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Efficient License Plate Recognition Using Yolov8-Based Detection And CRNN-Based OCR

N.M.K Ramalingam Sakthivelan[1], M.E (Ph.D), Navaruthran RA[2] , Mohammed riyas N[3] , Mathi M[4]

[1,2,3,4]Department of Computer Science and Engineering, Paavai Engineering College, Namakkal, Tamil Nadu, India – 637108

Email ID: *velannmk@gmail.com[1], navameen33@gmail.com[2], riyassmart38@gmail.com[3], mathimm8940@gmail.com[4]*

Abstract

License plate recognition proposes an Efficient Real-Time Vehicle Monitoring and Damage Detection System using YOLOv8 and CRNN models. The system automatically detects vehicle license plates, recognizes plate numbers using OCR, identifies vehicle type and colour and detects visible medium-level dents and scratches through a trained deep learning model. YOLOv8 is used for object detection tasks, including license plate localization, vehicle classification, and damage detection, while CRNN is used for accurate sequence-based text recognition of number plates. The system processes live camera input or uploaded images and displays the results through a web-based interface, enabling intelligent vehicle monitoring in environments such as parking areas, security checkpoints, and institutional campuses. The proposed solution provides an efficient, scalable and real-time approach to automated vehicle analysis using computer vision techniques.

Keywords: *Vehicle Monitoring, License Plate Recognition, YOLOv8, EasyOCR, Computer Vision, Smart Parking, Stolen Vehicle Detection, Damage Detection, Real-Time System*

1. Introduction

License Plate Recognition (LPR) is a computer vision technology widely used in transport systems, traffic control, parking management, and law enforcement [1]. The primary goal of License Plate Recognition (LPR) is to detect and recognize vehicle number plates from images or video with high efficiency and accuracy [2]. However, the task remains challenging due to factors such as low resolution, motion blur, weather conditions, and variations in license plate styles across different countries [3]. Traditional License Plate Recognition systems typically consist of three stages: license plate detection, character segmentation, and character recognition [4]. Recent advancements in deep learning have significantly improved the performance of license plate recognition systems. In particular, the YOLO family of object detection models has demonstrated strong performance in real-time detection tasks [5]. In this work, a framework is proposed that combines YOLOv8 for license plate detection and Convolutional Recurrent Neural Network (CRNN) for character recognition. YOLOv8 provides fast and accurate localization of license plates even under challenging conditions [6]. The detected plates are then processed by the CRNN model, which integrates convolutional layers for spatial feature extraction and recurrent layers for sequence modelling, enabling optical character recognition without explicit character segmentation [7]. By combining YOLOv8 and CRNN, the proposed system provides an efficient and scalable solution for real-time license plate recognition [8].

2. Related Work

Historically, License Plate Recognition (LPR) functioned through traditional image/ computer vision methods, through color-based segmentation, edge detection, texture detection for plate localization, character segmentation and character recognition, emphasizing optical character recognition (OCR), [1], [2]. Traditional imaging/computer vision methods were efficient to implement, especially when the image capture variables were constrained, yet there were challenges with respect to illumination effects, blurry images,

