An Efficient System for Detecting Multiple Traffic Violations and Recognizing License Plates Using Video Processing and Deep Learning

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***Abstract*—Traffic violations cause significant problems such as congestion, accidents, and deaths. It is highly desirable to have an effective automated system to detect and record these violations, thus improving traffic regulation enforcement and reducing human intervention. The proposed work aims to develop a cost-effective, efficient, and robust system that automatically detects traffic violations. The proposed system uses background subtraction technology to detect moving vehicles and the time and distance over which vehicles move to detect violations. The You Only Look Once (YOLO) and Convolutional Recurrent Neural Networks (CRNN) algorithms are utilized to identify the license plates (LPs) of violating vehicles with great accuracy, so that LPs are recognized using Optical Character Recognition (OCR) technology. The results achieved from our trial indicate promising system performance, with multiple violation real-time detection rate of 98.06% and an LP recognition accuracy of 98.22%. The superiority of the proposed work over other previous approaches has been proved in the comparison results.**

***Index Terms*—Convolutional Recurrent Neural Network (CRNN), License Plates (LPs), traffic violations, Optical Character Recognition (OCR), You Only Look Once (YOLO)**

I. Introduction

In the age of rapidly advancing technologies, breaking traffic laws has become a severe problem for most developing nations. As the population grows, so does the number of vehicles on the road, and traffic offenses rise exponentially [1]. Manual checking of vehicles is troublesome and mistake-inclined due to feeble and problematic human memory. Consequently, a need arises for an automatic violation detection system to deal with this errand, which can identify criminal traffic offenses. Traffic violations, such as high-speed driving, wrong-way driving, and non-compliance with traffic signals, produce significant road safety issues. Over the world, thousands of deaths and injuries are counted each year due to traffic accidents. Different techniques are utilized to achieve automatic detection of traffic violations, such as Radio Frequency Identification (RFID) [2, 3], which is also used in vehicle tracking [4], You Only Look Once (YOLO) representation [5, 6], genetic algorithm [7], Convolutional Neural Networks (CNN) [8], and Background Subtraction (BS) [9]. The researchers utilized different algorithms and methods for license plate (LP) detection and recognition, including Optical Character Recognition (OCR) [10], Optimal K-means with CNN [11], image processing techniques and template matching (TM) techniques [12]. Cameras are increasingly used to monitor and enforce traffic violations by capturing images of the offending vehicle's LP for identification. Exceeding the speed limit is an across-the-board traffic violation that increases the risk of accidents due to loss of vehicle control, slow response time, and short stopping distance [13]. Highway cameras have been installed to monitor the roads and detect violations, thus improving road safety and governing the traffic flow. Driving in the opposite direction is another dangerous traffic violation, as it often leads to head-on collisions, potentially resulting in more injury and death people. Cameras can detect wrong-way driving and alert traffic controls immediately, enhancing their response capacity and penalizing offenders quickly [14]. Also, cameras are installed at intersections to detect vehicles that do not respond to traffic signals, leading to confusing traffic flow and may lead to collisions [15]. These cameras are activated when a vehicle crosses the intersection after the red signal appears, capturing an image of the vehicle's LP for successive action. To conclude, these traffic violations present substantial road safety risks. However, with the implementation of camera-based surveillance systems, enforcement of traffic laws has seen marked improvements. By deterring reckless driving behaviors, these systems play a significant role in promoting safer roads [16].

Researchers have suggested different methods to detect traffic violations and recognize License Plates (LPs). In [5], a traffic light violation detection method was proposed using YOLO and Hough space analysis. The method

