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Automatic Number Plate Recognition for Seamless Toll Charging Without Stopping

AbdulMunem Abbas Hussein[1*]
[1]Department of Computer and Communications, Faculty of Engineering, Islamic University of Lebanon, Wardanieh, Lebanon.
*Corresponding Author.

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Abstract
Automatic Number Plate Recognition (ANPR) technology has offered a good solution tool for automating toll collection system processing and contributing solutions to complications such as traffic congestion, environmental problems, and operational inefficiencies. The investigation focuses on improving and organizing an ANPR-based system to allow smooth toll charging and letting cars pass through toll gates without pausing. The suggested system uses a deep learning algorithm and developed image processing techniques to consistently detect and recognize license plates of vehicles in real-time, even in difficult conditions, for instance, fast motion, low lighting, and bad weather. The ANPR system is connected to a centralized database and an automated billing system, confirming secure and real-time transactions. This method removes the need for manual intervention, decreases wait times, and improves user convenience. In addition, the system is designed to be adaptable to manage large traffic volumes while preserving both accuracy and efficiency. Extensive experimental evaluations were conducted to validate the system's performance, demonstrating high recognition accuracy, robust reliability, and minimal processing delays. By automating tolling operations, this solution improves the overall user experience and contributes to reduced vehicle emissions and energy consumption, aligning with sustainable transportation goals. The findings of this research underscore the potential of ANPR technology to revolutionize tolling systems and provide a blueprint for its large-scale deployment in smart transportation networks worldwide.
Keywords: ANPR, Electronic toll collection, Plate recognition, CNN, CRNN.

1. Introduction
Highways have historically been a significant part of virtually all countries' transportation infrastructure. Tolls are collected through manual systems and are based on a cash economy. Road classic systems in the form of toll collection barriers are primarily used at motorway entrances, which only allow vehicles with the appropriate transponder to pass through. If a toll violation is

detected manually, the fee and penalty are invoiced to the vehicle's owner, usually on the spot (1, 2). The traditional toll collection methods are cash or token-based collection or Radio Frequency Identification (RFID) card-based collection. Still, both have drawbacks, such as traffic congestion at toll plazas and high capital expenditure. The cash and token-based collections are manual, requiring human labor, and hence are prone to human error (3-6). Due to rapid technological development, mostly occurring in computer vision, communication, and sensor-based systems, it is now possible for any vehicle to be charged through a fully automatic system. Many of the larger countries have experimented with optical-based systems in recent years. These systems were also called all-time zero barriers systems, where no drivers had to stop and were charged based on license plates or transponders. Implementing a toll collection system aims to expedite vehicle flow, reduce pollution, and increase security. Considerable benefits can be foreseen by rendering this system fully automatic to control vehicles and charge almost silently (7-10). Despite featuring the best availability of microelectronics, remote sensing technology, and robust software systems, toll collection systems still suffer from several issues that directly impact their effectiveness and efficiency. Each method for identifying a vehicle arriving at a toll point has limitations. The optical devices sometimes fail to identify and recognize the enrolled vehicles due to light reflections and some specially painted vehicles (11). Some Electronic Toll Collection (ETC) technologies, such as touch cards, might fail to respond in extremely hot and cold conditions. Additionally, electronic devices used to keep the touch cards or RFID tags placed mainly in or near windscreens for recognition are not attached correctly in some vehicles. As a result, this might lead to vehicles remaining unidentified. Due to these and other reasons, some vehicles using toll facilities might have evaded their toll obligations until now (12-17). To address these issues and to have a more acceptable, suitably identified technology, we resort to Automatic Number Plate Recognition (ANPR), as it is more compact for the unique identification of vehicles. With a guarantee that the ANPR design is used, every country chooses a distinct font permitted for number plate distribution. These projects are implemented everywhere around innovative urban environments and are considered intelligent transportation systems managed in cities, some of which are called 'smart cities.' Intelligent transportation systems are designed for different transportation systems in a city that use the city's wireless network to continually accelerate and manage the city's transportation (18). ANPR used in smart cities can control several aspects, including public transportation and traffic volume, and it also controls and monitors parking. The ANPR system creates a data file for those license plates, either allowed or not, to avoid fines for non-payers and designate locations, especially in public places (19-22). The primary objective of this research is to design and develop an efficient Automatic Number Plate Recognition (ANPR) system for seamless toll charging, enabling vehicles to pass through toll gates without stopping. The study aims to address key challenges such as accurate number plate detection under diverse environmental and traffic conditions, real-time data processing, and automated billing integration. By focusing on these aspects, the research seeks to eliminate manual intervention, reduce traffic congestion, and enhance the overall efficiency of tolling systems. Moreover, the system enhances reliability and scalability, making it ideal for extensive deployment in contemporary transportation networks. This work aims to enhance smart transportation infrastructure by offering less time, more convenience, and environmentally friendly tolling solutions. The rest of the paper is structured as follows: Section 2 discusses the related work concerning automatic toll charging. Section 3 discusses the ANPR system and the number plate recognition process. Section 4 is specifically designed to experiment and result in evaluation. Finally, section 5 gives the conclusions and future directions.

