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Robust Vehicle License Plate Detection in Real-World Traffic Scenarios

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ABSTRACT

Intelligent transportation systems rely on Automatic Number Plate Recognition (ANPR) to support applications such as traffic surveillance, law enforcement, and automated parking management. However, in Pakistan, the lack of conventional plate sizes, the popularity of elaborate or personalized designs, the variety of fonts, and the range of color schemes make ANPR a difficult process. The accuracy of traditional recognition methods is seriously affected by these variables. This study proposes a robust ANPR outline precisely de- signed for Pakistani license plates. Convolutional neural networks (CNNs) are used to extract features, optical character recognition (OCR) is used to identify characters, and YOLOv8 and YOLOv3 are used to recognize license plates. The work was tried on 200 images of license plates from motorcycles and cars, and it attained a recognition accuracy of 97.5%. With an Detection accuracy of 96.7%, the experimental results presented that the proposed system was effective in handling the very difficult variations of Pakistani license plates, as well as the improved detecting capacity of up-to-date YOLO versions, such as YOLOv8

Keywords: Convolutional Neural Networks (CNNs); Optical Character Recognition (OCR); Automatic Number Plate Recog- nition (ANPR); YOLOv3; YOLOv8; Intelligent Transportation Systems; License Plate Detection; Pakistani Vehicles.

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I. Introduction

Automatic Number Plate Recognition (ANPR), a key el- ement in modern intelligent transportation systems, enables real-time vehicle monitoring and identification. It serves a wide range of applications, including traffic control, toll collection, parking automation, and crime reduction, especially in rela- tion to cases of stolen or unregistered vehicles. Despite its significance, it is challenging to establish an effective ANPR system in Pakistan due to the lack of standardized license plate formats, the popularity of appealing and customized plates, variations in character sets, and the availability of a wide variety of backdrop colors. These differences often reduce the accuracy of conventional recognition methods.

In this paper, we suggest a original ANPR system es- tablished especially for Pakistani license plates. The three main stages of the method are preprocessing, detection, and recognition. Preprocessing methods like noise detection, pic- ture scaling, and grayscale conversion are used to improve clarity. To find license plates, detection is done using both the YOLOv3 and the more existing YOLOv8 devices. After the plate is detected, optical character recognition (OCR) is used to recognize the characters and segment, and convolutional neural networks (CNNs) are used to extract the features of the characters.

The proposed technique was tried on a collection of 200 im- ages of Pakistani license plates, including those of motorbikes and automobiles. An experimental study established an overall accuracy of 96.7%, indicating the method's robustness. Fur- thermore, YOLOv8 provided earlier and more detailed recog- nition than YOLOv3, making it an extremely helpful tool for managing Pakistani number plate variances. These outcomes suggest that the proposed technique can meaningfully enhance Pakistan's vehicle identification processes, offering practical implications for law enforcement and traffic management.

LPR has develop a key knowledge in many areas, with applications including intelligent transportation border control and smart cities, relying heavily on it. LPR is very significant in the modern world because of its numerous uses. The ability to recover data rapidly and precisely from licenses, for instance, plates, makes it likely to do things that would be impossible and inefficient for humans, including look for a detailed car across a street in seconds as opposite to records (bazzanet al. [1]. LPR

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is an important instrument for refining the accuracy and speed of a variety of tasks in today's technically advanced culture because of its effectiveness.

A major problem is low-resolution images, which affects the complete value of LPR systems and lowers their reliability in real-world applications. There has been an attempt to investigate potential solutions to this problem. That increases the resolution of photos taken to strengthen LPR systems' resilience in practical situations. Using super-resolution (SR) techniques to improve image resolution has become more com- mon in current years. To improve the image accuracy analysis programs for both single-frame and multiframe applications, SR is a computational mission that returns HD (high definition) images from their unique low-resolution counterparts (cai et al. zhou et al.) [2][3]. The ability of HR photos to preserve finer details results in greater visual quality, which makes them important in a variety of fields. To expand the use of high-definition photographs in several fields, including digital security imaging, digital medical imaging, digital satellite imaging, and license plate detection [2]. The great potential for improving image quality is what drives efforts to develop

SR technology. Consequently, this improvement makes it more effective in key domains of picture processing and interpre- tation. Object identification and recognition tasks have been transformed by new growths in deep learning, particularly convolutional neural networks (CNNs). The You Only Look Once version 8 (YOLOv8) model is one of them that has become a potent and effective detector because of its high accuracy, real-time processing ability, and resilience to com- plicated backdrops. Even in difficult situations like occlusion, skewed angles, and low-resolution pictures, YOLOv8 offers an end-to-end solution that immediately detects and localizes license plates with high precision, in contrast to previous rule-based or handmade feature techniques.

This study uses a variety of deep learning-based models to identify and recognize Pakistani license plates, as shown in Fig. 1. This work is motivated by the unique problems of the local environment, which impact the performance of all models used for recognition. These difficulties include

• Plate Size and Shape Variations – Provinces and car types have different plate designs, fonts, and aspect ratios..

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• Vehicle-Type Differences – Trucks, buses, rickshaws, motorcycles, and cars all have different license plate orientations and locations..

• Design Inconsistencies –Background colours, provincial logos, and decorative patterns obstruct detection.

•Environmental Conditions – Errors such as bad lighting, motion blur, shadows, dust, and bad weather reduce accuracy.

