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REAL-TIME AUTOMATIC LICENSE PLATE RECOGNITION IN COMPLEX ENVIRONMENT

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Abstract
The Automatic License Plate Recognition (ALPR) system is a cutting-edge technology that can detect and read any shape and size of license plates in real-time. This system is essential for maintaining safety and security on the roads, The majority of methods for recognizing license plates work primarily in non-real-time and still need supervision from humans. The proposed ALPR solution in this work employs a combination of custom-trained YOLOv8, EasyOCR, and pre-trained ESRGAN models, to detect and recognize license plates in real-time with high accuracy. The system is versatile and practical, capable of operating even in complex environments such as low-light conditions. The methodology used in this paper involves training the YOLOv8 algorithm to detect license plates in images. ESRGAN is then used to enhance the quality of low-resolution images, resulting in a high-quality output. This output is then shared with YOLOv8, which detects the license plate in images by mapping the license plate coordinates, and the output of YOLOv8 is again transferred to EasyOCR. EasyOCR detects the characters in the license plate and finally displays the output. These novel aspects differentiate the proposed ALPR solution from existing methods by performing super-resolution enhancement and license plate detection in real-time which make it highly effective in maintaining safety and security on the roads. Experimental results show that the proposed system achieves a 97% F1 score and 98.5% mean average precision while operating in real-time.

Keywords:
Computer vision, Deep Learning, License plate detection, Character Recognition, YOLOv8

1. INTRODUCTION

Real-time detection and reading of license plates is possible thanks to license plate identification technology such as the ALPR system. For the maintenance of road safety and security, this system is crucial. Advanced algorithms and optical character recognition techniques are used by license plate recognition systems to precisely detect and read license plates. Because they enable authorities to immediately identify vehicles implicated in illegal activity, these technologies have the potential to significantly improve road safety and security. But there are also worries about data exploitation and personal privacy. To ensure the protection of individual rights, license plate recognition technology must be deployed responsibly and transparently. Additionally, poor weather or obstacles can render license plate recognition devices useless. This problem can be addressed by employing non-real-time programs that use super-resolution and YOLOv5[1].

Non-real-time ALPR applications can pose a significant challenge in terms of their effectiveness and efficiency. These systems may not be able to provide timely and accurate information to authorities, resulting in delayed response times and missed opportunities to identify vehicles involved in criminal activities. Additionally, non-real-time ALPR systems may be unable to keep up with quickly changing traffic circumstances, resulting in erroneous or obsolete data. Because authorities may not have the most up-to-date information to make informed judgments, this can have significant consequences for road safety and security.

In India, there have been several hit-and-run cases where license plate detection has been used to identify the culprits. For example, the artificial intelligence-based Automatic Number Plate Recognition (ANPR) system from EFKON India can recognize and record the license plates of more than 3,000 cars per day [2]. This technology has made it easier for law enforcement to help people and maintain road safety. However, it might be challenging for an ANPR system to precisely recognize and decode the license plate due to variances between Indian license plates which come in various shapes, sizes, and colors [3].

A crucial element in resolving this issue is the use of a Real-time ALPR system, it is an important consideration in terms of security aspects. Another approach is to collect and analyze sample images of Indian license plates to identify common patterns and improve the ALPR algorithms such that they can identify all shapes and sizes of license plates and should also be able to recognize differences between various license plate colors.

Artificial neural networks, or "Deep Learning," is a subfield of machine learning whose model is inspired by the organization and functioning of the human brain. Convolutional neural networks (CNNs), a relatively recent breakthrough in deep learning technology, have performed exceptionally well in object and picture identification. These methods can be used to categorize and characterize certain visual components from the image. Utilizing smaller, simpler patterns imprinted in its filters, CNNs combine patterns of increasing complexity by taking advantage of the hierarchical structure in the input. This means that CNNs employ the data's hierarchical structure. CNNs use filters to represent smaller and simpler components of an image or input instead of trying to understand the whole thing at once. To extract the relevant information, these filters are applied to various input sources. The network transitions between each of its layers, and these components come together to form more intricate patterns, allowing it to develop more advanced representations of the input.

