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An Efficient Deep Learning Approach for Automatic License Plate Detection with Novel Feature Extraction

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Abstract

In the domain of traffic management, road toll collection, and parking lot systems, vehicle number plate detection and identification play a pivotal role. Unlike conventional methods that treat license plate detection and character recognition as separate tasks, the system simultaneously addresses both challenges within a single neural network. Our Proposed methodology capitalizes on the efficiency and accuracy of the one-stage object detection algorithm known as YOLO (You Only Look Once) to locate license plates under diverse and challenging conditions. To augment the quality of input images with low resolution or poor clarity, we employ super-resolution generative adversarial networks (SRGANs). The image enhancement process substantially improves the visual quality of captured license plate images, facilitating more precise character recognition. Quantitative assessment of propounded system reveals compelling results. The license plate detection component achieves an outstanding average accuracy rate of 98.5%, surpassing previous methods by 15.2%. This comprehensive approach not only reduces the dependency on manual labour but also elevates processing precision. It seamlessly integrates into existing transportation infrastructure, resulting in heightened operational efficiency, reduced traffic congestion, and enhanced security measures. The rapid evolution of neural networks and deep learning techniques has streamlined the deployment of such applications, revolutionizing the field of traffic monitoring and management with unprecedented ease and precision. One-stage object detector, widely referred to as YOLO, is used to find licence plates in difficult circumstances.

Keywords: computer vision; traffic monitoring; road tolls; number plate detection; single network, YOLO.

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1. Introduction

Keeping a handwritten account of every car in the world today may not be feasible due to the growing number of automobiles. It takes time since it takes labour to write down the number. Moreover, manually saved data becomes inaccessible with time [1]. We thus created a system that would automatically detect the number plate that shows in Fig.1. and save it in its database in order to solveall of these issues. The information can be accessed later on as needed. Compared to a manually produced output, our approach produces the proper one [5]. The technology automatically collects and retainsphotographs as soon as the vehicle reaches the designated region, according to the functioning procedure [2]. The number plate detecting software that is installed on the machine is used to process the image. The gate opens if the vehicle fits the information that has been saved. The vehicle is not permitted to pass the gate and additional checks are conducted if it does not match or is listed on the blocked list. Number plate detection is a feature of service and contemporary transportation systems designed to enhance driver activity in the traffic [3]. In law and judiciary conditions relating to license plate detection and assessing fines, and restricting access to specific various kind of cars, number plate detection technologyused [4]. The Python programminglanguage is employed throughout the system. The contribution of the paper is the propounded model distinguishes itself by simultaneously addressing both license plate detection and character identification within a single neural network. By leveraging state-of-the-art one-stage object detection techniques like YOLO and employing super-resolution generative adversarial networks for image enhancement. our system achieves remarkable results in terms of both detection accuracy and character recognition performance. This paper is fractionally divided into five parts. The relevant work is described in Section 2. Section 3 of this paper discusses the proposed methodology. The fourth section illustrates the execution of the propounded framework and compares its accuracy to that of existing models. The conclusion of this paper is presented in Section 5.

Fig.1. Number plate at Parking

2. Related Work

The licence plate recognition system was created using a convolutional neural network [8]. The camera image is preprocessed by binarizing, noise- reducing, and converting it from RGB to grayscale. Using the linked element technique, which is based on parcels with main and minor length axes, area, and bounding boxes, the number plate is also detected. The uprooted licence plate textbook is divided into vertical and perpendicular reviews. A convolutional neural network finally recognized these characters (CNN) [14]. The automated system possesses three primary parts: character segmentation, number plate detection, and character recognition. A Holden Special Vehicles picture with number plate recognition is used as the new image input, and certain pollutants are sentforward. To identify the number plate, overlay CNN on the image as well [11]. The picture goes through further pre-processing during character segmentation. The characters in the picture were recognized using the alternative CNNmodel. Convolutional neural networks have recently gained popularity in moderntimes thanks to the rapid advancement of deep learning [16]. Number Plate identification was also recovered based on shallow to deep and progressively complicated networks, in line with this trend. Adoption of well-known network topologies like [10]. YOLO and its modifications are one of them. Deep learning technology has been used to CNN [12] shown in Fig.2. Because to itssuperior feature extraction capabilitiesover competing methods, CNN hasachieved great success in the fields of computer vision and image processing.