1.1. Related Works

Several uses of the Automatic Number Plate Recognition (ANPR) technology have gained significant consideration in recent decades due to its many traffic management, automated billing systems applications, and security. The advancement of ANPR systems can be distributed into three main categorizes: traditional image processing-based methods, the latest deep learning techniques, and machine learning-enhanced techniques. Every decade has advanced license plate detection, accuracy, speed, and robustness. Initial ANPR systems extensively utilized traditional image processing techniques such as pattern recognition, segmentation, and edge detection (23-26). For example, Smith and Patel (2005) designed an ANPR system that utilized morphological operations and linked component examination to detect license plates under-regulated lighting conditions. Although effective in optimal settings, these systems frequently face chilling with changing illumination, occlusions, and designs for plates (27). The overview of machine learning algorithms marked a major development in ANPR technology. Researchers, for instance, Khan et al. (2012) integrate support vector machines (SVM) and neural networks to improve the accuracy of character recognition. These methods enhanced the system's capability to generalize across several plate formats and environmental conditions (28). Nevertheless, both the computational complexity and the requirement for substantial feature engineering continued to pose challenges. Recent decades of advancements have led to the use of deep learning techniques, especially convolutional neural networks (CNNs), which have developed image recognition tasks. Studies in (29) showed that CNN-based ANPR systems could deliver great results, higher accuracy, and faster processing times compared to the covenantal approach. These systems are better equipped and adaptable to variations in lighting plate design angles, making them appropriate for real-life applications. Many research applications of ANPR in toll collection systems have been widely explored to support automated and efficient vehicle processing. Traffic jams and higher operating costs are caused by human error and delays that plague traditional toll collection technology such as fence gates and traditional ticketing. To solve these issues, we have proposed ANPR-based resolves that enable smooth toll payment without the requirement for vehicles to stop. For instance, Jain et al. (2018) created an ANPR system combined with RFID technology to simplify toll collection. Their system displayed shorter processing times and developed vehicle identification accuracy (30). Despite these improvements, current ANPR-based toll systems face many challenges. Conservational aspects such as rain, fog, and nighttime conditions cause damage to image quality, affecting recognition accuracy. Moreover, high-speed traffic needs fast image processing and decision-making to maintain a smooth flow, necessitating highly efficient algorithms and a robust hardware structure. For an efficient ANPR system, the automated billing infrastructure should be combined efficiently. Various studies have focused on making combined platforms that connect vehicle identification with billing and payment systems. Furthermore, a cloud-based ANPR system that connects license plate data allows for automated user account charging and management. This method highlighted the need for secure data transfer and real-time synchronization to prevent billing errors (31).