The YOLO (You Only Look Once) series represents a sophisticated object detection model that differs from previous approaches. Rather than estimating probabilities and bounding boxes for objects within a grid cell, it segments the input image into an S x S grid. Our selected model achieved notable success in predicting license plate orientation, angle, and characteristics, boasting a mean average precision of 98.5% and an F1 score of 97% on Ultralytics YOLOv8.

2. RELATED WORK

Ibrahim H. El-Shal et al. [1] proposed an end-to-end computer vision framework based on generative adversarial networks (GANs) to improve the accuracy of License Plate (LP) detection in digital images in a realistic environment. Small 72x72 License plate images can be handled by the proposed SRGAN (Super-resolution GAN) network, which can also produce realistic super-resolution images. Total Variation (TV) loss regularization, layer count, activation function, and proper loss regularization are all adjustments that the authors suggest making to the SRGAN network. The suggested SRGAN is capable of handling a variety of datasets, including those from optical character recognition (OCR), and visual analysis. Metrics such as PSNR and SSIM are used to evaluate the trained model. The results show that, in comparison to existing systems, the recommended SRGAN can provide super-resolution pictures that increase the accuracy of the LP identification step. The paper highlights the need for more efficient license plate recognition techniques that can handle various environmental conditions and registration plates, ensuring accurate and reliable license plate identification. For optimal performance, two categories of datasets were utilized in this work. The three metrics used to measure performance in this work are PSNR, SSIM, and accuracy. They managed to achieve PSNR, SSIM, and accuracy of 26.6db, 83db, and 93%, respectively.

Juan R. Terven and Diana M. Cordova-Esparaza et al. [4] conducted an in-depth review of the evolution of the YOLO (You Only Look Once) framework, from the first version (YOLOv1) to the most recent version (YOLOv8). The authors looked at the most significant changes, innovations, and advancements in every variation of YOLO. To provide the groundwork for the upcoming developments in the YOLO family, they started by investigating the fundamental ideas and architecture of the original YOLO model. The report then went into detail on the improvements and adjustments made in each version, starting with YOLOv2 and ending with YOLOv8. These enhancements covered a range of topics, including input resolution scaling, loss function adjustments, anchor box changes, and network architecture. The authors sought to provide a comprehensive explanation of the YOLO framework's development and its implications for object detection by looking at these advancements, coming to the conclusion that YOlOv8 gives better and more accurate results than its predecessors

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Aashna Ahuja and Arindam Chaudhuri et al. [5] proposed a system that utilizes a unique combination of technologies to address the challenge of vehicle monitoring in metropolitan areas. The system uses the Mask R-CNN model to detect the type of vehicle, along with WpodNet and Pytesseract to identify its license plate and predict the letters on it. The increasing number of cars on the roads has made vehicular monitoring a significant problem for cities. The authors of this study have developed a model with an impressive f1 score of 72%, aimed at helping users find a specific vehicle based on its type and license plate number.

Chenyang Wei et al. [6] Proposed a novel model named SG-YOLOv5 that can effectively detect license plates and helmets of electric motorcycles on time. The model reduces the backbone network and neck component of the original YOLOv5 by combining two lightweight networks, ShuffleNetv2 and GhostNet. Additionally, the number of model parameters and floating-point operations is greatly decreased by employing an add-based feature fusion technique. To eliminate interference from parked car license plates and pedestrians' heads, a scene-based non-truth suppression technique is employed. The RHNP dataset, which has four categories- rider, helmet, no-helmet, and license plate is used throughout the testing phase. The findings show that SG-YOLOv5 and the original YOLOv5 have comparable mean average precision, accompanied by a significant reduction in model parameters (90.8%), floating-point operations (80.5%), and model file size (88.8%).