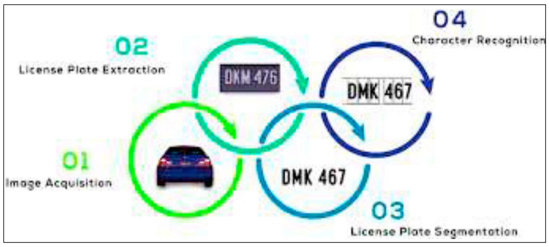

Fig.2. Related Work

3. Proposed Work

The purpose of the vehicle being utilized is a significant contributing factor to the occurrence of congestion in traffic and infractions. Number Plate Detection seeks to optimize the management of traffic flow and minimize instances of traffic violations through the implementation of automated systems. Although ANPR frameworks are frequentlyemployed in India, their effectiveness is quite low. The recommended strategy is to enhance and increase efficiency. The system underwent initial training through the Object Identification Technique (OIT).

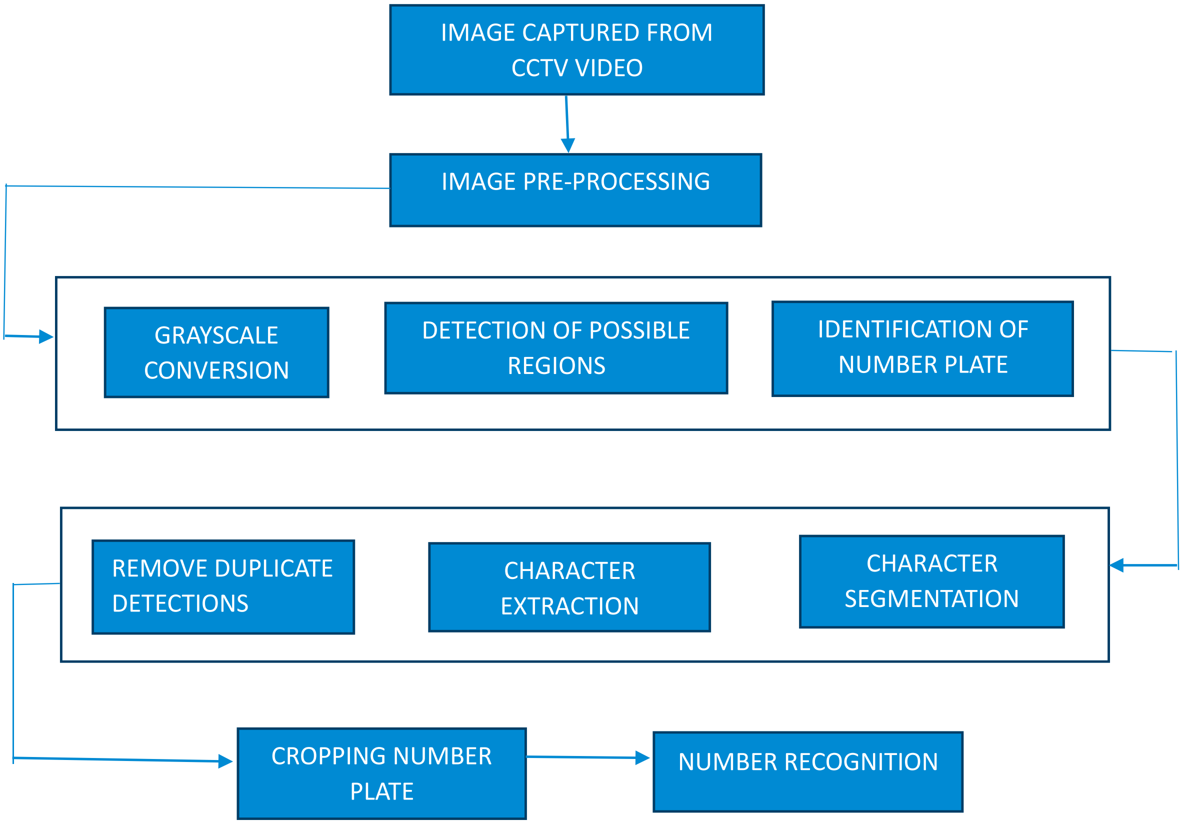

Fig.3. Block Diagram of YOLO

This approach, while not spectacular, is adequate for detection. a framework for image AI with high identification abilities.Python was incorporated in the development process, and OIT was utilized for training the automated system with vehicle and licence plate recognition. Fig. 3. shows the Block Diagram of YOLO.