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autonomously processes videos and adapts to varying conditions, achieving an accuracy rate of 88.24% in detecting violations. The researchers in [17] proposed a system to detect vehicles that exceed the limited speed using YOLOv3, where the accuracy achieved was about 92.80%. In [18], the mean shift algorithm was used for vehicle tracking and Binary Large Object (BLOB) technology to detect vehicles violating traffic signals, and the system achieved a detection accuracy of 71%. In [19], the YOLOv3 technology was utilized to identify speeding offenses, and the system obtained an identifying accuracy of 89.24%. A prototype model to calculate a vehicle's speed was introduced in [20]. The Simple Online and Real-time Tracking (SORT) video tracking technique, Google Collab platform, and Leveraging OpenCV library were utilized, achieving an accuracy rate of 78%. In [21], the researchers proposed a system for detecting vehicles that exceed the speed limit and identifying their LPs. They employed sensors to detect such violations and OCR to recognize LPs, where the system achieved 90% and 56.67% accuracy rates, respectively. Not respecting the traffic signals violations were detected in [22] using spatial analysis and Machine Learning (ML) techniques. The authors tested the Gradient Boosted Decision Tree (GBDT) and Random Forest (RF) techniques, where the outcomes showed that the GBDT is the best technique that achieved an accuracy rate of about 96%.

Different approaches have been presented in the last decade for detecting and recognizing vehicles' LPs. In [12], the system achieved an accuracy rate of about 96% when using the TM technique to recognize Iraqi LPs. vehicles' LPs were detected using the YOLO algorithm and recognized using the OCR technique in [23], achieving 98.22% and 78% accuracy rates, respectively. In [24], the authors utilized the Region-based Convolutional Neural Network (R-CNN) algorithm to recognize LPs, achieving an accuracy rate of 83.67%. The CNN and OCR techniques were employed in [25] to recognize Vehicles' LPs, achieving an accuracy rate of 89.15 %. Vehicles' LPs were identified in [26] using a combination of Long Short-Term Memory (LSTM) and CNNalgorithms, with an accuracy rate of 85%. In [27], the YOLO and CNN methods were employed to detect and recognize vehicles' LPs, achieving 87% and 93% accuracy, respectively. A CNN method was utilized in [28] to identify LPs, achieving a 98.13% accuracy rate.

The proposed system simultaneously scans three traffic violations in real-time and sends a message to the traffic control center and vehicle owner regarding each violation. The violations are detected using video processing, including the BS technique and speed calculation. The contribution of the proposed system can be viewed in the number of violations detected and the accuracy rates achieved, which is distinct from others designed to detect a single type of violation and did not reach the desired accuracy. It is also intended to detect LPs containing Arabic numbers and English letters, representing the new form of the Iraqi traffic system. The LPs are detected using the well-known algorithm for object detection, YOLO, in conjunction with the CNN model. Finally, the identification of LPs is carried out with the OCR technique, which is suitable for recognizing different text types.

II. BACKGROUND

The proposed system utilizes BS technology to detect moving vehicles and determine the time and distance over which they move to identify violations. It employs the YOLO and CRNN algorithms to accurately identify the LPs of violating vehicles. The OCR technology is used to recognize vehicle plates with high precision. The methods mentioned will be explained in the following subsections.

A. Background Subtraction (BS)

The BS technique is used in object segmentation, security enhancement, pedestrian tracking, counting the number of visitors, number of vehicles in traffic, etc. It can learn and identify the foreground mask by extracting the moving foreground from the static background, as shown in Fig. 1.

Most BS methods follow a similar technique. It includes two significant steps: background initialization with maintenance and foreground detection. Background initialization constructs an initial background model according to a specified number of frames. In foreground detection, a comparison is made between the current frame and the background model for each frame, leading to calculating the scene's foreground. Typically, the results of the foreground detection are fed back into the background model for updating [29].

(a) (b)

Fig. 1. Background subtraction (a) Original image, (b) background subtraction result.

The Mahalanobis distance is a measure of the distance between a point and a distribution. In the context of background subtraction, each pixel's color or intensity values are treated as a point in a multi-dimensional space, and the distribution represents the statistical properties of the background model.

The Mahalanobis distance (d_m) between the pixel and the background model is calculated as in Eq.(1) [30].

$$d_m = (x-\mu)^T \Sigma^{-1} (x-\mu) \tag{1}$$

where x is the color vector or intensity values in the video's current frame, μ is the mean vector of the background model that represents the average color or intensity values of the pixel over a series of frames, and Σ^{-1} is the inverse of the covariance matrix of the background model for each pixel location. The covariance matrix captures the variability and correlation of the color or intensity values of the pixel over the background frames. A threshold value is chosen to determine whether the object is a vehicle. If the distance is above the threshold, the pixel is considered a foreground; otherwise, it is regarded as a background. Therefore, the new pixel intensity is set to the pixel's value if it exceeds the threshold; otherwise, the pixels are set to 0.