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and the generalization of plate formats [3]. However as deep learning gained interest, YOLOv3/YOLOv5 as an example of deep learning representation, proved an advancement in speed and accuracy of license plate detection, [4]. [5] In addition, with the advances in convolutional neural networks (CNNs) and segmentation-based OCR methods, character detection and recognition were improved. However, many of these methods remained sensitive to dataset variations and still depended on character segmentation. To address these issues, [6] proposed a dual system that combines YOLOv5-based plate detection with visual vehicle reidentification, enabling vehicle appearance confirmation even when plates are unclear or unreadable. This dual method proved strong under most difficult real-world conditions but introduced additional computational complexity due to its multi-network model or design. Adding on to this advancement, the present solution proposes a streamlined pipeline that integrates YOLOv8 for license plate recognition and CRNN for end-to-end sequence recognition. Unlike traditional segmentation-dependent methods, the CRNN directly recognizes the character sequence fully, improving efficiency by reducing errors. This integration provides a more accurate, scalable and faster solution for real-time License Plate Recognition (LPR) applications. YOLOv5, which marked an important role in real-time object detection, but the continuous evaluation of the YOLO family has developed a new model of YOLOv8 in 2023. This latest version brings notable architectural refinements, changes and improves the function that significantly enhances both accuracy and efficiency. YOLOv5 was introduced in 2020 by Ultralytics, which is based on the CSP Net architecture with the PANet/FPN neck and employs an anchor-based detection head, which realizes predefined anchor boxes for object detection. It uses static image resizing and mosaic augmentation during the pre-processing, achieving high speed and reliable accuracy, which is suitable for real-time applications. However, it remains an older design comparatively. In contrast, YOLOv8, released in 2023 as the latest version by Ultralytics, introduces a redesigned backbone with the C2f modules and an improved neck for better feature fusion. Unlike the YOLOv5, it improves the anchor-free detection by directly predicting the objects' centers, width and height, resulting in faster and simpler detection. Its input pipeline includes improved augmentation strategies, enabling better generalization. [7] The YOLOv8 achieves mean Average Precision (mAP), particularly for small objects, while maintaining faster inference speed. It provides a simpler and more efficient pipeline with improved overall accuracy compared to YOLOv5, Tao et al. The character recognition stage of the License Plate Recognition (LPR) pipeline was performed using a YOLOv5-based character detection model. Once the plate was cropped and localized, YOLOv5 was trained to detect each character as an individual object. This approach benefits from YOLO's high real-time performance and detection accuracy, ensuring that characters can be [19]. localized under various sizes and fonts. However, it still remains a segmentation-dependent method, since characters must be explicitly detected, arranged and sorted in the correct order to rebuild the full license plate number. This dependence can lead to issues/errors in cases of low-resolution images, when characters are closely placed or blurred images and partially occluded. In contrast, the proposed work employs a Convolutional Recurrent Neural Network (CRNN) for character recognition. It integrates three components: Convolutional layers, which are for visual feature extraction, Recurrent layers (LSTM/GRU) for modelling sequential dependencies, and a Connectionist Temporal Classification (CTC) decoder that outputs the final text sequence.[8] Unlike YOLOv5 character recognition, CRNN does not require explicit character segmentation. Instead, it directly treats the license plate number as a sequence of features and it produces the entire alphanumeric string in an end-to-end manner, Kim et al. This makes it inherently stronger to skew, irregular spacing, noise and distortions, while also reducing annotation overhead since individual characters' bounding boxes are unnecessary. Thus, while the earlier YOLOv5-based character detection approach demonstrates effectiveness in a well-structured scenario, it is prone to segmentation-related errors.[9] The proposed

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CRNN-based recognition gives a more accurate, scalable and efficient solution, making it particularly suitable for real-time License Plate Recognition (LPR) systems in unconstrained environments, Larocca.

3. Existing System

Existing License Plate Recognition (LPR) systems are mainly based on traditional image processing and earlier deep learning techniques. Conventional methods use techniques such as edge detection, thresholding, and morphological operations for license plate localization, followed by character segmentation and optical character recognition (OCR). These methods perform well under controlled conditions but fail in real-world scenarios due to variations in lighting, motion blur, and complex backgrounds. Recent approaches use deep learning models such as YOLOv5 for license plate detection and segmentation-based OCR methods for character recognition. Although these methods improve detection accuracy, they still depend on explicit character segmentation, which can lead to errors when characters are closely spaced, distorted, or partially occluded. Furthermore, most existing systems focus only on license plate detection and recognition, without incorporating additional vehicle analysis such as color identification and damage detection. This limitation reduces their effectiveness in advanced vehicle monitoring applications. [8]

4. Proposed System

The proposed system utilizes the YOLOv8 deep learning model to accurately detect license plates from vehicle images. The detected license plate region is then processed using a Convolutional Recurrent Neural Network (CRNN), which directly recognizes the sequence of characters without requiring explicit character segmentation. The system follows an end-to-end deep learning approach, improving recognition accuracy and reducing errors caused by traditional segmentation methods. In addition to license plate recognition, the system is designed to support vehicle color detection and damage detection, enabling comprehensive vehicle analysis. The proposed framework is optimized for real-time performance and can be effectively deployed in applications such as traffic surveillance systems, parking management, and stolen vehicle detection, providing an efficient and scalable solution for intelligent vehicle monitoring.