Vrinda Agarwal et al. [7] proposed a system that is a real-time traffic monitoring concept that provides a simple alternative to outdated, ineffective, and manual surveillance methods. The suggested system can operate with high performance and accuracy to detect both face and license plate with an accuracy of 92% for license plate and 99% for facial recognition using YOLOv8.

Rishabh Rathi et al. [8] proposed a technique to automatically detect a vehicle's license plate from any video feed using YOLOv4 deep learning. The number was taken out of the number plate image using an OCR method. This tactic could improve the efficacy and accuracy of license plate recognition. The accuracy of the system's license plate detection is roughly 89%.

D.R. Vedhaviyassh et al. [9] proposed the following three modules: Character recognition, License plate detection, and Image collection for number plate recognition. After analyzing the performance of EasyOCR and Tesseract OCR, it was determined that EasyOCR exhibits a higher reading accuracy rate of 95% for number plates, while Tesseract OCR only achieved 90%. The disparity in accuracy can be attributed to the employment of a deep learning technique for object detection in EasyOCR, these findings suggest that EasyOCR may be a better option for applications that require high accuracy in license plate recognition.

Marko Horvat et al. [10] conducted a comparison between the performance of the YOLOv5 model for the classification and localization of images. Using a common picture dataset, the study compares several iterations of the YOLOv5 model and offers researchers detailed recommendations for choosing the best model for a particular issue type.

Upile Handalage et al. [11] conducted a study of the object-detecting technique known as You Only Look Once (YOLO). The paper discusses the key features and innovations of the YOLO framework, as well as its performance in real-time object detection tasks.

Haitong Lou et al. [12] proposed a small-size item identification method that is more precise and ensures that the detection accuracy for each size is not less than the existing method that has been described in some circumstances. Three major advancements are introduced by the algorithm.: a new down-sampling method, an improved feature fusion network, and a new network structure. The algorithm outperforms other object-recognizing algorithms such as YOLOX, YOLOv3, YOLOv7(tiny), scaled YOLOv5, and YOLOR on three reliable public datasets: Visdron, Tinyperson, and PASCAL VOC2007.

Ruihan bai et al. [13] proposed an enhancement of the object identification algorithm YOLOv8-n that emphasizes the use of Wasserstein Distance Loss, FasterNext, and Context Aggravation techniques. According to the findings, when all three strategies are used, the model's performance is greatly improved, mAP is increased, and model complexity is decreased. The YOLOv8-n model outperforms existing models in terms of model accuracy, complexity, and striking the ideal balance between the two. Additional image inference tests confirm the model's effectiveness and demonstrate its excellent detection skills.

Subash Gautam et al. [14] proposed a workable approach to ASD screening that makes use of face photos and the YoloV8 model. The authors produced outstanding results using YoloV8, a deep learning approach, using a dataset from

Kaggle. Their model scored an astounding F1-score of 0.89 and a classification accuracy of 89.64%. The successful attainment of a high F1 score exemplifies the promise of deep learning models for ASD kid screening. The latest YoloV8 version, which is often used for object identification, may be used to classify photos that are autistic and those that are not, according to the authors.

Dillion Reis et al. [15] proposed a generic flying object detection model in real-time that can be used for further research and transfer learning, as well as a polished model that is prepared for usage. The YOLOv8 single-shot detector is used to determine the ideal balance between inference speed and mAP. Their final modified model obtains an improved mAP of 0.835 while maintaining an average inference speed on 1080p films of 50 fps.