2. Materials and Methods

The proposed ANPR addresses the limitations of existing solutions by incorporating robust methodologies and advanced technologies into a toll collection system. Even in adverse environmental conditions, the system offers real-time processing, seamless integration with automated billing systems, and recognition accuracy. As shown in **Figure 1**. the system consists of the following phases:

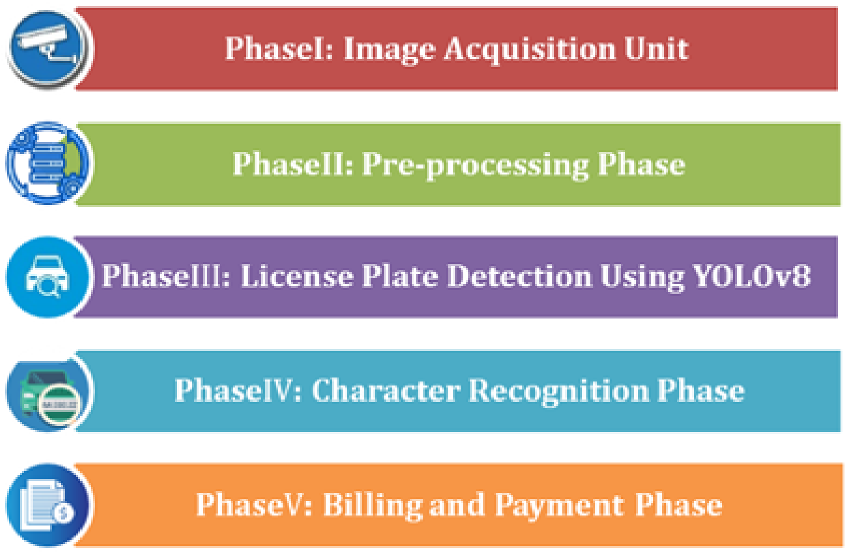

Figure 1. ANPR system development phases.

2.1. Image Acquisition Unit

Supply precise imaging for different lighting conditions, such as night and day. In this unit, the speed cameras are equipped with possibly infrared capabilities and wide-angle lenses. To obtain high visibility of license plates and low obstruction, cameras should be put in unique positions, such as angled or overhead. To avoid motion blur and capture the details of vehicle plates from a distance, the cameras should have a high frame rate and a high resolution above 4K, respectively. This will help with accurate plate recognition.

2.2. Pre-processing Phase

This phase converts a captured image (I) to a grayscale. For environmental conditions such as glare, poor lighting, or fog, the system improves the quality of images by increasing visual clarity and decreasing noise. **Figure 2.** illustrates all the functions performed during the preprocessing phase.

Figure 2. Illustration of the pre-processing steps applied to a car image

2.2.1. Grayscale Conversion

Grayscale conversion transforms a color image into a single-channel image, where each pixel intensity represents brightness. This process simplifies image data, making processing easier in noise reduction or feature extraction tasks. The equation for converting an RGB image (I) to grayscale is shown in Equation (1):

$$I_{GRAY} = (0.2989 \times R) + (0.5870 \times G) + (0.1140 \times B) \tag{1}$$

The parameter *(R)* is the red channel intensity, with a weight of 0.2989, reflecting its contribution to the perceived brightness. Similarly, *(G)* denotes the green channel intensity, assigned the highest weight of 0.5870, as the human eye is most sensitive to green light. Finally, *(B)* represents the blue channel intensity, with the most negligible weight of 0.1140, given that human vision is least sensitive to blue light. Together, these weights ensure that the grayscale image captures brightness information aligned with human perception.