4. Methodology Loading the Vehicle image

The system receives the image once it has been taken. Following the determination of the plate's placement inside the vehicle picture, the plate is forwarded to the following stage for scaling. a sample CCTV recorded input picture for the number plate detection system.

4.1. Conversion of Original image to Grayscale

As grayscale photographs can be handled more quickly than coloured ones, the original image is changed to grayscale in this stage. The following equation transforms the colour picture to a 256-grayscale image [1].

$$\mathbf{AGL = (3AR + 6AG + AB)/10} \tag{1}$$

where AGL denotes the converted grey level picture. The R, G, and B spectrums of the coloured picture are represented by AR, AG, and AB, respectively. Blurring isused after grey scaling to eliminate noise and distortion from the image. The Gaussian filter is applied to the greyscale image, and unnecessary features and noiseare removed. Equation depicts Gaussian blur 2-d. [1].

$$g(x,) = \frac{1}{2\pi\vartheta^2} e^{\frac{i^2+j^2}{2\vartheta^2}} \tag{2}$$

The standard deviation of a Gaussian distribution is, where i stands for the distance estimated from the origin along the horizontal axis and j for the distance determined from the origin along the vertical axis. The adoption of Gaussian distribution values facilitates the generation of a convolution matrix, which is subsequently employed for the purpose of applying modifications to the original image. The new value of each pixel is determined by computing a weighted average of the values of its adjacent pixels. The original pixels will receive the largest weight allocation, and the nearby pixel will receive a lower weight. The result will be a smoothed picture that better preserves borders and boundaries than others. Image converts original into gray scale shown in Fig.4.

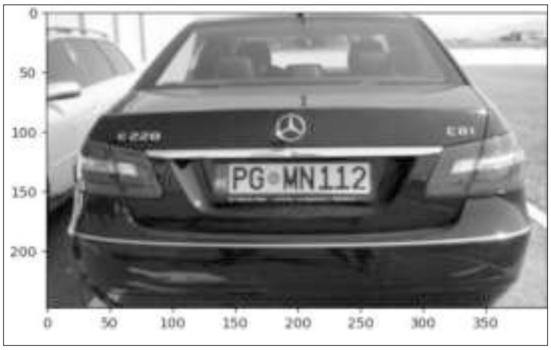

Fig.4. Conversion of OriginalImage to Grayscale

4.2. Filter and Edge Detection

Filters and edges are both useful techniques in number plate detection, with filters used to pre-process the image to isolate the number plate area and reduce noise, and edge detection used to extract the characters and digits on the number plate shown in Fig. 5.

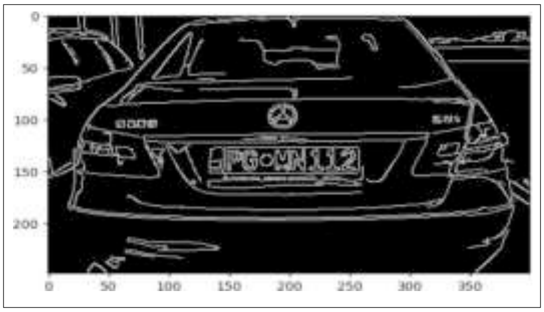

Fig.5. Applying filter and edges

4.3. Number Plate Area Detection

Finding all the contours in the picture is necessary and some refinement so that we can focus on the license plate's areas where the curve width is greater than the curve height [13]. This is because the breadth of the number plate typically exceeds its height. The number plate region from the picture is retrieved the pre-processingstage. The position of the detected plate is now in the indicated region. Number plate area detection is a crucial step in number plate detection, as it enables subsequent processing steps to focus on only the relevant part of the image, reducing computation time and increasing the accuracy of the detection system shown in Fig.6.