3. METHODOLOGY

3.1 DATASET PREPARATION

The dataset utilized for this study includes the license plates dataset, which has 10,126 photos of various shapes and sizes of the license plate, it also uses data-augmented images mimicking low-light and high-speed conditions to enhance blur or low-light LP detection. The required data is acquired from openly accessible websites, GitHub repositories,

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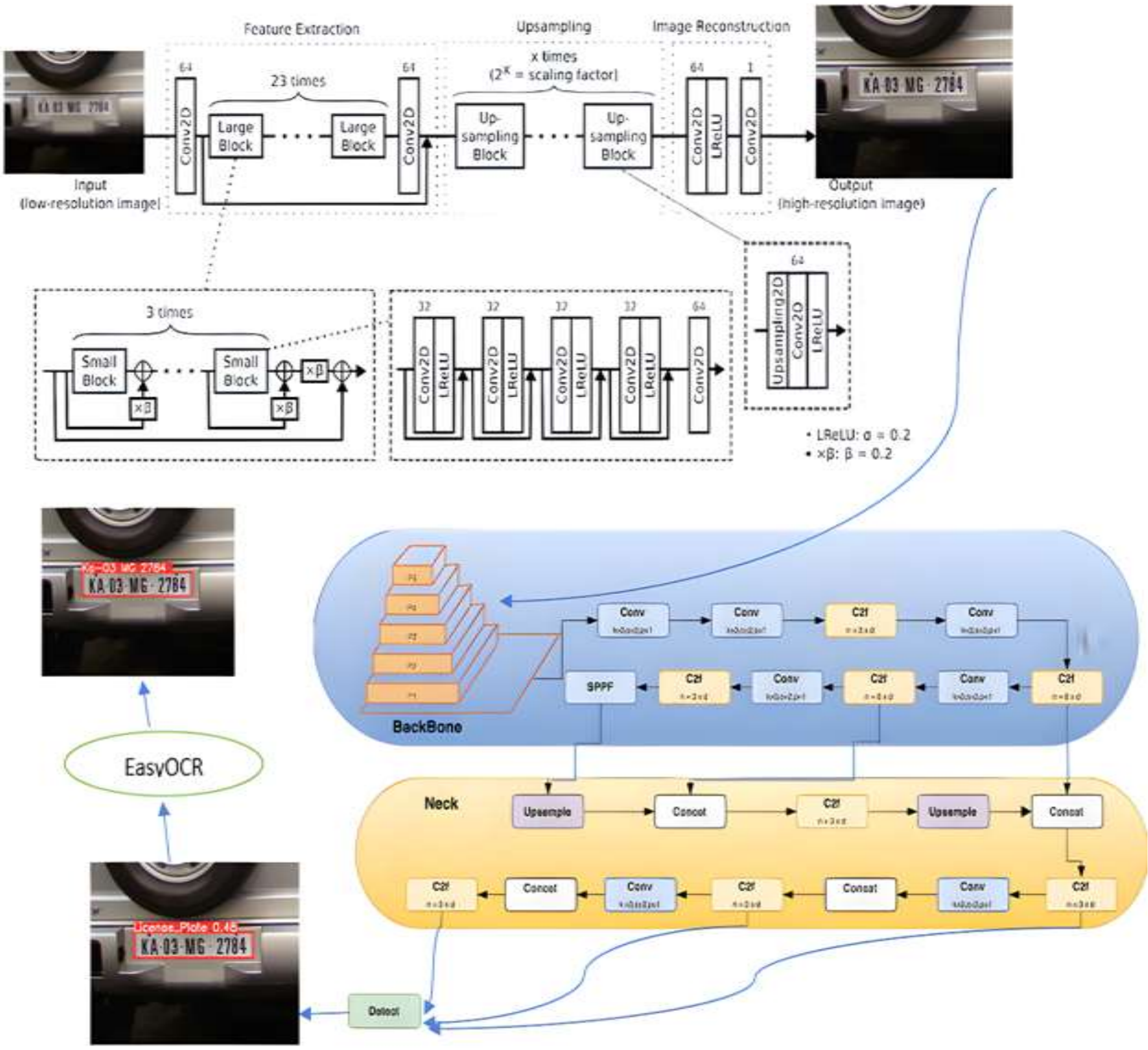

Fig. 1 Proposed model architecture.

surveillance footage on YouTube, and the Robolfow dataset collection [16]. Using restoration techniques to eliminate any noisy data from the dataset, then resize the images to fit the YOLO format which is 640 default image size. For the dataset, there are training, testing, and validation sets. The dataset is split into proportions of 70% for training, 10% for testing, and 20% for validation set. In YOLOV8 dataset is made up of labels and images. The bounding box coordinates are included in these labels. YOLOV8 had a YAML file in it. Information about the dataset, including the number of license plates, their coordinates, and their route, is included in the YAML file.