2.2.2. Noise Reduction

Then, the Gaussian filter applies a weighted average to each pixel in I_{GRAY}, where the Gaussian function defines the weights (32). This minimizes noise without significantly distorting important image features like edges (see Equation (2)). This step is crucial for robust license plate detection in noisy or low-quality images.

$$I_{SMOOTH} = \frac{1}{2\pi\sigma^2}\ EXP\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \times I_{GRAY} \tag{2}$$

Where (I_{GRAY}) is the grayscale version of the original image used as input for smoothing. The σ is a standard deviation of the Gaussian distribution; controlling the extent of blurring larger σ values result in more smoothing. The *x* and *y* are spatial coordinates relative to the Gaussian kernel's center, determining a pixel's distance and influence on the smoothing.

2.2.3. Adaptive Histogram Equalization

Adaptive Histogram Equalization (AHE) enhances image contrast and brightness, particularly in poorly lit conditions, by redistributing pixel intensity values (33). This ensures that the details of an image, such as license plate characters, become more distinguishable. A commonly used variation is CLAHE (Contrast Limited Adaptive Histogram Equalization), which prevents noise over-amplification and avoids excessively high contrast in homogeneous regions. Equation (3) describes the function of adaptive histogram equalization.

$$I_{OUT}(x, y) \frac{I_{IN}(x, y) - \min(L_R)}{\max(L_R) - \min(L_R)} \times (L_{MAX} - L_{MIN}) + L_{MIN} \quad (3)$$

Where $I_{IN}(x, y)$ represents the input pixel intensity at coordinates *(x, y)* in the original image. L_R is the local histogram range for the neighborhood window around *(x, y)*, with its size determining the algorithm's adaptability. The $min(L_R)$ and $\max(L_R)$ are the minimum and maximum pixel intensities within this region, while L_{MAX} and L_{MIN} represent the global intensity range, typically 0 to 255 for 8-bit images.

2.2.4. Contrast Adjustments

Contrast adjustment is a crucial image processing step that enhances the visual distinction between objects of interest (e.g., license plate characters) and the background. Increasing the intensity difference between the foreground and background makes the license plate characters more prominent and more accessible to detect. The developed system utilizes a linear contrast stretching method for contrast adjustment. The adjusted pixel intensity at coordinates *(x, y)* after contrast adjustment is calculated in Equation (4).

$$I_{ADJ}(x, y) \frac{I_{IN}(x, y) - L_{MIN}}{L_{MAX} - L_{MIN}} \times (N_{MAX} - N_{MIN}) + N_{MIN} \quad (4)$$

Where $I_{IN}(x, y)$ presents the original pixel intensity at *(x, y)* in the input image. L_{MIN} and L_{MAX} are the minimum and maximum intensity values in the input image, defining its dynamic range. N_{MIN} and N_{MAX} are the desired intensity ranges in the output image, typically set to 0 and 255 for 8-bit images to achieve total contrast adjustment.

2.2.5. Edge Enhancement for License Plate Detection

Edge enhancement techniques highlight boundaries and transitions in intensity within an image, making features like the edges of a license plate more distinct. These methods improve the accuracy of detection algorithms by emphasizing the structural details critical for recognition (34). A widely used technique for edge enhancement is the **Sobel filter**, which computes the image intensity gradient in two perpendicular directions (horizontal and vertical). The process applies convolution for I_{GRAY} with the Sobel kernels (*Gx and Gy*) to compute the gradients in the horizontal and vertical directions. Next, calculate the gradient magnitude *(G)* to highlight edges.

2.3. License Plate Detection Using YOLOv8

The proposed system utilizes the YOLOv8 (You Only Look Once version 8) deep learning model to detect the region of interest (ROI) containing the license plate. YOLOv8 can detect objects in real-time, making it suitable for vehicle license plate recognition applications (35). It divides the image into a grid, predicting bounding boxes with confidence scores and class probabilities for each grid cell. YOLOv8 calculates each predicted box's coordinates, width, height, and confidence score. After predictions, Non-Maximum Suppression (NMS) filters out redundant boxes based on confidence and overlap. The bounding box with the highest score is selected as the detected license plate. This process enables rapid and accurate license plate detection in real-time applications. **Figure 3.** effectively visualizes the end-to-end process of YOLOv8.