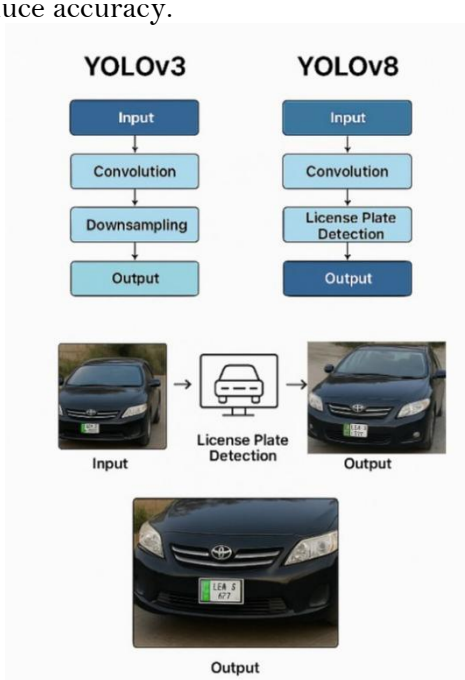


Fig. 1. A scenario of YOLOv8 and YOLOv3 being used for real-time car detection in traffic situations in Pakistan.

II. Related Work

Earlier studies on license plate recognition mostly con- centrated on rule-based algorithms and manually constructed feature extraction. These traditional methods were essential to the early development of LPR systems.

A. Traditional LPR Techniques

Traditional LPR techniques typically involve four steps: feature extraction, character recognition, character segmenta- tion, and license plate localization. These approaches typically use reasonably high-quality photos as input and are typically applied to images captured by fixed cameras (ani et al. angelika et al.) [4][5]. However, the difficulties in taking these pictures in actual situations are impacted by other vari- ables. Images are frequently altered by factors including the surrounding environment, technical limitations, and weather. There are problems with using a

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captured image alone to detect plate characters, especially when low-quality and low- resolution photos are involved (Silva et al. hijji et al.)[6][7]. Particularly in dynamic settings involving moving vehicles and complicated environments, this traditional LPR technology presents a serious obstacle for later improved computer vision applications. This highlights the crucial need for reliable com- puter vision techniques in systems that identify license plates. Improvements in LPR approaches are necessary to overcome these obstacles and guarantee adaptability and dependable performance in real-world conditions, which signifies a main development in license plate recognition technology.

B. Foundational Detectors:YOLOv3 and Improvements

Redmon et al. proposed YOLOv3's (You Only Look Once version 3) accuracy and speed balance for embedded appli- cations, making it a common baseline for real-time detection research. Numerous subsequent ALPR comparisons rely on the architectural and multiscale prediction foundation provided by Redmon and Farhadi's classic description of YOLOv3.[8] choi et al. To improve bounding-box dependability in safety- critical settings (like autonomous driving), Gaussian YOLOv3 enhanced YOLOv3 by incorporating localization uncertainty with Gaussian parameterization.[9]

C. YOLOv8 Architecture and General Applications

Yaseen et al. modern design choices like anchor-free heads, C2f modules, and novel training recipes were introduced by YOLOv8 (You Only Look Once version 8), which has been thoroughly examined in recent architecture studies that provide better speed–accuracy tradeoffs than previous YOLO families.[10]

Reis et al. showed how YOLOv8 may be used for tasks other than the typical ones, such as real-time flying object identification, which emphasizes how the model can be used to address domain issues like ALPR.[11]

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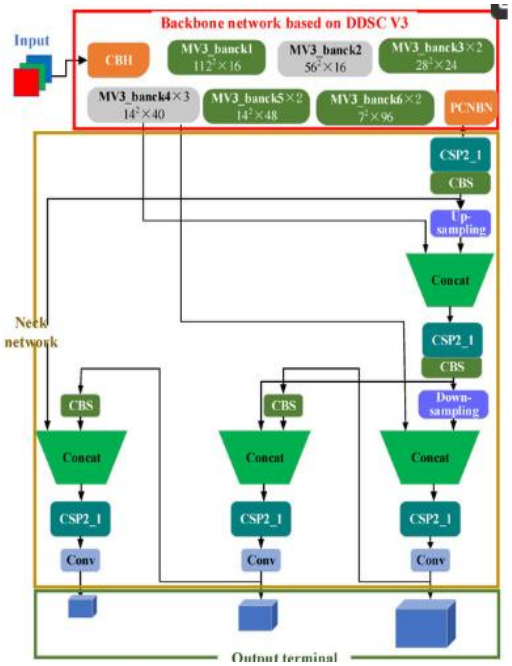


Fig. 2. Proposed Source Network:yaseen2024 [10]

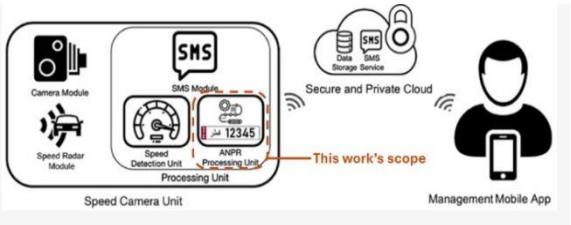
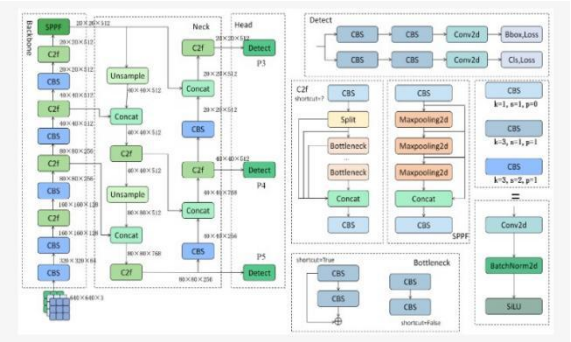