3.2 LICENSE PLATE RECOGNITION MODEL

The integration of Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN), You Only Look Once version 8 (YOLOv8), and EasyOCR presents a robust and efficient solution. The initial phase of the process involves the enhancement of the input image, a critical step as the quality of the input image directly influences the subsequent stages of license plate detection and character recognition. ESRGAN, a type of Generative Adversarial Network (GAN), is employed for this purpose. It generates high-resolution images from low-resolution inputs by learning a mapping from the low-resolution input space to the high-resolution output space. The generator network attempts to produce images

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that resemble real high-resolution images, while the discriminator network strives to distinguish between real and generated images. The two networks are trained concurrently, with the generator network's objective being to deceive the discriminator network, ESRGAN operates by initially extracting features using a set of combined convolution layers, comprising large blocks that contain smaller blocks consisting of a combination of convolutional neural networks (CNN) and rectified linear units (ReLU). The generator then up-samples the feature map extracted from the previous stage and reconstructs the image from scratch by mapping the feature map using image reconstruction with convolution and ReLU units as shown in Fig.1, This process culminates in a high-resolution image output, making ESRGAN a powerful tool in image enhancement.

The License plate is then cropped and passed to EasyOCR, EasyOCR employs two deep learning models for this purpose - CRAFT for text detection and CRNN for text recognition. CRAFT, which stands for Character Region Awareness for Text Detection, is based on a Convolutional Neural Network (CNN). CNNs are particularly adept at extracting features from images due to their hierarchical architecture that mimics the human visual cortex. In the context of EasyOCR, CRAFT uses a CNN to scan the license plate images and identify regions that likely contain text. Once the text regions are detected by CRAFT, they are passed on to the next stage - text recognition. This is where the Convolutional Recurrent Neural Network (CRNN) comes into play. Unlike CNNs, which are great for image feature extraction, RNNs excel at processing sequential data like text. The CRNN in EasyOCR takes the detected text regions and processes them sequentially to recognize and output the actual text. the EasyOCR model is trained on a large dataset of labeled images containing text in different languages and under various conditions. This extensive training enables it to accurately map the extracted features to corresponding characters, thereby recognizing the text.

Upon successful enhancement of the image, it is fed into YOLOv8 for license plate detection. This model has been custom-trained on a dataset of 10,000 images of license plates, enabling it to accurately detect license plates under various conditions. YOLOv8 operates by dividing the input image into a grid and predicting multiple bounding boxes and class probabilities for each grid cell. Each bounding box is associated with a confidence score that reflects both the likelihood of the box containing an object and how accurate it believes the box is. In this context, the object of interest is a license plate. Therefore, the model has been trained to recognize license plates and assign high confidence scores to bounding boxes that likely contain a license plate, and it is also trained to work in real-time with integrated ESRGAN.