Fig.6. Number Plate area detection minimizing the number Plate area

Further proceeding is to create a new image by cropping the designated region, then processing the newly created image. This will make it easier to see and interpret each character when it appears inthe new picture shown in Fig 7.

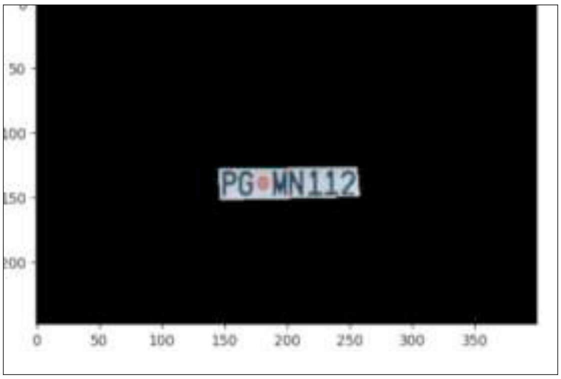

Fig.7. Minimizing the number plate area

4.4. Number Plate Identification

Identification of the number plate using LSTM (Long Short-Term Memory) is a crucial component in an Automatic Number Plate Recognition (ANPR) system. This step involves recognizing and extracting the characters or digits from the detected number plate region. The LSTM is a variant of the recurrent neural network (RNN) architecture that demonstrates exceptional performance in the realm of sequential data processing, making it very appropriate for the present undertaking. In this step, the cropped number plate region is divided into smaller segments, each containing a single character. These character segments are preprocessed to enhance their visibility and remove any noise or artifacts. Then, they are fed into the LSTM-based model, which has been trained to recognize characters.

The LSTM model learns the temporal dependencies and patterns within the sequence of character segments, which is crucial for accurate character recognition. It can handle variations in character fonts, sizes, and orientations, making it robust in different scenarios. As the model processes each character segment, it assigns a probability distribution over possible character. Decoding techniques like beam search or argmax are often used to convert these distributions into actual characters.

The LSTM-based character recognition step plays a pivotal role in ANPR accuracy and robustness. It allows the system to accurately read and interpret license plate information, providing valuable data for various applications such as traffic management, parking enforcement, and security.

4.5. Character Segmentation

The process of character segmentation involves removing the letters and numbers from the picture of a licence plate shown in Figure 8. The character segmentation work is hampered by a variety of factors, including picture noise, plate frame, space mark, plate rotation, and light variation [7]. To address these issues, a variety of character segmentation techniques have been proposed. We followed the steps outlined in a prior study. Segmenting each designated character into distinct pictures-based character recognition system [6]. Using Easy OCR to read the text shown in Fig.8., Character segmentation is a crucial step in license plate detection and requires a combination of image processing and deep learning techniques to accurately identify and separate the individual characters in a license plate image real [15].

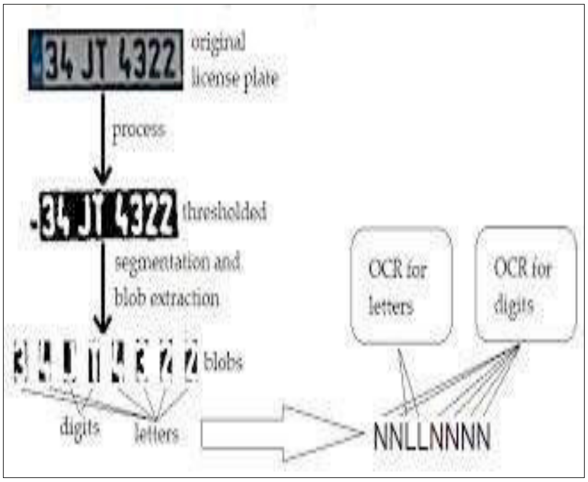

Fig.8. Reading the text

4.6. Remove Duplicate Detections

Removing duplicate detections is a critical post-processing step in object detection tasks, including Automatic Number Plate Recognition (ANPR). One of the most widely used techniques for duplicate removal is Non-Maximum Suppression (NMS). NMS is a systematic and efficient method that post-processes the output of the detection model. It operates by considering the confidence scores associated with each detection. The steps involved in NMS are as follows:

Step 1: Sort Detections- Begin by sorting all the detections in descending order based on their confidence scores. Higher confidence scores indicate a more reliable detection.

