OBJECT DETECTION METRICS

Class	Images	Instances	Precision	Recall	mAP
all	1233	1233	0.872	0.89	0.936
Ambulance	1233	22	0.807	0.864	0.923
Auto	1233	2	1	0.876	0.995
Bicycle	1233	14	0.829	0.929	0.972
Bike	1233	200	0.946	0.995	0.982
Bus	1233	79	0.832	0.937	0.972
Car	1233	554	0.922	0.969	0.983
Motorcycle	1233	49	0.883	0.772	0.878
Truck	1233	69	0.587	0.515	0.635
Auto-rickshaw	1233	56	0.872	0.929	0.974
Bus	1233	30	0.981	1	0.995
Car	1233	94	0.976	0.915	0.952
Lorry	1233	42	0.928	0.922	0.927
Mini truck	1233	22	0.768	0.955	0.982

Table V represents object detection metrics for various classes in a dataset. Each row corresponds to a specific class (e.g., Ambulance, Auto, Bicycle), and the columns include information such as the number of images, instances, precision, recall, and mean Average Precision (mAP) at different thresholds. These metrics are commonly used to evaluate the performance of object detection models. The values in the table show how well the model performs in detecting and classifying instances of different objects in the given dataset.

In the context of number plate recognition, YOLOV8 emerges as a promising choice due to its well-balanced tradeoff between precision and recall. While YOLOV8 exhibits slightly lower precision values compared to its predecessors (YOLOV5 and YOLOV7), it compensates with higher recall rates and an overall improved mAP. In number plate recognition, it is crucial to accurately detect and classify license plates while minimizing false positives. YOLOV8's emphasis on recall ensures that a higher proportion of actual license plates are successfully identified, making it particularly suitable for applications where capturing all instances of license plates is imperative. Moreover, YOLOV8's superior performance in capturing relevant objects contributes to its potential as an effective solution for tasks like vehicle surveillance and traffic monitoring, where precision and recall are both critical metrics for reliable and accurate results.

VI. CONCLUSION

This study offers an overview of the latest ANPR models and evaluates their performance with the appropriate datasets. Furthermore, we have showcased the scalability and efficiency of these models, affirming their suitability for real-time applications.

The YOLOv8 model tested on real world data shows excellent results and the process of license plate recognition using OCR is further improved with the use of super resolution GANs. Put togethor these two technologies provide a system that can be used in applications such as parking management.

The overall findings of the research paper suggest that ANPR models built on deep learning have the potential to revolutionize traffic monitoring and control. These models enable the development of ANPR systems that surpass traditional systems in terms of accuracy, efficiency, and scalability.

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