Fig. 4. Proposed Source Network:alhasan2024enhanced

loss.[1



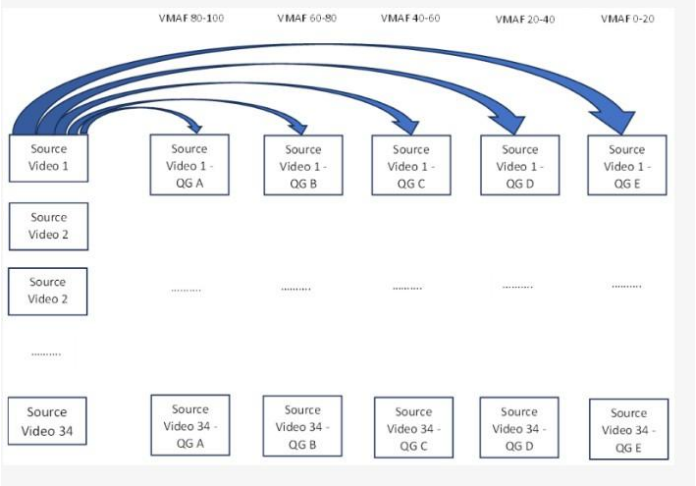


Fig. 5. Proposed Source Network: zhu 2025 Improved [13]

D. License Plate Detection — YOLOv8-Based Systems

Al-Hasan et al. described robust detection and recognition for real-world deployment of their improved YOLOv8-based ANPR system, which is customized for Qatari plates and uses aggressive augmentation to address lighting and occlusion.[12] To increase mAP while maintaining real-time inference, Zhu et al.

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proposed an enhanced YOLOv8n variant designed for license plate detection by rebuilding C2f/SPPF(Spatial Pyramid Pooling–Fast) modules and implementing WIoU

In order to show that localization + OCR tailoring to regional plate styles produces strong end-to-end recognition, Sarhan et al. constructed a YOLOv8 + Easy Optical Character Recognition (EasyOCR) + Convolutional Neural Networks (CNNs) pipeline for Egyptian plates.[14]

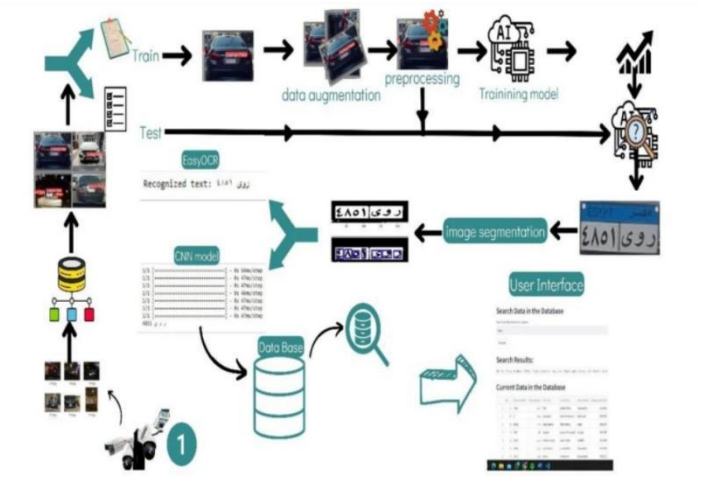


Fig. 6. Proposed Source Network:sarhan2024egyptian [14]

E. ALPR on Small/Low-Resolution Plates and Super-Resolution

When compared to traditional Generative Adversarial Net- work Super-Resolution (GAN SR) models, DiffPlate (AlHa- lawani et al.) demonstrated that SR enhances downstream char- acter identification when using diffusion models for license- plate super-resolution.[15]

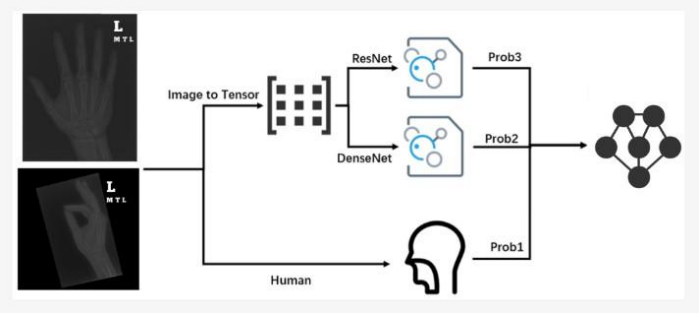
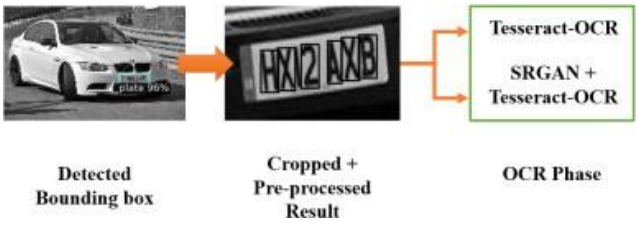


Fig. 7. Proposed Source Network:alhalawani2024diffplate [15]

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In their comparison of YOLOv8 and Faster Region-Based Convolutional Neural Network (Faster R-CNN) under Super- Resolution (SR) preprocessing, Mulia et al. demonstrated the usefulness of SR in ANPR pipelines by reporting that YOLOv8 + SR produces better detection + OCR performance on low- resolution plates. [16]



F. Small-Object Detection: YOLOv8 Variants and Enhance- Ments

To improve small-object mAP in traffic and aerial situa- tions, Khalili and Smyth et al. offered SOD-YOLOv8, which incorporates attention modules and a shallow detection layer to better maintain fine spatial details.[17]

Ni et al. (Remote Sensing) suggested a scale-normalization Feature Pyramid Network (FPN) and parallel multi-scale fea- ture extraction module (PMSE) for Unmanned Aerial Vehicle UAV/aerial small-object detection, demonstrating enhanced recall/precision on datasets similar to VisDrone/DIOR. [18]

G. Improved YOLOv8 Variants for UAV/Aerial Scenarios

Using multiscale fusion and modified detection heads, Feng et al. suggested IMCMD-YOLOv8 variations (small/large) for aerial small-object identification to improve mAP on drone datasets. [19] For aerial drone photos.