B. You Only Look Once (YOLO)

The YOLO algorithm is the fastest real-time object detection method based on a unified deep neural network [31]. It has undergone several stages of development, with each stage addressing and improving upon the limitations of its predecessor.

Different versions of YOLO have been released to improve their utilization in various applications. The 1st release is YOLOv1, which divides the image into a grid of cells, predicts objects in each cell using bounding boxes, and classifies them simultaneously. YOLOv2 brought significant improvements in performance and speed through technologies such as Darknet-19. Further improvements in performance and accuracy have been made in YOLOv3 through deeper networks and new techniques such as saturation and size predictions. Significant improvements in speed and accuracy are achieved in YOLOv4 by improving classification and detection processes using advanced technologies like CSPDarknet53 and features like PANet [32].

Although the newer YOLO models may have higher accuracy due to the number of layers, they may be more complex and slower to operate compared to YOLOv4. Therefore, the YOLOv4 model is chosen based on its performance and processing speed, which balances accuracy and speed, as the goal is to obtain good results at an acceptable speed. In other words, YOLOv4 is sufficient for achieving the goal of designing the proposed system.

C. Optical Character Recognition (OCR)

OCR is a technology that converts written or printed text in images into editable and searchable text. The OCR technology is integral to image processing and artificial intelligence [33]. The procedure for performing an OCR operation is summarized as follows [34]:

- *Getting Images*: The first step is to prepare images that contain text, where they can be scanned papers, snapshots, or any other type of picture that includes visible text.
- *Preprocessing*: Different processes are applied to improve the quality of the acquired imagesbefore proceeding with the text detection. This step could entail skew correction, binarization (turning the image into black and white), and noise reduction.
- *Text Detection*: This process locates the areas of the image that have text by separating the text from other items that are not text.
- *Character Segmentation*: In this step, the text is divided into individual characters. Accurately identifying each character depends on how accurate this step is.
- *Feature Extraction*: OCR algorithms examine every segmented character's characteristic, extracting crucial information that sets one character apart from another. Aspects like shape, size, and spatial relationships could be included in these traits.
- *Character Recognition*: Every character is identified using the attributes that were extracted. To match the retrieved features with predetermined character patterns, OCR algorithms use machine learning models, neural networks, or pattern recognition approaches.

D. Convolutional Recurrent Neural Network (CRNN)

The network architecture used by the end-to-end text line recognition method combines CNN and Recurrent Neural Network (RNN) [35]. Fig. 2 shows the three sections that make up the entire identification network: convolutional, recurrent, and transcription layers, which are explained as follows [36]:

- *Convolutional layers*: They include asymmetric convolution layers and feature reuse networks, which form the foundation of the entire system responsible for feature extraction. CNNs automatically extract feature sequences from various convolution layers for each input image. Next, the RNNs forecast every frame in the feature sequence taken from the CNNs.
- *Recurrent layers*: They consist of an attention mechanism and bidirectional LSTM, which transform feature sequences into per-frame predictions.