Step 2: Select the Highest Confidence Detection - Start with the detection having the highest confidence score, and consider it as a legitimate detection.

Step 3: IoU (Intersection over Union) Calculation- Calculate the IoU between this selected detection and all the remaining detections. IoU measures the overlap between bounding boxes. If the IoU of a detection with the selected detection exceeds a predefined threshold (e.g., 0.5), it is considered a duplicate.

Step 4: Discard Duplicates - Remove duplicate detections by discarding those with high IoU values compared to the selected detection. Only the detection with the highest confidence score within a group of duplicates is retained.

Step 5: Repeat-Repeat steps 2 to 4 until all detections have been considered.

The result of this process is a set of non-overlapping bounding boxes, each associated with a single object. This post-processing step ensures that the ANPR system outputs clean and distinct license plate detections, reducing redundancy and facilitating accurate character recognition. While LSTM is not directly involved in duplicate detection, it's essential to maintain a professional and accurate approach to this crucial post-processing task to enhance the overall efficiency and reliability of an ANPR system.

5. Result and Discussion

This section outlines the outcomes gained as a result of carrying out the suggested tasks. The various datasets were gathered in the beginning. The system stores the source photos and xml lines for the datasetin different flyers for test and training images. Real-time picture input is transformed to frames. The neural network model was given one image frame to develop the quality [9]. Fig.9. shows the final output.

Fig.9. Number Plate Detection

The propounded YOLO detection model in account is subjected to a comprehensive analysis, focusing on distinct measures of performance. The outcomes of the propounded deep learning algorithm are computed, and parameters such as accuracy, precision, and recall are evaluated within the training datasets to assess their applicability and estimate their significance. The performance evaluation of the proposed YOLO and the existing models such as the Region-based Convolutional Neural Networks (R-CNN), Deep Q-Networks, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), LSTM , GRU (Gated Recurrent Unit), Deep Neural Networks (DNNs) are shown in figure 10, 11 and 12.