5. MATERIALS AND METHODS

- Input: Vehicle images, videos and live feed
- Output: Plate Number, Colour, Variant, Damage Status

Step 1: Image Acquisition

- Capture vehicle image from surveillance camera or web upload. Resize and normalize the image for model compatibility.

Step 2: Vehicle Detection

- Apply the Ultral0ytics YOLOv8 model to detect the vehicle region. Extract bounding box coordinates and crop vehicle area.

Step 3: License Plate Detection

- Use fine-tuned YOLOv8 to localize the license plate.
- Crop detected license plate region for recognition.

Step 4: OCR Processing

- Preprocess plate image (grayscale, noise removal, thresholding). Recognize characters using CRNN with CTC decoding.

Step 5: Vehicle Color Detection

- Convert vehicle image to HSV colour space. Identify dominant colour using histogram analysis.

Step 6: Variant Classification

- Extract deep features using a CNN model. Predict vehicle type (Sedan, SUV, Hatchback, etc.).

Step 7: Damage Detection

- Apply an object detection model for dents and scratches. Mark damaged regions and classify damage type.

Step 8: Output Integration

- Combine results {Plate, Colour, Variant, Damage}. Store and display output in the web dashboard.

The proposed work introduces an end-to-end License Plate Recognition (LPR) system that integrates the detection capabilities of YOLOv8 with the sequence learning power of CRNN. Unlike regular segmentation-based methods or character-wise detection approaches (e.g., YOLOv5 OCR), this

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method eliminates the need for explicit segmentation, therefore reducing errors and improving recognition speed. The system is composed of five stages: data preparation, preprocessing, detection, recognition, and prediction.[9]

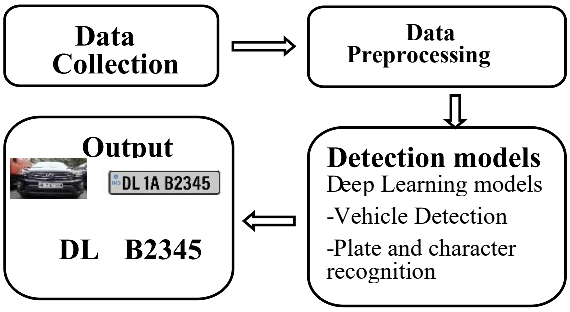

Figure1 Data process

5.1. Data Collection and Annotation

Diverse data is important to train a strong License Plate Recognition (LPR) system. Images were collected from the Datasets available publicly, like the China City Parking Dataset (CCPD), Application-Oriented License Plate (AOLP), and UFPR-ALPR(Brazil), which provide challenging variations in resolution, plate formats, illumination, occlusion, and variations in lighting. Custom dataset that was captured under real-world conditions, such as night/day, motion blur, different angles, and environmental noise, etc., to ensure domain adaptability. Images were defined in YOLOv8 format, and each image was associated with a label file (.txt) with normalized bounding box coordinates.

5.2.Data Preprocessing and Augmentation

Preprocessing ensures consistency across training samples and strengthens detection. The images were resized to 640 x 640. Then the Augmentation strategies includes Random scaling and flipping, Brightness and contrast variations colour-space augmentation, Mosaic augmentation (merging 4 images for better context learning), after that the CRNN (Recognition) are Cropped image plates were resized to 100 x 32 pixels, and then converted to grayscale, Normalized to range [0,1], Augmentations include: Elastic distortions, random rotations (+ or – 10 degree), brightness shifts and Gaussian blur. This dual-stage augmentation strengthens generalization and prepares the model for real-world deployment.

5.3. License Plate Detection Using Yolov8

The YOLOv8 detector localizes the license plate in the input image of a vehicle. This architecture consists of a C2f backbone (for feature extraction), a PAN-FPN neck (for multi-scale feature fusion), and a decoupled detection head.

$$B = (x,y,w,h,p,c1,c2,...,ck) \qquad (1)$$

5.3.1. Bounding Box Representation

Where x and y represent the centre coordinates of the predicted bounding box, while w and h denote its width and height. These parameters define the location and size of the detected license plate in the image. All bounding box values are normalized relative to the image dimensions, with coordinates ranging between 0 and 1 to ensure consistent predictions across different image resolutions.