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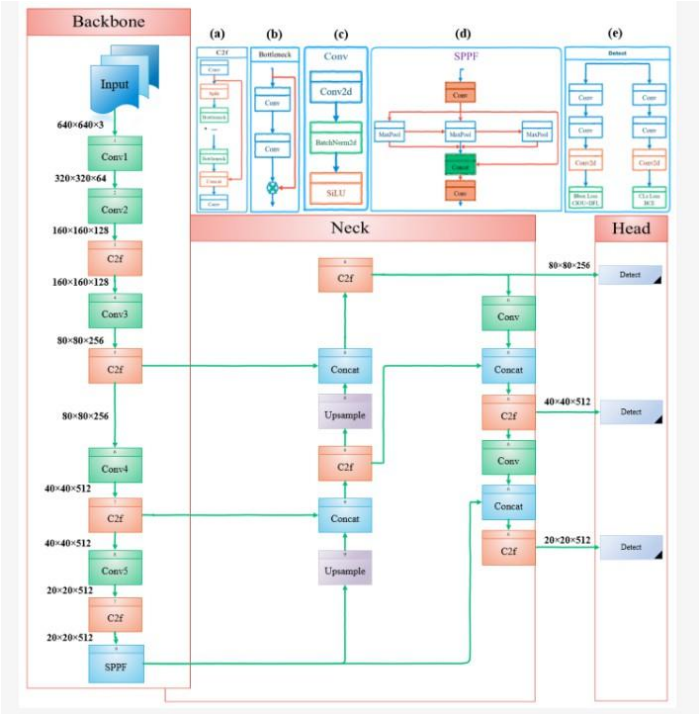
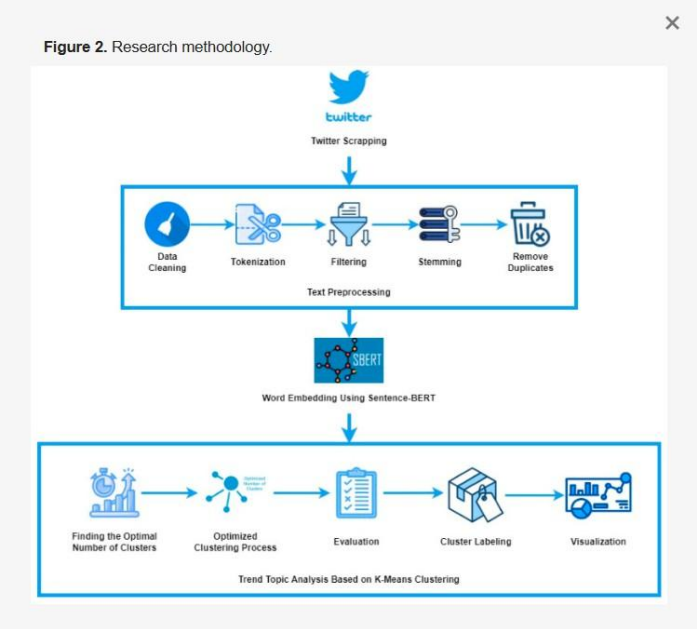


Fig. 9. Proposed Source Network:khalili2024sod [17]

Liu et al. (ICCC 2024) offered an enhanced YOLOv8; their work focuses on neck/head adjustments and dataset augmentation to improve tiny-object detection in high-altitude imagery.[20]



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H. Multi-Stage ALPR Pipelines and OCR Integration

Ammar et al. a multi-stage vehicle and plate recog- nition pipeline with real-time distributed inference is proposed.[21](Sensors 2023); the system demonstrates the interaction between detection, cropping, and character recog- nition modules in deployed ANPR.[12]

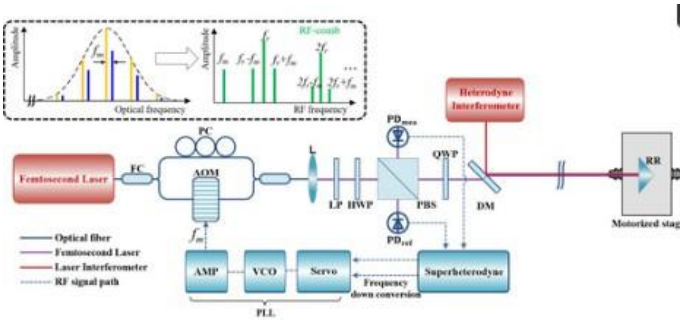


Fig. 11. Proposed Source Network:ammar2023multistage [21]

As an applied baseline for short dataset ANPR evalua- tions, Moussaoui et al. (Scientific Reports 2024) demonstrated high end-to-end accuracy on a curated dataset by integrat- ing YOLOv8 detection with state-of-the-art Optical Character Recognition (OCR). Reference:[22]

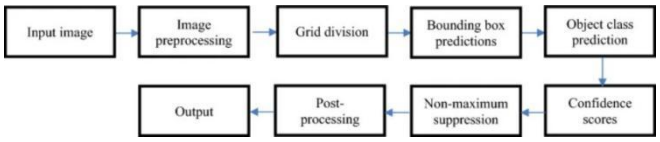


Fig. 12. Proposed Source Network:moussaoui2024enhancing [22]

In 2025, Huang et al. and colleagues presented YOLOv8- DDS (You Only Look Once version 8 – Device Deployment Simplified), a YOLOv8 variation that is optimized for edge deployment and is lightweight. The model combines TensorRT (Tensor Real-Time) acceleration with structured pruning (SP) to lower latency and computational cost while preserving excellent detection accuracy. They show how to detect ob- jects in real time on devices with limited resources. This study demonstrates the effectiveness of integrating hardware- level optimization with model compression for deep learning implementation.[23]

I. Cross-Dataset Generalization and Dataset Issues

In their study of cross-dataset generalization in LPR, Laroca et al. demonstrated