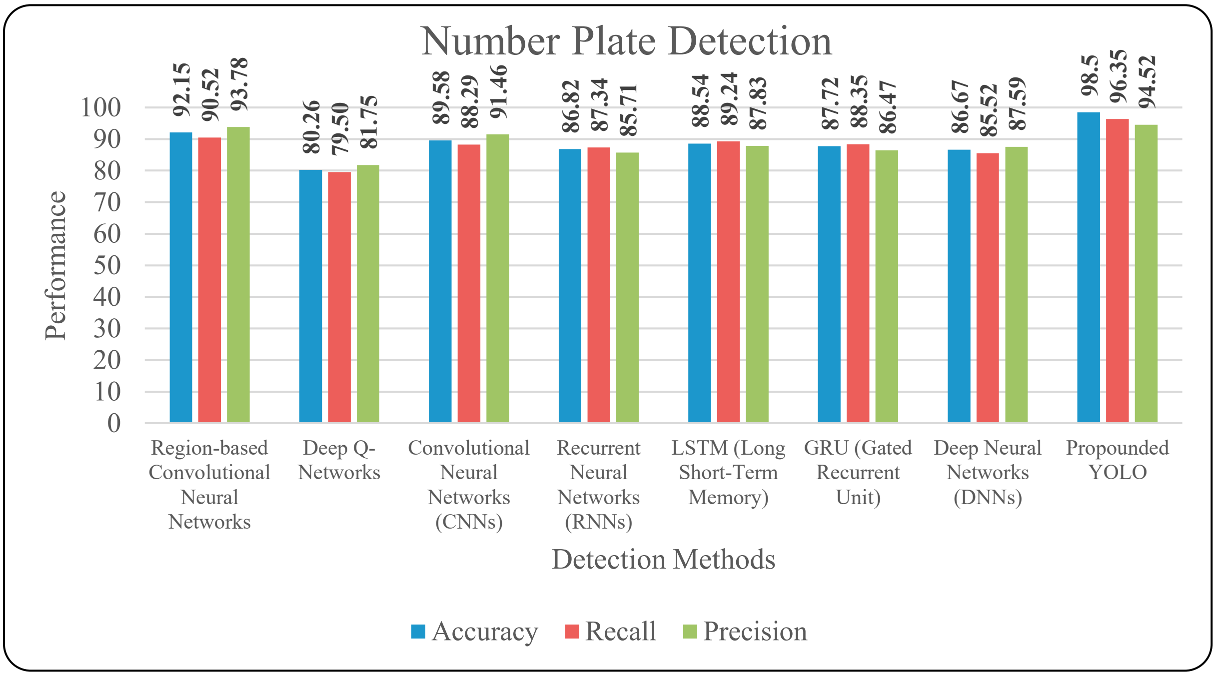

Fig.10. Performance Analysis of Number Plate Detection

Figure 10 flaunts the performance analysis for number plate detection. The existing R-CNN model has 93.78% precision value, Deep Q- Networks has 81.75% precision value, CNNs, RNNs has 91.46%, 85.71% precision value. The LSTM, GRU and DNNs has 87.83%, 86.47%, 87.59% precision value. The propounded YOLO framework has 94.52% precision which is 10.43% higher than the traditional approaches. The existing R-CNN model has 90.52% recall value, Deep Q- Networks has 79.50% recall value, CNNs, RNNs has 88.29%, 87.34% recall value. The LSTM, GRU and DNNs has 89.24%, 88.35%, 85.52% of recall value. The propounded YOLO framework has 96.35% recall value that is 12% higher than the traditional approaches. The existing R-CNN model has 92.15% accuracy value, Deep Q- Networks has 80.26% accuracy value, CNNs, RNNs has 89.58%, 86.82% accuracy value. The LSTM, GRU and DNNs has 88.54%, 87.72%, 86.67% of accuracy value. The propounded YOLO framework has 98.5% of accuracy which is 12% higher than the traditional approaches.

Fig.11. Performance Analysis of Letter Detection

Figure 11 flaunts the performance analysis for letter detection. The existing R-CNN model has 92.83% precision value, Deep Q- Networks has 80.65% precision value, CNNs, RNNs has 90.62%, 84.68% precision value. The LSTM, GRU and DNNs has 86.38%, 85.74%, 86.75% of precision. The propounded YOLO framework has 92.48% precision value that is 8% higher than the traditional approaches. The existing R-CNN model has 89.64% recall value, Deep Q-Networks has 78.35% recall value, CNNs, RNNs has 87.72%, 86.43% recall value. The LSTM, GRU and DNNs has 88.42%, 87.45%, 84.25% of recall. The propounded YOLO model has 94.62% recall value that is 11% higher than the traditional approaches. The existing R-CNN model has 91.35% accuracy value, Deep Q- Networks has 79.62% accuracy value, CNNs, RNNs has 88.85%, 85.28% accuracy value. The LSTM, GRU and DNNs has 87.45%, 86.27%, 85.67% of accuracy. The propounded YOLO model has 97% accuracy which is 15% higher than the traditional approaches.