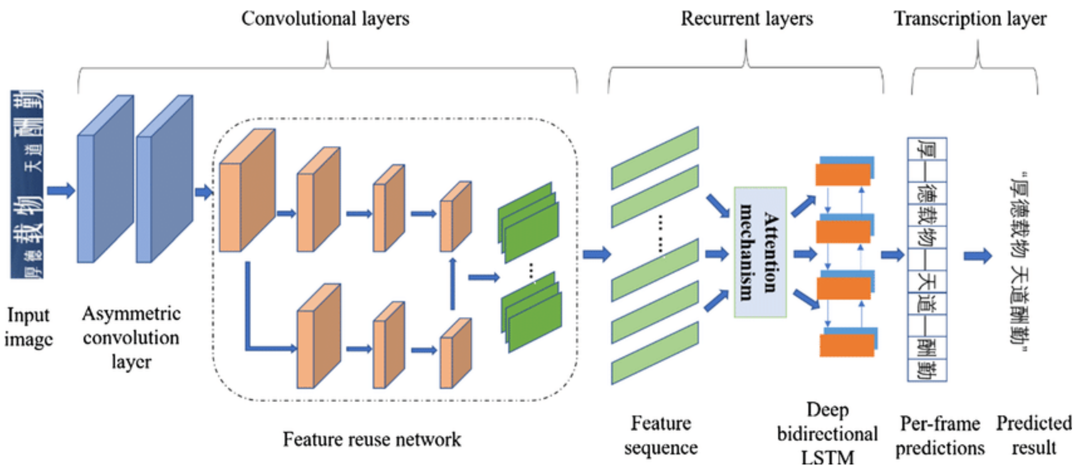


Fig. 2. CRNN network's structure [36].

- *Transcription layer*: It outputs the final predicted labels based on the recurrent layer's per-frame predictions. Transcribing the predictions from RNNs into actual labels is the transcription layer's responsibility, the network's final component.

III. Methodology

The proposed system uses video processing, YOLO, and OCR techniques to detect traffic violations and recognize LPs using only a camera as a sensor.

A. Video Processing

Video processing includes many procedures, such as detecting moving objects and distinguishing them from one another, in addition to checking for any violations.

- *Object Detection*: The detection mask will be determined in this step, as the white pixels represent vehicles, and the black pixels represent the background of the video. If the mask values are greater than 200, they become 255 (white), but if the mask values are less than 200, they become 0 (black). Morphological operations are used to process the binary image to ensure obtaining a clear mask and removing the noise. This process helps remove noise and close small gaps to detect compounds strongly and separate them from the background.
- *Frame processing*: The assumption is that each vehicle is initially considered new in the current frame. The distance between the vehicle's center in the current frame and its center in the next frame will be measured. Suppose it is within a maximum displacement of 100 (the maximum distance the vehicle can move between two frames); it is regarded as an existing vehicle, not a new one, and its information is updated and checked. When the vehicle crosses the first line, the starting time is saved, and when it crosses the second line, the ending time is saved. If the distance exceeds the maximum displacement, the vehicle is considered new, and its information is recorded. This event indicates that the vehicle was not present in the previous frame, and its appearance in the current frame causes the displacement to exceed the threshold value.
- *Checking violations*: The first check-in traffic violation detection is for the traffic light. If the light is red and a vehicle crosses the stopping line, a violation for "Disrespecting the traffic signal" will be issued. The second check is for speed. If the speed exceeds zero, it will be compared with the specified speed limit of 80 km/h. An "Exceeding the speed limit" violation will be issued if the speed exceeds the limit. However, if the speed is negative, the system will flag a penalty for "driving in the opposite direction".

B. Vehicle Detection

As explained previously, the vehicles are detected in the captured video using the BS method. Initially, each frame image is converted to the binary type. Then, the frame differencing is used to detect motion between consecutive frames by calculating the Mahalanobis distance between the successive frames using (1). Finally, a threshold should be applied to isolate only the relevant changes in the frames to detect all moving vehicles on the street.

C. Violation Detection and Determination

The system is designed to detect three traffic violations:

- Exceeding the speed limit
- Driving in the opposite direction
- Non-compliance with the Traffic Signal

1) Exceeding the speed limit

As the process is accomplished using the recorded video via a camera, the speed is computed by sketching two lines on the street's image.

When the vehicle crosses the first line, the time at that moment, which is denoted as (T_0), is recorded. In addition, when the vehicle reaches the second line, the (T_1) time is recorded. The time difference (T_d), which is spent between the two lines, is calculated as in Eq. (2):

$$T_d = T_1 - T_0 \tag{2}$$

The vehicle speed S is calculated as in Eq. (3):

$$S = D/T_d \tag{3}$$

where D is the distance between the two lines.

The vehicle will be recorded as a violation if it exceeds the speed limit, as shown in Fig. 3.

2) Driving in the opposite direction

The driving in the opposite direction can be detected by calculating the vehicle speed using (3). When the vehicle moves in the opposite direction, it crosses the second line first and then touches the first line, making the time difference (T_d) in (2) negative because T_0 is greater than T_1. Therefore, when the speed appears to retain a negative value, the vehicle moves in the opposite direction, as illustrated in Fig. 3 and shown in Fig. 4.