This project aims to recognize a license plate in real time. The input source first passes through the pre-trained ESRGAN model, followed by trained YOLOv8 and EASYOCR for character recognition. Ultralytics YOLOv8 is a cutting-edge model that incorporates novel features and enhancements to augment its operational efficiency and versatility. It is a significant upgrade to the prior YOLO iterations. The versions of this YOLO series include v1, v2, v3, v4, v5, v6, v7, and v8. Now, YOLOV8 is the most recent version. The fact that YOLOv8 is anchorless sets it apart from earlier YOLO versions in a significant way. When a model is used to identify items in an image, predetermined anchor boxes are avoided. This method is known as "anchorless object detection." The model directly determines the bounding boxes for the image's objects. The model's accuracy and adaptability can be increased with this strategy because it is not restricted by the predetermined anchor boxes. YOLOv8 uses an anchor-free detection head to make bounding box predictions in a pixel-wise manner, similar to image segmentation. Anchor-free object detection is a method that directly predicts the bounding box concerning some fixed reference in the image, without relying on pre-defined anchor boxes. This approach has shown great progress in detecting objects with large size variations and dense and overlapping objects since it is designed to be quick, precise, and easy to use, it is a great choice for a range of object detection and tracking applications. The YOLOv8 model is available in five distinct sizes: nano, small, medium, big, and extra-large. The sizes are YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), and YOLOv8l (Large), The slowest of them all is YOLOv8x(extra-large) while being the most accurate. Each of the bounding boxes for the image has the following features: classes (license plate), the center of the enclosing box (Bx, By), and C The values for an object's width (Bw), height (Bh), and PC are 1, if the item is present in each grid, and 0 otherwise.

The YOLO principle is

Y= (C, Bw, Bh, Bx, By, Pc)

The YOLO (You Only Look Once) object identification system's most current iteration is referred to as YOLOv8, it is noteworthy that YOLOv8 represents a significant advancement over previous YOLO techniques, as it utilizes a CNN that comprises two distinct components, namely, the backbone and the head. The backbone, which is founded on the

CSPDarknet53 architecture, employs cross-stage partial connections to enhance information flow between its 53 convolutional layers. On the other hand, the head is composed of multiple convolutional layers followed by a series of fully connected layers [12], as shown in Fig. 1, which enables it to predict the bounding boxes, object scores, and class probabilities for the objects identified in an image. One of the salient features of YOLOv8 is its use of a self-attention mechanism in the subject's head. By leveraging this self-attention mechanism in the network's brain, YOLOv8 enables the model to selectively focus on various regions of the image and adjust the value of specific parts according to the task at hand. The model's capacity to do multi-scaled object identification utilizing a feature pyramid network that recognizes items at different sizes allows it to identify both big and tiny things in a picture.

Steps for License plate recognition with Yolov8

1) Take the input data without any augmentations
2) Set the image size in input data to 640x640 resolution
3) Split data into 3 sets: train, test, and validate.
4) Import all yolov8, tensorhub, EasyOCR modules
5) Load pre-trained ESRGAN model from tensorhub
6) Train the dataset using yolov8
7) Test and validate the dataset using yolov8
8) Run the commands to detect the license plate recognition in real time

4. RESULT AND DISCUSSION

In this work, the trained YOLOv8 model is saved in the.pt (Pytorch) format in this study as an object detection model. You may obtain the Ultralytics YOLOv8 repository from https://github.com/ultralytics/ultralytics. This is used to train several trained objects and is the official repository of the Ultralytics yolov8. When training is finished, the algorithm detects any license plates that are visible in the frame based on the confidence value in the images and videos.

All the experiments are performed using The Google Collaborator GPU with 15GB memory and a Ryzen 7 4800H, 4th generation CPU, and 12GB of RAM is used for all of the studies in this study, The libraries that used in this experiment are PyTorch, Ultralytics, TensorFlow, EasyOCR, Tensorhub, hydra, cv2. To recognize number plates in real-time, Figures 2(a) and 2(b) show the mAP (mean average precision) using ioU (intersection over union) of the license plate detection system using the YOLOV8 algorithm, where the first is ioU = 50-95 for 2(a) and for 2(b) ioU = 50, which was trained using the YOLOV8 algorithm with default settings of 21 epochs, a batch size of 64, and a learning rate of 0.001. It is obvious that accuracy has increased. The accuracy of the method was very nearly 98.5%. The precision of the system is shown in Fig. 3. The precision of the model in our work is 97.5%. Fig. 4 shows a 96.3% system recall.