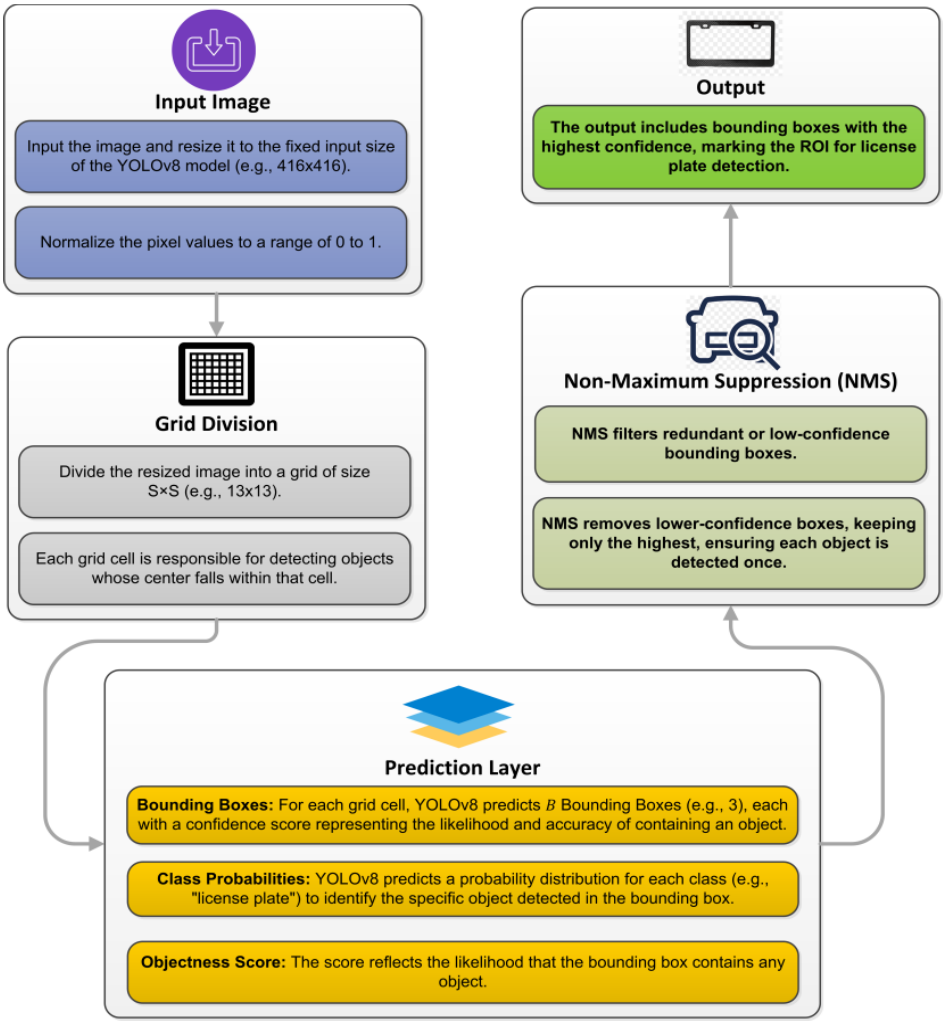

Figure 3. Workflow of YOLOv8 object detection process

2.4. Character Recognition Phase

Optical Character Recognition (OCR) is used to interpret and extract text from images, such as reading the characters on a vehicle license plate. Traditional OCR systems often struggle with noisy, distorted, or low-resolution images because they rely on fixed, hand-crafted features. To address these limitations, deep learning-based OCR models like Convolutional Recurrent Neural Networks (CRNNs) have gained prominence for their ability to handle complex, real-world data. CRNNs combine the strengths of Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) for sequence prediction, making them especially effective in OCR tasks where the sequence of characters matters. The following essential components can represent CRNN:

The first step in using a CNN is to extract spatial features from the input image. The CNN supplies twisted filters to the image, taking hierarchical patterns such as edges, textures, etc., to illustrate the characters.