3) Non-compliance with the Traffic Signal

The system can identify vehicles not adhering to traffic signals by crossing the stop line when the signal is red, as illustrated in Fig. 3. The stop line, indicated by the pedestrian crossing lines, is visible to drivers. The system creates a virtual line on each video frame and compares its coordinates with those of each vehicle to determine whether it crosses the line or not.

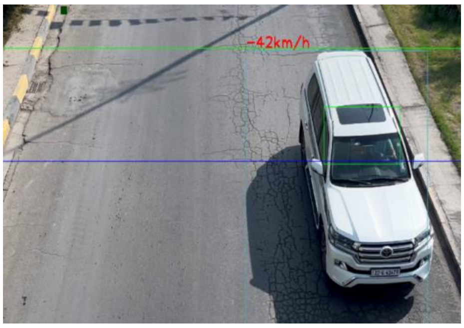


Fig. 4. A vehicle is moving in the opposite direction.

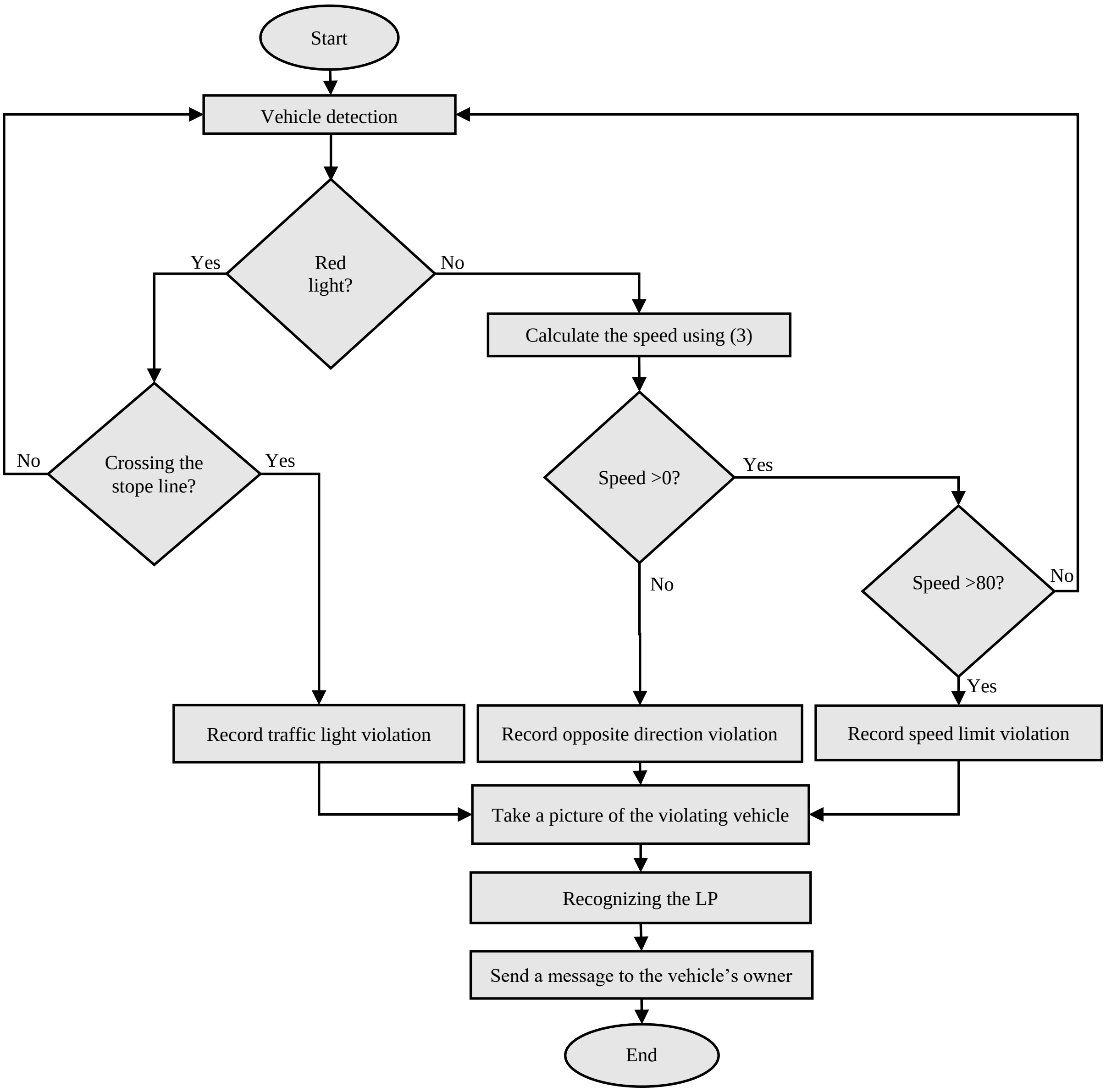


Fig. 3. Flowchart of the violations detection system.

D. LPs Detection and Recognition

The vehicle's LP is detected using YOLOv4 by determining its location in the image. Besides, the LPs are recognized using OCR and CRNN algorithms. According to the previous work, utilizing YOLO, CRNN, and OCR algorithms produces the best results for detecting and recognizing LPs compared to other methods. Therefore, the proposed work uses the same procedure for saving time. The procedure is as follows:

1) Detecting the LP using the YOLOv4 algorithm

The YOLO algorithm is used for LPs detection in conjunction with a CNN model. As seen in Fig. 5, it divides the input image to $K \times K$ grid cells. Every one of the grid cells predicts the object alone. There is a fixed number of boundary boxes predicted for each grid cell [23]. Predicting the five bounding box coordinates (b_x, b_y, b_w, b_h, c) is the responsibility of grid cell housing the item in its center. The object center in relation to the grid