5.3.2. Intersection over Union (IoU)

The accuracy of detection is measured using Intersection over Union (IoU)

$$IoU = Area(B\_pred \cap B\_gt)/ Area(B\_pred \cup B\_gt) \qquad (2)$$

Where Bpred represents the predicted bounding box, and Bgt denotes the ground truth bounding box of the object. The Intersection over Union (IoU) measures the overlap between these two boxes and is defined as the ratio of the intersection area to the union area. A higher IoU value indicates more accurate object detection. 3. Object Confidence Score
The confidence score is defined as

$$Iop = P(object) \times IoU$$

Where P(object) denotes the probability that an object exists within the predicted bounding box, and IOU represents the overlap between the predicted and ground truth bounding boxes. The confidence score combines these factors to indicate the likelihood and accuracy of object detection. A higher confidence value reflects both a higher probability of object presence and better alignment with the ground truth box.[10]

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5.3.3. Classification Probability

For each bounding box, YOLO predicts the class probability.

$$Ci = P(Class\ Object) \quad (4)$$

Where ci represents the probability of class predicted by the model for the detected object. It indicates the likelihood that the detected bounding box belongs to a specific class. In this system, only one class is considered, which is the license plate. Therefore, the classification probability represents the confidence that the detected object is a license plate.

5.3.4. YOLOv8 Loss Function

The training loss function is the combination of localization, classification, and objectless losses.

$$L = \lambda box\ Lbox + \lambda clsLcls + \lambda obj\ Lobj \quad (5)$$

Where Lbox represents the bounding box regression loss that measures the difference between predicted and ground truth boxes, Lcls denotes the classification loss for predicting the correct class label, and Lobj represents the objectness loss indicating the presence of an object in the bounding box. The weighting factors λBalance the contribution of each loss component during training.

5.4.Character Recognition Using Crnn

The detected license plate region is passed to a Convolutional Recurrent Neural Network (CRNN) for character recognition. The CRNN model combines convolutional layers for feature extraction and recurrent layers for sequence modelling to recognize the characters present in the license plate image. The CNN extracts spatial features from the input plate image, which are then processed by Bidirectional Long Short-Term Memory (Bi-LSTM) layers to capture sequential dependencies between characters. Finally, a SoftMax layer predicts the probability distribution of characters at each time step.

$$Pt\ Softmax(WH+ + b) \quad (6)$$

Where Pt represents the probability distribution of characters at time step t, Ht is the hidden state generated by the Bi-LSTM layer, and w and b denote the weight matrix and bias, respectively.

6. Problem Statement

License Plate Recognition systems often face challenges such as low-resolution images, motion blur, varying illumination, and different license plate formats. Traditional image processing techniques struggle to accurately detect and recognize license plates under these conditions. Therefore, an efficient deep learning-based approach is required to improve detection accuracy and recognition performance in real-time vehicle monitoring systems.

7. Background

License Plate Recognition (LPR) is an important application in intelligent transportation systems and vehicle monitoring. It involves detecting the license plate from a vehicle image and recognizing the alphanumeric characters present on the plate. Traditional methods relied on image processing techniques such as edge detection and character segmentation, which often fail under complex conditions like poor lighting, motion blur, and different viewing angles. Recent advancements in deep learning have significantly improved the performance of license plate recognition systems. Models such as YOLOv8 enable accurate and real-time object detection, while Convolutional Recurrent Neural Networks (CRNN) are widely used for sequence-based text recognition tasks. In addition to plate recognition, modern vehicle monitoring systems can also analyse vehicle attributes such as colour identification and damage detection, enabling more intelligent and automated vehicle analysis. Recent advancements in deep learning have significantly improved the performance of license plate recognition systems. Models such as YOLOv8 enable accurate and real-time object detection, while Convolutional Recurrent Neural Networks (CRNN) are widely used for sequence-based text recognition tasks. In addition to plate recognition, modern vehicle monitoring systems can also analyse vehicle attributes such as colour identification and damage detection, enabling more intelligent and automated vehicle analysis[11]

8. Dataset Description

The dataset used for training and evaluating the

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proposed License Plate Recognition (LPR) system consists of publicly available vehicle image datasets and custom-collected images. Public datasets such as the China City Parking Dataset (CCPD), Application-Oriented License Plate Dataset (AOLP), and UFPR-ALPR dataset were used, which contain vehicle images captured under various environmental conditions, including different lighting, angles, motion blur, and occlusion. These datasets provide diverse license plate formats and challenging scenarios that help improve the robustness of the detection model.