CNN can be represented as a mathematical formula: $F=CNN(I)$ (5)

The I and F are the input images and the extracted feature map.

The sequence of characteristics is fed into a Recurrent Neural Network (RNN) to model the time-related dependencies between the characters, which is the output of the CNN. The RNN operates this sequence gradually, predicting the characters one at a time. The F=[f1,f2,…,fT] is the feature sequence from the CNN, then the RNN formulated as:

$$S=RNN(F) \tag{6}$$

Equivalent to the sequence of characters on the license plate, the S is the sequence of outputs predicted by the RNN. Enhancing the conventional OCR's ability to manage multiple inputs and complex by enabling CRNNs to decode text from images in noisy or cluttered environments precisely.

2.5. Billing and Payment Phase

After the license plate is denoted, the system identifies it with the vehicle's list in the database, ensuring its registration for tolls. The account balance is checked, and suitable toll fees based on the route or area are calculated. Credit/debit cards, mobile payments, or more advanced options are used in the system.

3. Results and Discussion

The TensorFlow/Keras deep learning framework and Python are used to implement the model. The training and development were executed in an environment with an NVIDIA GPU, such as the RTX 3080, to ensure accelerated inference and training. This research assesses the output of Optical Character Recognition (OCR) systems and deep learning-based OCR models, especially Convolutional Recurrent Neural Networks (CRNNs) for license plate identification. The evaluations were executed on a dataset with 150 images extracted from three videos, taken at various times with different angles, motion conditions, and lighting. This dataset supplies a challenging benchmark and is realistic for examining OCR output. The dataset was divided into (70%, 105 images) and (30%, 45 images) for training and testing. To execute the output of OCR and the CRNN model in identifying license plates under real-world conditions, the training set is used to train the CRNN model, while the test set serves as the benchmark. This partition applies enough data for training and maintaining a robust execution protocol.

Conventional OCR systems, which rely on fixed, hand-crafted output, have high limitations when executing in dynamic conditions, and diversity is represented in the dataset. These system's goals have 67.2% accuracy in the test set, with output decreasing in challenging scenarios like extreme plate angles and motion blur. However, the CRNN model, trained on the 105 images from the training set, achieves 91.4% accuracy in the test set to show the ability to adapt to difficult conditions. The model's end-to-end learning structure and ability to obtain hierarchical and contextual attributes permitted it to learn conventional OCR consistently. The outcomes confirm the advantage of deep learning-based approaches, especially CRNNs, in real-world license plate recognition. The dataset's various conditions, caught from three videos at different times and locations, focus on the actual quality of CRNN models in treating noise, deformation, and other affronts where conventional OCR procedures falter, as shown in **Table 1**.

3.1. Accuracy Comparison

To assess the advanced system's efficiency and robustness, we tested its accuracy under lighting differences, motion blur and deformation, and plate direction with obstructions. The study converges on the system's capacity to confirm and maintain high output under these scenarios, as shown in **Table 1**.

A. Analysis of Accuracy in Lighting Variations

Lighting circumstances can greatly affect the features of captured images, which is essential to license plate recognition challenges. The dataset comprises images captured at various times of the day and conducted in different lighting statuses. Conventional OCR held in minimum-light scenarios with 59.9% accuracy, while the CRNN maintained 88.3% accuracy, highlighting its robustness.

B. Evaluating Accuracy in Motion Blur and Distortions

Images from mobile vehicles, particularly at high speeds, often hold motion blur and deformations. Images taken away from videos usually include motion blur or deformations due to motion. Conventional OCR completed 57.7% accuracy in these cases, but it was extraordinarily misinterpreted or failed to detect characters. CRNN completed 86.8% accuracy in disparity, effectively recognizing patterns as the affront input.