cell location is represented by the coordinates (b_x, b_y), while the width and height of the object in relation to image dimensions are represented by the coordinates (b_w, b_h). An object's presence in a grid cell is indicated by its confidence score (c). Therefore, the LP is denoted by [37]:

$$LP = (b_x, b_y, b_w, b_h, c) \quad (4)$$

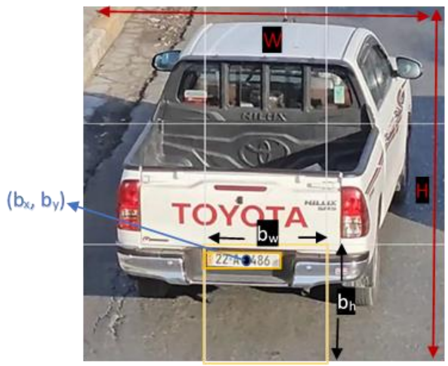


Fig. 5. LP detection using YOLO with 3×3 grid cells.

2) *Splitting the LPs*

The vehicle plate is divided into two parts: the first part contains the word Iraq filled in with one of the five colors that represent the type of vehicle. It is recognized as shown in Fig. 6, and the second part consists of a letter and a series of numbers specific to the vehicle. It is recognized using the OCR method.

Fig. 6. Iraqi vehicle LP.

3) *Color detection*

The color of the rectangular portion on the LP left side represents the type of vehicle. In actuality, the width of the colored portion divided by LP's whole width is approximately 0.0738255. As a result, by multiplying the detected LP's overall width by 0.0738255, the width of the colored portion within the detected LP is approximated. The average color is computed considering the light illumination, dust, and some paint removal. The resulting average color is then subjected to a threshold value set to 200 pixels according to the results obtained by the trial-and-error tests. It is reset to 0 if the average color value is less than 200 and set to 255 if it is greater than 200. The details of the LP color are shown in Table I.