When ioU is in the 50-95 range, as shown in Fig. 2(a), the value is often lower than mAP50 since mAP 50-95 is compared to a variety of thresholds, A lower mAP value results from the model's difficulty in achieving high accuracy as the IoU threshold rises.

Losses for the training box, class, and dfl are shown in Figs. 5, 6, and 7. The model's class loss and dfl loss both drop as the number of epochs grows, mirroring the behavior of the box loss, which reduces as epochs increase.

One of the primary limitations of the proposed ESRGAN model is its dependence on GPU for faster image processing. Additionally, integrating ESRGAN with YOLOv8 and all its dependencies poses significant challenges that must be addressed. The challenge is overcome by integrating a pre-trained ESRGAN model from the tensorhub imported directly with the trained YOLOv8 model.

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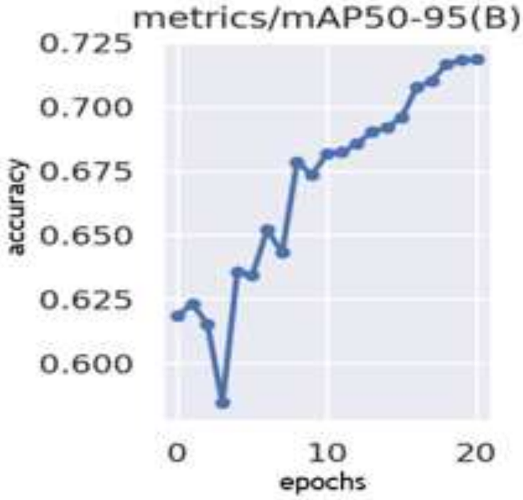