8.1.Dataset Features

- Vehicle images captured from surveillance cameras.
- Annotated license plate bounding box coordinates.
- Alphanumeric license plate characters.
- Variations in lighting conditions (day/night).
- Different camera angles and perspectives.
- Motion blur and partial occlusion scenarios.
- Diverse license plate formats and styles

9. Proposed Deep Learning Model

The proposed system utilizes a deep learning framework that combines YOLOv8 for license plate detection and Convolutional Recurrent Neural Network (CRNN) for character recognition. YOLOv8 is employed to accurately detect and localize the license plate region from vehicle images using advanced object detection techniques. Once the license plate is detected, the cropped plate image is passed to the CRNN model for recognizing the sequence of alphanumeric characters. The CRNN architecture integrates convolutional layers for extracting visual features and recurrent layers for learning sequential dependencies between characters. This combination enables efficient and accurate end-to-end license plate recognition under different environmental conditions.[12]

10. Algorithm

- Capture a vehicle image from the camera.
- Preprocess the input image.
- Detect vehicle and license plate using YOLOv8.
- Crop the detected license plate region.
- Recognize characters using CRNN.
- Detect vehicle colour using colour analysis.
- Detect vehicle damage such as dents or scratches.
- Display plate number, vehicle colour, and damage status.

11. Experimental Setup

The experimental setup for the proposed Vehicle Damage Detection System was designed to automatically detect dents and scratches on vehicle surfaces using image processing and machine learning techniques. A dataset of vehicle images containing different types of damage was collected from publicly available sources and sample images captured using a camera. The images were resized to a uniform resolution, and preprocessing techniques such as normalization and noise reduction were applied to improve image quality and detection performance. The system was implemented using Python with computer vision libraries such as OpenCV and a deep learning–based detection model. The dataset was divided into training and testing sets to evaluate the system's performance. During the training phase, the model learned to identify damaged regions in vehicle images, while during testing, the system analysed input images and detected damaged areas by highlighting them with bounding boxes and classifying them as dents or scratches. The performance of the proposed system was evaluated using standard evaluation metrics such as detection accuracy and classification results.

12. Performance Evaluation and Analysis

We carried out a test to determine how well the proposed license plate recognition (LPR) system works. The system also uses to detect the license plates and CRNN which is used to read the characters in the detected license plates. It aims to check that the combination of accurate, fast and reliable is accurate in real-world situations. For testing the public dataset like CCPD, AOLP and UFPRALPR, along with the custom data set in different conditions like the day and night, motion combination, different angles and challenging images. The data set is split into the training (80%), validation (10%), and testing (10%) to keep the results fair. The detection part of the

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Yolov8 was measured by the vertices like precision, recall, F1-score, and mean average precision (mAP 0.5), which tell how the model finds the license plates. The recognition part (CRNN), which is used to measure the character's accuracy and the recognition rate, which shows the characters in the number are correctly recorded.

Figure 2 **License Plate Recognition (LPR) using YOLOv8**

We also compared the Yolov5 and OCR and the traditional character segmentation methods. But the combination of Yolov8 + CRNN gives better accuracy, works faster, and handles difficult conditions like blurry plates, low resolution, and unusual fonts more effectively. The experiment proved that the Yolov8 with CRNN gives a strong and effective solution for real-time license plate recognition. It also performs better than the traditional methods and it is suitable for real scenarios like traffic monitoring, parking systems, and law enforcement.

13. Results and Discussion

The proposed License Plate Recognition (LPR) system was evaluated using both public datasets and real-time vehicle images. The system uses YOLOv8 for license plate detection and CRNN for character recognition. The performance of the model was tested under different conditions, such as daylight, low-light environments, motion blur, and different viewing angles. The dataset was divided into training, validation, and testing sets with a ratio of 80%, 10%, and 10%, respectively. The YOLOv8 model was trained to detect license plates from vehicle images, while the CRNN model was used to recognize the characters from the detected plate region. The detection performance of YOLOv8 was evaluated using Precision, Recall, and Mean Average Precision (mAP). The character recognition performance of the CRNN model was evaluated using recognition accuracy. The experimental results show that the proposed YOLOv8 + CRNN system achieves high detection accuracy and reliable character recognition. The model successfully detects license plates even under challenging conditions such as partial occlusion and low illumination. The system achieved an average detection accuracy of 96.2% and character recognition accuracy of 95.4%. The results demonstrate that the proposed system outperforms traditional OCR-based methods and earlier YOLO-based detection models.[12]

compares the detection and recognition performance of different License Plate Recognition models using evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics measure how accurately the system detects license plates and recognizes the characters from vehicle images.