TABLE I: INFORMATION REGARDING THE LP COLORED REGION

Color	Average pixel values	Vehicle Type
Blue	[255, 0, 0]	Government
Yellow	[0, 255, 255]	Cargo
Red	[0, 0, 255]	Taxi
Green	[0, 255, 0]	Defense
White	[255, 255, 255]	Personal

The mean of the colored region matrix is calculated by obtaining the average or the mean of each column (*C*), as in (5), where the sum of the column values (*V*) is divided by the number of elements in the column (*N*).

$$\text{Mean } (C) = \frac{\sum V}{N} \tag{5}$$

Let **A** be a 3×3 matrix.

$$\mathbf{A} = \begin{bmatrix} 12 & 28 & 219 \\ 26 & 30 & 221 \\ 19 & 20 & 205 \end{bmatrix}$$

Therefore, the mean of $\bar{\mathbf{A}}$ is

$$\bar{\mathbf{A}} = [19 \quad 26 \quad 215]$$

For every color class, the standard average pixel values are compared with the computed average color. In the example depicted in matrix **A**, the average color becomes [0 0 255], which refers to the red color as a private car, when applying the threshold value.

4) *OCR*

In general, pattern recognition techniques, such as the methods used in face recognition [38], depend on the features extracted from the entire image. Text recognition uses a different technique that depends on the features of each object (symbol, letter, or number) included in the image. Thus the OCR is utilized in the proposed work due to its practical features regarding speed and accuracy in text recognition. It is used to identify the second part of the Iraqi LP, which contains a series of Arabic numbers and an English letter, as illustrated in Fig. 6.

E. *Sending a Message*

The system sends a text message to the owner of the violating vehicle to inform them about the financial fine and to pay it before the due time to double it, as well as the general traffic department to issue a fine for the violating vehicle. This message contains the type, time, and place of the violation, as well as the vehicle's LP, as shown in Fig. 7. The message is sent using the Twilio application via the GSM technology.

Fig. 7. Message sent to the vehicle's owner.

IV. EXPERIMENTAL RESULTS

Using Windows 11 with a 2.3 GHz processor and 16 GB RAM, the experiments are carried out with the PYTHON programming language.

A. *Offline LP Recognition*

One of the most essential stages of recognition systems is data collection. The YOLOv4 detector in the proposed work is trained on Google's Open Image dataset [39], which consists of tens of thousands of object photos with annotations for object detection and segmentation. The portion of this dataset that deals with vehicles comprises 1500 training and 300 testing photos. This experiment uses offline images to evaluate the system's ability to identify LPs under different aspects and lighting conditions. The system demonstrates a high performance rate of approximately 90%, showing its effectiveness in recognizing various LPs, which can be successfully applied to online recognition.

B. *Real-Time Traffic Violation Detection*

In this experiment, the system has been established to monitor traffic violations using a high-resolution camera. It is capable of detecting three types of violations:

- Exceeding the speed limit
- Driving in the opposite direction
- Not respecting the traffic signal

If more than one vehicle commits a violation simultaneously, and if one vehicle commits multiple violations, all of them will be punished accordingly. The system uses the BS model to identify vehicles, and their speeds are calculated according to (3). The YOLOv4 algorithm is used to determine the vehicle's LP, and the recognition of the LP is done using the OCR technique. For the violation of not respecting the traffic signal, the camera is located in a place that covers the stop line. In addition, we use the "r" key on the computer keyboard to change the signal from green to red and vice versa, but in practice, the traffic controller must inform the system about the red light signal. The results of detecting the three violations in real time are presented in Table II.

TABLE II: EXPERIMENTAL RESULTS FOR ALL VIOLATIONS DETECTION AND RECOGNITION OF IRAQI LPS

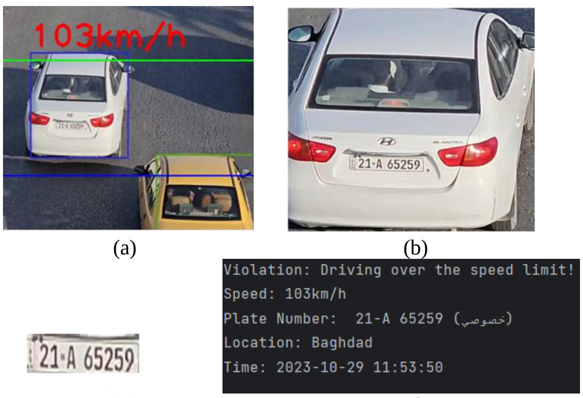
Violation type	No. of violating vehicles	No. of vehicles detected	Violation Detection rate (%)	Recognition rate of LPs (%)
High-speed	72	69	95.83	97.11
Opposite Direction	30	29	96.67	98.53
Traffic signal	105	105	100	99.02
All violations	207	203	98.06	98.22

For the high-speed violation detection, 72 vehicles assumed to exceed the limited speed are tested, whereas 69 are correctly detected. Besides, the accuracy rate of real-time recognition of the LPs is 97.11%.