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that algorithms developed on one domain or dataset typically lack robustness to others; this encourages region-specific evaluation (e.g., Pakistani plates) and meticulous dataset curation.[24]

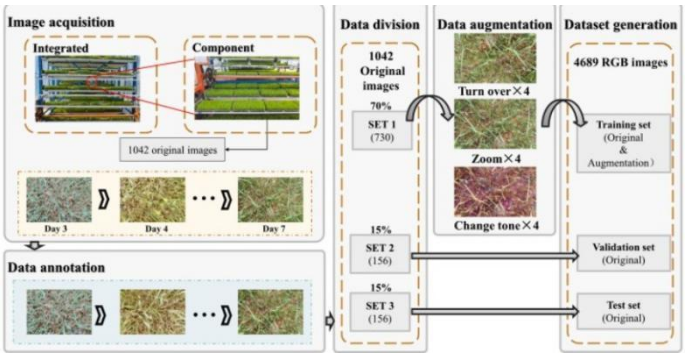


Fig. 13. Proposed Source Network:yolov8dds2025 [23]

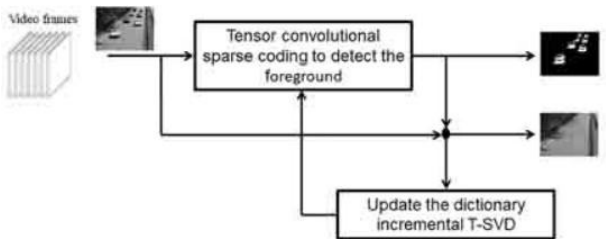


Fig. 14. Proposed Source Network:laroca2022cross. [24]

J. Summary and Research Gap

There are multiple SR+detector pipelines, small-object en- hancements, and ALPR systems based on YOLOv8 in the cur- rent literature. This study fills the gap by comparing YOLOv3 and YOLOv8 in a controlled head-to-head evaluation on the same region-specific dataset using consistent preprocessing, SR ablation, and deployment measures.

Automatic License Plate Recognition (ALPR) systems have been greatly enhanced by recent developments in deep learning-based object detection. Models like YOLOv3 and YOLOv8 have been widely used for detecting license plates and vehicles in a variety of regional and environmental set- tings. Improved versions of these designs, such as end-to-end OCR integration, lightweight model optimization, and super- resolution preprocessing, have been suggested by a number of researchers. Major contributions in this field are summarized in Table I.

III. Our Contribution

We suggest a system for real-time license plate detection that is adapted to Pakistani

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traffic conditions and makes use of the YOLOv8 object detector. The system successfully recognizes several license plates in difficult situations like changing lighting, different plate sizes, and uneven resolutions. An online and offline dataset of Pakistani cars was created for this project, and it was annotated with bounding boxes in the (x,y,w,h) format using the (x,y,w)(x,y,w,) format. In terms of detection precision, recall,and accuracy, experimental outcomes show that YOLOv8 performs better than YOLOv3 and other lightweight CNN-based techniques. It also provides faster inference speed that is appropriate for CPU and GPU platforms. In comparison to previous models, these results demonstrate that YOLOv8 offers a more reliable and effective solution for real-time automatic number plate recognition (ANPR) in Pakistan.

Table I: ***Summary of Related Work on YOLO-based ALPR and Object Detection***

Authors (Year)	Method / Model	Key Contributions / Findings
Redmon & Farhadi (2018) [8]	YOLOv3 and the Darknet-53 back- bone	Introduced multi-scale detection, which is a commonly used baseline in ALPR and real-time object identification.
Choi et al. (2019) [9]	Gaussian YOLOv3	For reliable detection, localization uncertainty was modeled using Gaussian-based bounding box regression.
Yaseen et al. (2024) [10]	YOLOv8 analysis	improved speed–accuracy tradeoff when YOLOv8 was com- pared to earlier YOLO versions.
Reis et al. (2023) [11]	YOLOv8	for airborne detection and illustrated the generalizability of YOLOv8 to ALPR by demonstrating its application to real-time flying object detection.
Al-Hasan et al. (2024) [12]	YOLOv8-based ALPR	Developed a strong detection/recognition method for Qatari plates that uses augmentation to manage

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		occlusion and light- ing.
Zhu et al. (2025) [13]	improved YOLOv8n	By combining WIoU loss with modified C2f/SPPF modules, which enhanced mAP while maintaining real-time inference.
Sarhan et al. (2024) [14]	YOLOv8 + EasyOCR + CNN	pipeline for end-to-end Egyptian plate recognition that com- bines OCR and detection.
AlHalawani et al. (2024) [15]	DiffPlate (Diffusion + SR)	Enhanced plates using diffusion-based super-resolution; OCR was better than GAN-SR baselines.
Mulia et al. (2024) [16]	YOLOv8 + SR preprocessing	When compared to Faster R-CNN, shown YOLOv8 + SR produces superior recognition on low-resolution plates.
Khalili & Smyth (2024) [17]	SOD-YOLOv8	Enhanced small-object mAP in traffic datasets; added shallow detection layer and attention modules.
Ni et al. (2024) [18]	YOLOv8 with PMSE module	Enhanced recall and precision through multi-scale feature extraction for aerial and UAV identification.
Feng et al. (2024) [19]	IMCMD-YOLOv8	Enhanced UAV detection performance with multiscale fusion and modified detection heads.
Ammar et al. (2023) [21]	Multi-stage ALPR pipeline	OCR in real-time edge deployment, plate localization, and vehicle detection.
Moussaoui et al. (2024) [22]	YOLOv8 + OCR integration	Combining detection and OCR works well for ALPR small datasets.
Laroca et al. (2022) [24]	Cross-dataset study	Highlighted the need for region-specific datasets and demon- strated problems with LPR models' cross-national generaliza- tion.