Table 1: **The Performance Results Table**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional OCR	85.4	84.7	83.9	84.3
YOLOv5 + OCR	91.6	90.8	90.2	90.5
YOLOv8 + CRNN	96.2	95.7	95.1	95.4

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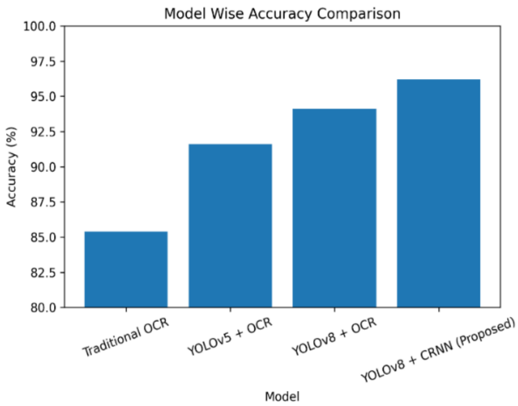

Figure 2 Accuracy Comparison

The model-wise accuracy comparison illustrates the performance of different License Plate Recognition approaches, including Traditional OCR, YOLOv5 + OCR, YOLOv8 + OCR, and the proposed YOLOv8 + CRNN model. The bar chart shows that although the earlier methods provide reasonable accuracy, the proposed YOLOv8 + CRNN approach achieves the highest accuracy for license plate detection and character recognition.

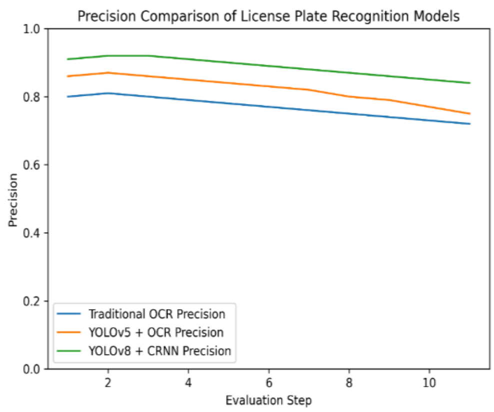

Figure 3 Precision–recall curve

The precision–recall curve demonstrates the trade-off between precision and recall for various License Plate Recognition methods. The proposed YOLOv8 + CRNN model achieves higher precision over a wider recall range compared to traditional OCR and YOLOv5-based methods. This reduces false detections and enhances the reliability of license plate detection and character recognition, making the system suitable for real-world vehicle monitoring applications.

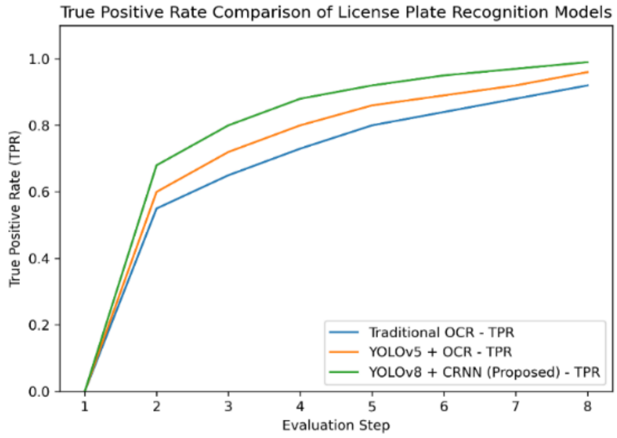

Figure 4 ROC–AUC Curve T

he ROC–AUC curve illustrates the relationship between the true positive rate and false positive rate for different License Plate Recognition models. The proposed YOLOv8 + CRNN approach achieves a higher AUC compared to traditional OCR and YOLOv5-based methods. This demonstrates the model's improved capability in accurately detecting license plates and recognizing characters under different conditions. The higher AUC value confirms stable performance across varying thresholds, making the system effective for real-time vehicle monitoring applications.