When testing the detection of driving in the opposite direction violations for 30 vehicles, 29 vehicles are detected, and the real-time recognition rate of LPs is 98.53%.

During the test, all violating vehicles were detected to identify vehicles that did not respect a red signal. Additionally, the LP real-time recognition rate is 99.02%. Upon detecting a violation, the system automatically sends a message to the traffic directorate to report the violation and inform the vehicle owner, as illustrated in Fig. 7.

Fig. 8 shows the stages of detecting the violating vehicle, from entering the camera's view until the LP is identified and a violation is issued.



(a) (b) (c) (d)

Fig. 8. Violation detection: (a) Calculating vehicles' speed (b) Acquiring images of the violating vehicles (c) Detecting of LPs, and (d) Recording the violations.

C. Comparison with Other Work

It is crucial to compare the proposed work outcomes with those of the related work. As per the literature survey, there is no common dataset employed in all or most approaches. However, each approach has used a dedicated dataset created by collecting some images. Therefore, a comparison is made in Table III with the related work despite the dataset used. It is worth noting that the system works to detect more than one violation at a time, in addition to using the camera only without using any sensor to detect violations.

TABLE III: COMPARISON WITH THE RELATED WORK REGARDING THE VIOLATIONS DETECTION

Ref. No.	Method	Violation Type	Accuracy rate (%)
[5]	YOLO and Hough space analysis	Traffic signal	88.24
[17]	YOLOv3	High-speed	92.80
[18]	BLOB	Traffic signal	71
[19]	YOLOv3	High-speed	89.24
[20]	SORT	High-speed	78
[21]	Sensors	High-speed	90
[22]	GBDT	Traffic signal	96
Proposed Work	BS and YOLOv4	High speed, Opposite direction, and Traffic signal	98.06

As illustrated in Table III, the proposed work achieves an accuracy rate of about 98.06%, outperforming other related work. Moreover, the proposed system detects three violations simultaneously, unlike the others that can detect one type of violation.

In the case of real-time recognition of the LPs, a comparison between the proposed work and the related work is made in Table IV.

According to the results presented in Table IV, the proposed work achieves a recognition rate of about 98.53%, which is the best among related work. In contrast to the related approaches, the proposed work detects and recognizes LPs of moving vehicles rather than stationary ones.

TABLE IV: COMPARISON WITH THE RELATED WORK REGARDING THE RECOGNITION OF LPS

Ref. No.	Method	Accuracy rate (%)
[12]	TM	96
[21]	OCR	56.67
[23]	OCR	78
[24]	R-CNN	83.67
[25]	CNN+OCR	89.15
[26]	LSTM+CNN	85
[27]	CNN+YOLO	93
[28]	CNN	98.13
Proposed work	OCR + CRNN	98.53

V. CONCLUSION

This work introduces a robust system for detecting traffic violations using video processing and deep learning. Moving vehicles are detected using the BS technology, whereas identifying the LPs is carried out with the YOLOv4 model, and the OCR and CRNN technologies are utilized to recognize them. The proposed system demonstrates an applicable real-time approach for detecting traffic violations, achieving an impressive 98.06% overall accuracy rate for offenses such as exceeding the speed limit, disregarding traffic signals, and driving in the opposite direction. On the other hand, the proposed system has achieved excellent results in recognizing LPs, with a 98.22% success rate. This achievement is necessary to accurately identify the violating vehicles and enforce relevant penal efforts. The comparisons with the previous approaches show the superiority of the proposed work, which achieves the highest accuracy rate in violation detection and LP recognition. In the future, the research may focus on enhancing the system's performance under various lighting and weather conditions and detecting more traffic violation kinds.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors conducted and analyzed the research; the first and second authors wrote and revised the paper; all authors approved the final version.

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