Fig. 2(a). mAP50-90

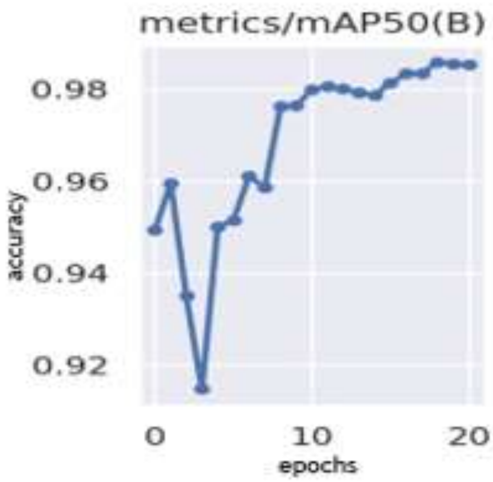

Fig. 2(b). mAP50

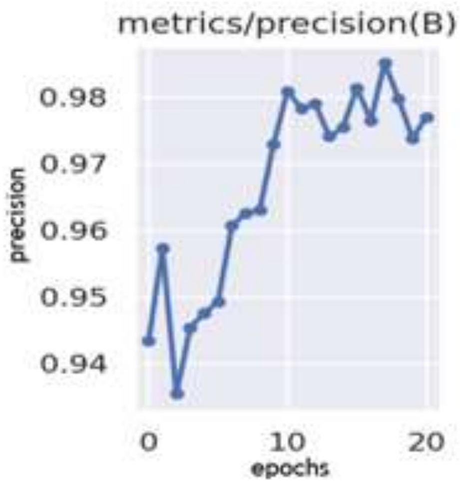

Fig. 3. Precision

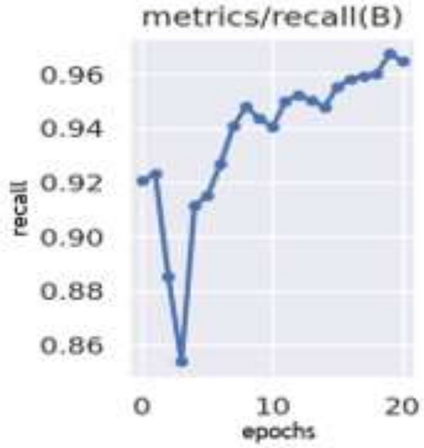

Fig. 4. Recall

Fig. 5. Training Box_loss

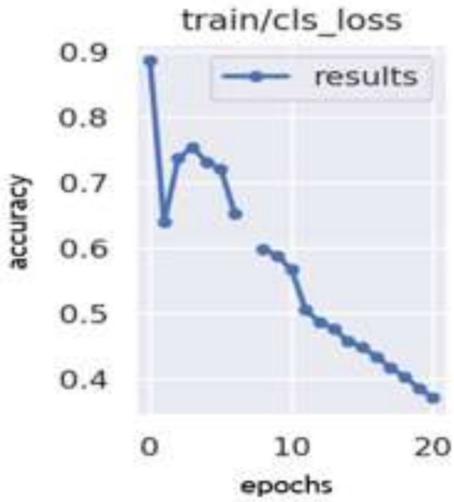

Fig. 6. Training Class_loss

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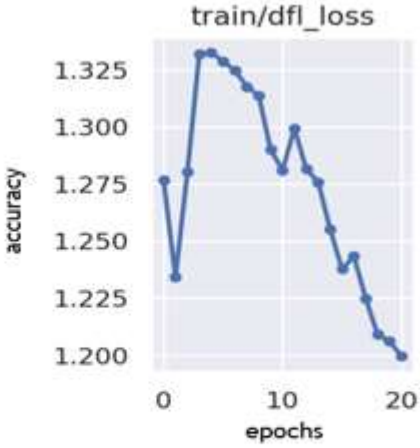

Fig. 7. Training dfl_loss

Fig. 9. License number recognition from image

Fig. 8. License number recognition from video footage

Fig. 10. Real-time recognition output

Fig. 8. Represents the output for a license plate with ESRGAN and EasyOCR for video format, Fig. 9. Represents the output for a license plate with ESRGAN and EasyOCR for image, Fig. 10. Represents the output for a license plate with ESRGAN and EasyOCR for real-time.

The work is measured using the following metrics.

$$\text{Accuracy}=\frac{TP+FP}{TP+FP+TN+FN} \quad (1)$$

$$\text{Precision}=\frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall}=\frac{TP}{TP+FN} \quad (3)$$

$$\text{F1 Score}=\frac{2 * \text{Precision} * \text{Recall}}{\text{Precision}+\text{Recall}} \quad (4)$$

TP: True PositiveFP: False Positive

TN: True Negative FN: False Negative

The formulas to determine accuracy, precision, recall, and F1 Score are represented with equations (1), (2), (3), and (4), respectively. A comparison of the YOLOV5, SRGAN with YOLOV8, ESRGAN, and EasyOCR assessment measures is shown in Table I

TABLE I. Comparing current algorithms and their combination with existing ones.

Algorithms	**Metrics**		
	Accuracy	***Real-time detection***	***Execution time***
YOLOV8+ ESRGAN+ EasyOCR	**98.5%**	**Yes**	**0.01sec**
YOLOV5+ SRGAN	95.4%	No	0.03sec

5. CONCLUSION AND FUTURE WORK

A method for automatically recognizing license plates in real-time has been developed to monitor and manage law enforcement services. The method uses ESRGAN to enhance the resolution of license plate images and EasyOCR for character recognition. The YOLOV8 algorithm has been implemented to improve accuracy, precision, and recall compared to previous YOLO models, resulting in a higher F1 score. The proposed model achieved an F1 score of 97% and a mean average precision (mAP) score of 98.5% for all license plate shapes and sizes.

In the future, there is potential to enhance ALPR systems by incorporating more parameters such as driver facial recognition and vehicle speed. Additionally, it would be beneficial to create a user-friendly interface for the system

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