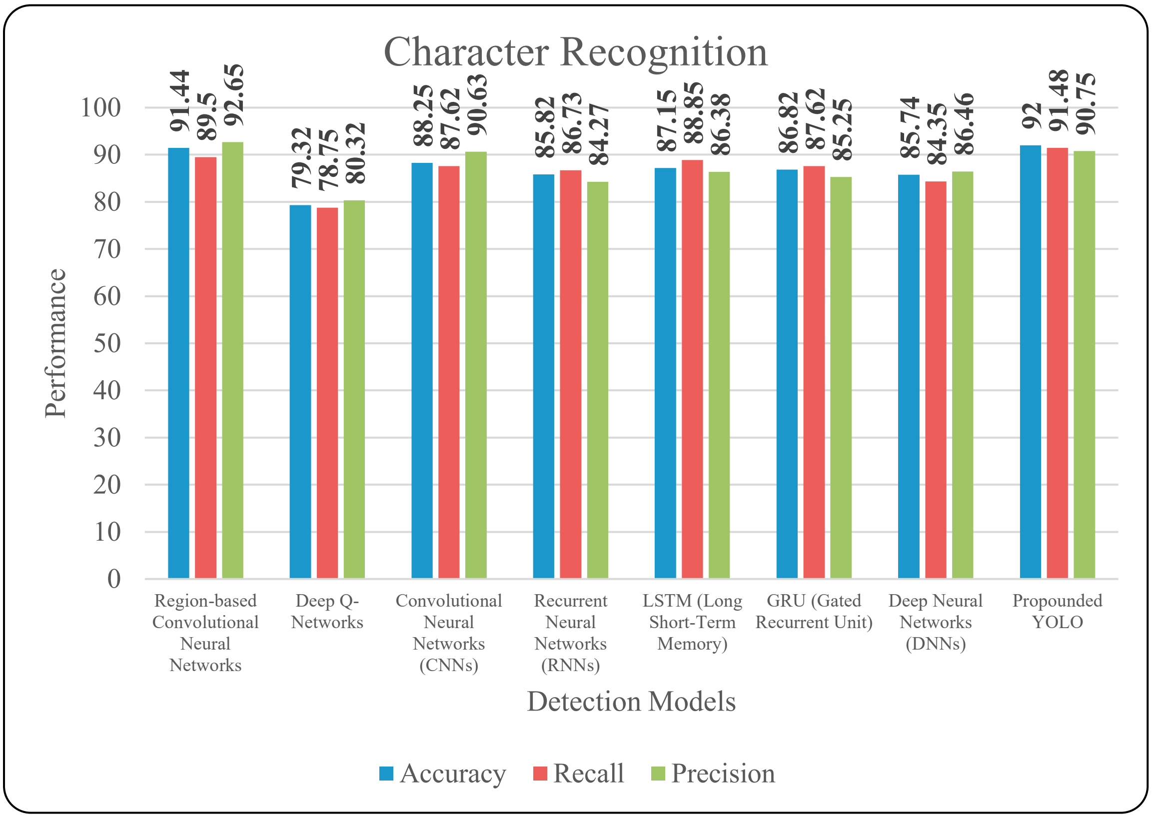

Fig.12. Performance Analysis of Character Recognition

Figure 12 flaunts the performance analysis for character recognition. The existing R-CNN model has 92.65% precision value, Deep Q- Networks has 80.32% precision value, CNNs, RNNs has 90.63%, 84.27% precision value. The LSTM, GRU and DNNs has 86.38%, 85.25%, 86.46% of precision. The propounded YOLO framework has 90.75% precision which is 5% higher than the traditional approaches. The existing R-CNN model has 89.50% recall value, Deep Q- Networks has 78.75% recall value, CNNs, RNNs has 87.62%, 86.73% recall value. The LSTM, GRU and DNNs has 88.85%, 87.62%, 84.35% of recall value. The propounded YOLO framework has 91.48% recall value that is 8% higher than the traditional approaches. The existing R-CNN model has 91.44% accuracy value, Deep Q-Networks has 79.32% accuracy value, CNNs, RNNs has 88.25%, 85.82% accuracy value. The LSTM, GRU and DNNs has 87.15%, 86.82%, 85.74% of accuracy value. The propounded YOLO framework has 92% accuracy value that is 9% higher than the traditional approaches.

6. Conclusion

In conclusion, license plate detection represents a pivotal challenge in computer vision, with diverse applications spanning management, parking administration, and the legal sector. The advancements in deep learning algorithms have significantly simplified the task of achieving accurate license plate detection. Nevertheless, the complexities persist due to the inherent variations in plate sizes, positions, and lighting conditions, necessitating ongoing research efforts to enhance the reliability of license plate detection algorithms. The propounded methodology furnishes the average accuracy rate of 98.5% which is 15.2% higher than the traditional mechanism. Despite these formidable challenges, practical implementations of license plate recognition systems have demonstrated their effectiveness in various real-world scenarios. With the continuous evolution of computer vision technology, researchers can confidently anticipate the emergence of even more precise and dependable systems in the foreseeable future.

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