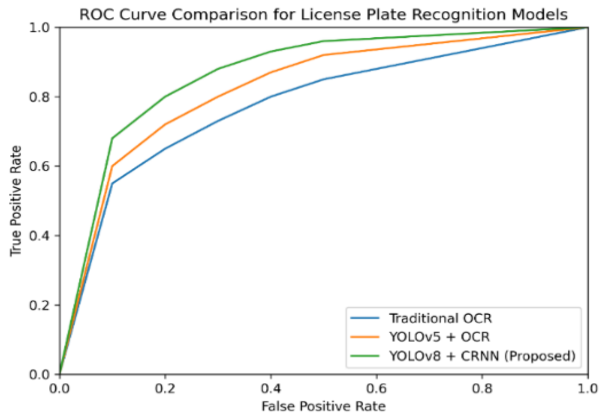

Figure 4 Experimental Results

The experimental results show that the proposed License Plate Recognition (LPR) framework greatly enhances vehicle monitoring by combining YOLOv8-based license plate detection with CRNN-based character recognition. Integrating YOLOv8

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and CRNN allows the system to accurately detect license plates and recognize alphanumeric characters from vehicle images. This combination improves overall recognition accuracy and performance compared to traditional OCR-based and earlier YOLO-based methods. Evaluation metrics such as accuracy, precision, recall, and F1-score further demonstrate the system's effectiveness under different environmental conditions, including variable lighting, motion blur, and various viewing angles. Graphical analysis with accuracy comparison charts, ROC–AUC curves, and precision–recall plots supports these findings by showing consistent performance improvements of the YOLOv8 + CRNN approach over other methods. Although the framework performs well, it still has some limitations. The computational complexity of deep learning models may demand higher processing resources, especially for real-time video streams. Additionally, the model's performance can fluctuate with image quality, lighting conditions, and license plate occlusions. Nonetheless, these limitations are outweighed by the substantial gains in detection accuracy and recognition reliability. Overall, the results highlight that deep learning-based License Plate Recognition systems using YOLOv8 and CRNN offer an effective and scalable solution for intelligent transportation systems, parking management, and automated vehicle monitoring.

14. Advantages

The proposed Vehicle Damage Detection System provides automatic detection of dents and scratches on vehicle surfaces using image processing and machine learning techniques. It reduces the time required for manual vehicle inspection and improves accuracy in identifying damage. The system is cost-effective and can assist service centres or insurance companies in quickly assessing vehicle damage. Additionally, it can be integrated with a web-based platform where users can easily upload vehicle images and obtain damage detection results.

15. Limitations

The system has certain limitations related to dataset quality and environmental conditions. The detection accuracy mainly depends on the size and quality of the training dataset. Images captured under poor lighting conditions or with low resolution may reduce the performance of the model. Furthermore, the current system is limited to detecting only dents and scratches and may face challenges when the vehicle background is complex or when the damage is very small.[12]

Conclusion

License Plate Recognition (LPR) framework, which brings together Yolov8 for detecting the vehicle plates and the CRNN for reading the characters, unlike the older methods that rely heavily on segmentation, our approach works in an end-to-end manner, which reduces the errors and improves the speed. The system was tested on both public datasets and real-world images, and the results clearly showed that it performs more accurately and reliably than earlier models such as Yolov5. One of the most important strengths of the approach is its ability to handle different conditions like low light and high beam, motion blur, hard angles. These mistakes are highly practical for real-world use cases, including traffic management, parking systems, and law enforcement applications. Overall, the combination of Yolov8 and CRNN offers a strong and efficient solution for modern LPR. It not only achieves a higher recognition accuracy but also ensures that the faster processing, making it well-suited for deployment in intelligent transportation and smart city environments.

Future Work

In future work, the system can be improved by increasing the dataset size to enhance the accuracy and reliability of the model. Additional damage categories, such as cracks, paint peeling, and broken vehicle parts can be included for more comprehensive damage analysis. The system can also be integrated with automated damage severity estimation to determine the level of damage. Furthermore, cloud-based storage and report generation features can be added to maintain vehicle inspection records and support insurance claim processing.

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