C. Evaluating Accuracy in Plate Orientations and Obstruction Scenario

Actual-world scenarios often contain plates captured at non-frontal angles or slightly blocked vision consequent to filth, objects, or other vehicles. Plates captured at maximum angles or slightly closed posed an affront for conventional OCR, completing 54.7% accuracy in similar scenarios. CRNN outperformed it, with 85.1% accuracy, by leveraging its consecutive modeling abilities.

Table 1. Accuracy comparison of conventional OCR and CRNN in various situations.

condition	Traditional OCR Accuracy	CRNN Accuracy
Overall Accuracy	67.2%	91.4%
Low Lighting	59.9%	88.3%
Motion Blur/Distortions	57.7%	86.8%
Plate Orientation	54.7%	85.1%

As shown in **Figure 4**. these results confirm the value of leveraging precedent OCR settling for new license plate recognition systems, mainly in mobile environments where accuracy is critical.

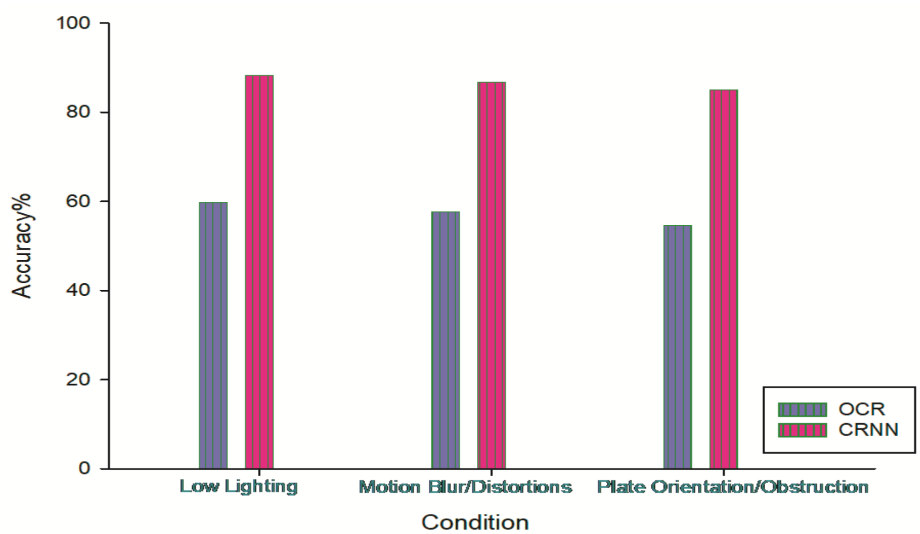

Figure 4. Comparison of accuracy between conventional OCR and CRNN processes across different situations

4. Conclusion

The evaluation and enforcement of the proposed ANPR-based toll collection system confirm its chances of revolting against the conventional tolling process. The system obtains reliability and accuracy by deep learning and leveraging preceding image processing techniques, even in affront situations like lousy lighting, reverse weather, and high-speed motion. Combining a center on database and automated billing infrastructure includes real-time cooperation, security, boosting user approval, and decreasing wait times. Furthermore, the system's efficiency and scalability in curing the rising traffic volumes make it appropriate for diffuse adoption. The empirical outcomes highlight the system's capability to reduce handling delays and look after robust achievement, confirming its bias with possible transportation objectives by decreasing vehicle revival and energy consumption. These returns attitude ANPR technology as a transformative setting for new tolling systems, paving the direction for its great-scale overall deployment in intelligent transportation networks. Future studies should converge on the beneficial robustness of proposed models to withstand extreme environmental situations, such as dense rain, snow, and fog. This can be completed by combining data-raising techniques and training on massive, extra-varied datasets.

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Conflict of Interest

The authors declare that they have no conflicts of interest.

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