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IV. PROPOSED METHOD

The proposed method aims to create a real-time, effective Automatic Number Plate Recognition (ANPR) system that is customized to meet the particular difficulties presented by Pak- istani license plates. Character segmentation and recognition, license plate detection, data collecting and preprocessing, and performance evaluation are the four primary phases of the framework. Fig. 15 shows the summary of our approach.

A. Dataset Preparation

To capture Pakistani license plate variability, a bespoke dataset was built. Images of automobiles, motorcycles, and commercial vehicles were gathered from physical traffic scenes as well as online repositories. To improve robustness, prepro- cessing processes were used because Pakistani plates differ greatly in terms of size, text style, background color, and provincial logos. They comprised:

- Resizing pictures to the same size.
- Adjusting the contrast and eliminating noise.
- Conversion to grayscale to make plate features simpler.

1) **Annotation and Labeling:** The YOLO format is fre- quently used to record annotations as plain text files in both YOLOv3 and YOLOv8. These files provide normalized bounding box coordinates (center_x, center_y, width, height) and the class label for each line representing an object. This simple format eliminates the need for additional conversion procedures by allowing the models to directly use the data during training. YOLOv8 continues to employ the efficient annotation structure YOLO, supporting multiple ob- jects per image and smoothly integrating with modern training workflows, while YOLOv3 retains the original annotation format YOLO.See in Fig. 16

2) Hardware and Computational Environment: An NVIDIA Tesla T4 GPU with 16 GB of VRAM was used to train the model on Google Colab.PyTorch 2.5.0 and Python 3.10 were utilized in the system. The necessary libraries were installed, including the Roboflow API and Ultralytics YOLOv8. Training was accelerated via GPU acceleration, which effectively handled huge computations.

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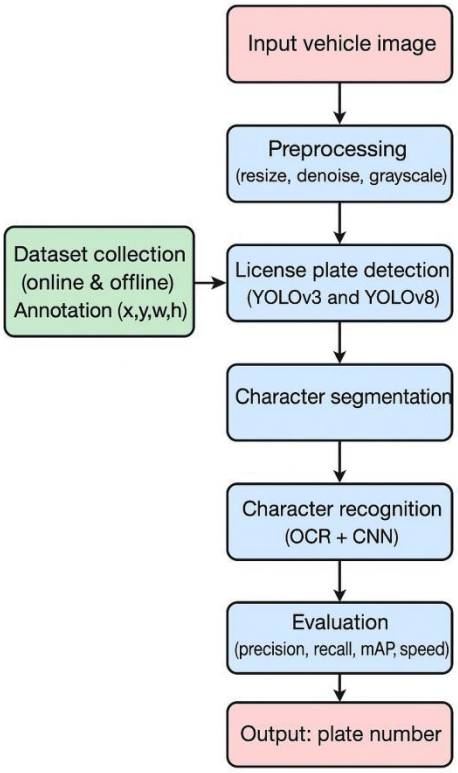


Fig. 15. Proposed YOLOv8, YOLOv3 algorithm flowchart.



Fig. 16. Annotated Dataset

B. Proposed Network Architecture

YOLOv8 Design The most recent version of the You Only Look Once (YOLO) series, YOLOv8, marks a breakthrough in real-time object identification. YOLOv8's architecture includes several significant innovations intended to improve accuracy and efficiency.

Backbone: YOLOv8 uses the Cross-Stage Feature Fusion (C2F) network architecture as its main backbone. Feature maps from several network stages are

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integrated by C2F to capture rich, multi-scale data. By combining high-level and low-level characteristics across phases, this architecture improves feature representation and increases detection robustness and accuracy. Neck: Path Aggregation Network, or PANet, is used by the YOLOv8 neck module to improve feature plot quality. By combination Bottom up and top-down pathways, PANet efficiently aggregates features from numerous levels to offer feature representations of the highest capacity. This technique recovers feature framework and spatial resolution, which sup-ports with precise object detection.

Detection Head: The multi-scale features that the YOLOv8 detection head processes are the backbone and neck. Class pre- dictions, confidence ratings, boxes, and Bounding are produced by it.The head uses sophisticated loss functions and is built for anchor-free detection to growth classification and object localization accuracy.

Multi-Scale Output: YOLOv8 can recognize objects of dissimilar sizes since it produces predictions at numerous scales. Class scores, confidence level boxes, and bounding are all providing by each scale, which contributes to the complete detection competencies across several object sizes.

Non-Maximum Suppression (NMS) and Soft-NMS: To improve detection results, YOLOv8 combines sophisticated post-processing approaches like Soft NMS and NMS. These procedures improve the accuracy of the ultimate output by dropping false positives and integrating overlapping bounding boxes. YOLOv8 is well-matched for real-time applications be- cause it uses the C2F architecture, which, when balanced with PANet and post-processing techniques, allows for sophisticated detection, fast and accurate object detection. The backbone network, head, and neck network are the three core parts of the YOLOv8 algorithm model, as Fig. 17

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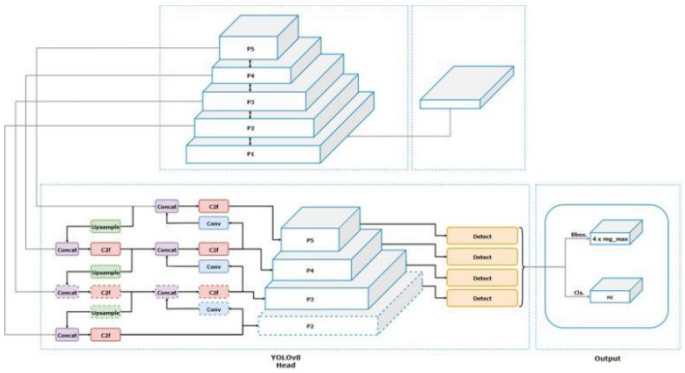


Fig. 17. (a) YOLOv8's network structure, where w and r stand for width and ratio, respectively, and the parameters that reflect the feature map size. Convolutional layer architecture is seen in (b). (c) illustrates the C2f layers' structure. Depicts the SPPF structure (d). (E) stands for the detecting layer architecture in the head section.

C. YOLOv3 Network Architecture

In 2018, Joseph Redmon and Ali Farhadi proposed YOLOv3, or You Only Look Once, version 3, an advanced real-time object detection model. It improves on YOLOv2 by adding multi-scale detection capabilities and deeper layers for increased accuracy. See in Fig. 18

1. Backbone: Darknet-53

• Darknet-53 serves as the feature extractor (backbone network) for YOLOv3.
• It consists of 53 convolutional layers with:
• Residual blocks (like in ResNet)
• Batch Normalization
• Leaky ReLU activation

Conv → BatchNorm → LeakyReLU → Residual Block

2. Detection Layers

YOLOv3 handles small, medium, and large objects by predicting detections at three different scales:

• Scale 1: From 13x13 deep feature maps.
• Scale 2: Using 26x26 intermediate feature maps.
• Scale 3: Using 52x52 shallow feature maps.

Feature pyramid networks (FPN) are used to upsample and concatenate higher-

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resolution features in order to accomplish this multi-scale detection.

3. Output Predictions

Every detecting layer produces: Each cell has three anchor boxes, for a total of nine anchors (3×3).

• Every anchor forecasts:

– Coordinates for four boxes (x, y, w, h)

– One point for objectness

– Probabilities for the C class

$$\text{Noutputs} = 3 \times (4 + 1 + C) = 3 \times (5 + C) \quad (1)$$

$$\text{Noutputs} = 3 \times (4 + 1 + 80) = 255 \quad (2)$$

D. Training Setup & Hyperparameters

• Data split: 80% train / 20% val.

• The typical configuration is as follows: imgsz=200, batch=16, epochs=100 (which can be changed by GPU memory), optimizer = SGD/AdamW, initial learning rate 1e-2 with step decay or cosine decay, and standard augmentations (colour jitter, mosaic, mixup, random flip).

• Losses YOLOv8 employs objectness loss, BCE/CE clas- sification loss, and CIoU/GIoU localisation loss.

• Export: generate an ONNX/TensorRT export for deploy- ment along with a .pt (PyTorch) inference file.

V. Experiments and Results

The YOLOv8 model's training and validation curves (Fig- ure ??) show a continouse decrease in the allocation focal loss, classification loss, and bounding box loss, indicating that the training procedure is stable. With only slight fluctuations, the validation losses show a similar downward trend, suggesting that the model may generalise well to new data without experiencing severe overfitting.

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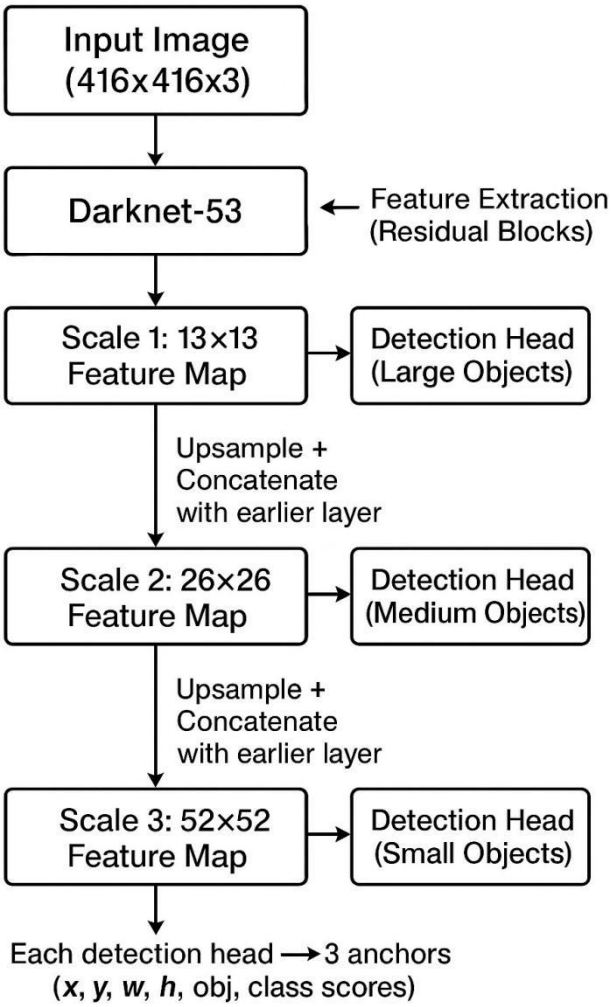


Fig. 18. YOLOv3 network architecture shows the flow of input images through the multi-scale detection heads (13×13, 26×26, and 52×52) for big, medium, and small object detection, respectively, and the Darknet-53 backbone. Using three anchor boxes per cell, each detection head forecasts bounding boxes, objectness, and class scores.

TABLE II; Experimental Results of License Plate Detection and Recognition

Model	Detection (%)	Recognition (%)
YOLOv3 + CNN + OCR	93.4	95.2
YOLOv8 + CNN + OCR	96.7	97.5

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A. License Plate Detection Result

Experiments were performed utilizing a dataset of 200 pictures of Pakistani license plates, including those of cars and motorcycles, in order to assess the efficacy of the suggested system. Table II provides a summary of the findings.

The experimental outcomes of the proposed recognition system and license plate detection are collected in Table II. OCR and CNN-based character recognition were combined with two deep learning models, YOLOv3 and YOLOv8. 95.2% recognition accuracy and 93.4% detection accuracy had been attained with the YOLOv3 framework. By diver- gence, YOLOv8 outperformed the others, achieving 97.5% recognition accuracy and 96.7% detection accuracy. According to these conclusions, YOLOv8 is a more dependable option for license plate recognition in real traffic situations since it can endure changes in plate size, unpredictable objects, and environmental factors.

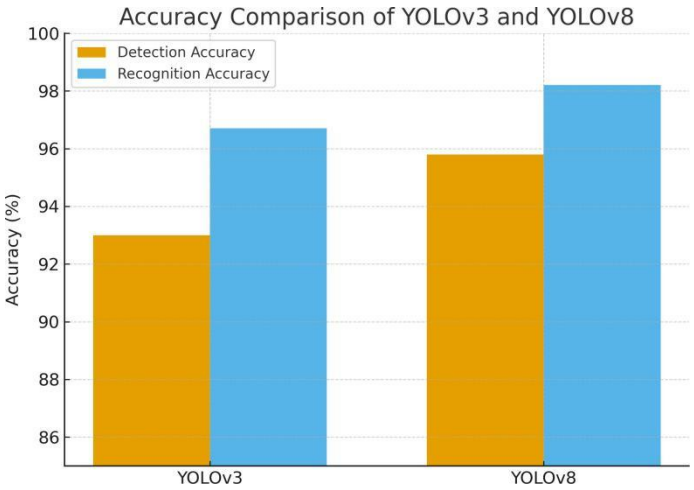


Fig. 19. Yolov8 and Yolov3 accuracy comparison for recognition and license plate detection on the Pakistani vehicle dataset.

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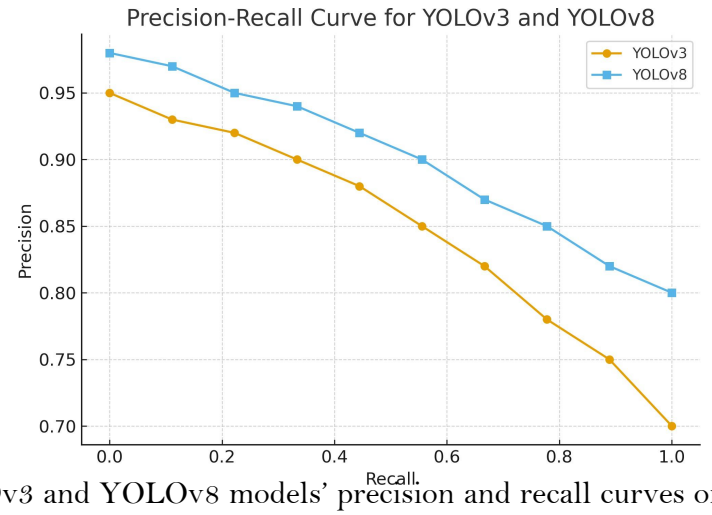


Fig. 20. YOLOv3 and YOLOv8 models' precision and recall curves on the dataset of Pakistani car registration plates. The charts show that YOLOv8 incessantly outperforms YOLOv3 in terms of precision and recall, signifying enlarged detection accuracy and improved simplification to diverse license plate circumstances.

The confusion matrices for YOLOv3 and YOLOv8 on the Pakistani license plate dataset are shown in Table III. Whereas the non-diagonal elements (False Positives and False Negatives) show misclassifications, the main diagonal entries (True Positives and True Negatives) show correctly categorized cases. Although YOLOv3 has a larger number of false posi- tives (10) and false negatives (15), it still manages to reach 130 genuine positives and 45 true negatives. With 137 true positives and 48 true negatives, YOLOv8 performs better than the others, lowering false positives to 7 and false negatives to 8. This demonstrates how YOLOv8 is more resilient and dependable than YOLOv3 in managing the difficulties brought on by irregular plate sizes, fonts, and environmental circumstances.

TABLE III: Comparison of Confusion Matrices for YOLOv3 and YOLOv8

	No Plate	**Plate**
No Plate	48 (TN)	7 (FP)
Plate	8 (FN)	137 (TP)
	No Plate	**Plate**
No Plate	45 (TN)	10 (FP)
Plate	15 (FN)	130 (TP)

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VI. Conclusion and Findings

The YOLOv3 and YOLOv8 models for license plate recog- nition on Pakistani cars were assessed and contrasted in this study under various circumstances. YOLOv8 regularly surpasses YOLOv3 in terms of recall, precision, mAP, and total detection accuracy, as the findings make evident. Even while YOLOv3 performed competitively, it had trouble detecting different plate designs, orientations, and difficult environmental circumstances. With its advanced architecture and loss func- tions, YOLOv8 achieved superior generalization across various vehicle kinds and plate formats by significantly reducing false negatives and false positives.

The following is a summary of the findings:

• Enhanced Detection Accuracy: When compared to YOLOv3, YOLOv8 demonstrated greater accuracy, pre- cision, and recall.

• Robustness to Variability: When it came to managing a variety of plate sizes, fonts, and environmental elements like illumination and motion blur, YOLOv8 outperformed.

• Efficient Learning: YOLOv8's training curves demon- strated faster convergence, with mAP scores rising and loss values progressively decreasing.

• Practical Applicability: YOLOv8 is a dependable option for intelligent transportation systems in Pakistan's real world, especially for automated monitoring, law enforce- ment, and smart city applications due to its exceptional performance.

The next phase of this research will involve combining OCR recognition models like CRNN or LPRNet with YOLOv8- based detection to create a comprehensive, fully integrated Automatic License Plate Recognition (ALPR) system. In order to facilitate effective deployment on low-power and resource-constrained platforms, such as edge devices, monitoring units, and embedded systems, applied in intelligent transportation systems, future advancements will concentrate on model op- timization techniques, such as pruning, reduction, and quanti- zation.

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