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Real-time Jordanian license plate recognition using deep learning

Salah Alghyaline

The World Islamic Sciences and Education University, Faculty of Information Technology, Department of Computer Science, Tabarbour, Amman, Jordan

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ABSTRACT

Countries have different specifications for License Plates (LPs), therefore developing one Automatic license plate recognition (ALPR) system that works well for all LPs types is a difficult task. This paper aims to develop an accurate ALPR for Jordanian LPs. Two-stage Convolutional Neural Networks (CNNs) are used in the proposed approach, the CNNs are based on the YOLO3 framework. The sizes of LPs' characters are very small compared with the frame size, therefore the YOLO3 network architecture is modified to a shallow network to detect small objects. The proposed approach uses temporal information from different frames to remove false predictions. A set of arrays data structure is used to track the vehicles' LPs and eliminate incorrect ones. To my knowledge, the proposed approach represents the first end-to-end Jordanian ALPR that processes video stream in real-time. To my knowledge, there is no dataset for Jordanian license plates, therefore this paper proposes a new dataset called JALPR dataset. The dataset is available online and includes many real videos for moving vehicles in Jordan. Two well-known commercial software packages are used for comparisons. The experimental results in real videos from YouTube show that the proposed approach is very efficient in recognizing the Jordanian license plates and achieved 87% recognition accuracy, whereas the commercial systems have recognition accuracies that are less than 81%.

1. Introduction

Nowadays the number of moving vehicles is increasing very fast. In many cases, it is necessary to check the identity of these vehicles for different purposes such as finding stolen vehicles, enforcement of the traffic law, managing parking lots, toll collection. However, it is difficult to check this huge number of moving vehicles manually. Therefore, developing an accurate and fast ALPR system is an important task to develop an Intelligent Transportation System (ITS). The goal of ALPR is to extract the vehicle number from images of moving vehicles. ALPR includes two major steps; detecting the plate location and its dimensions in pixels and recognizing the plate content. ALPR has been studied by many researchers and many approaches have been proposed, however, the ALPR problem is still open due to many challenges in the image processing field such as variation in viewpoint, illumination, occlusion, scaling, and intra-class variation. Additionally, each country has its specifications for the license plate (plate size, plate material, using alphabetic characters or not, the language of the used characters … etc.), this intra-class variation makes it difficult to develop a single ALPR system that works perfectly with all license plates for all countries. Another important challenge in ALPR is that many of the proposed approaches work well with a stationary camera, and the recognition accuracy will be poor with a moving camera. Most of the studied plates were from outside the Middle East (such as the USA, Europe, China, Brazil, Korea) (Goncalves et al., 2016; Jung, 2017; Kim et al., 2017; Laroca et al., 2018), and few works were done in Jordanian license plate recognition (Yousef et al., 2015; Alhaj Mustafa et al., 2018). Most of the previously proposed approaches were based on handcrafted-features such as SIFT (Lowe, 1999), HOG (Dalal and Triggs, 2010), (Panchal et al., 2016) and (Saleem et al., 2016). The approaches used still images and ignored the temporal features (features from a sequence of frames). Any proposed ALPR system should work on a video stream or CCTV camera, this makes the system applicable to the real-world applications. The moving vehicle should be tracked in a sequence of frames and the detection result appears during or after missing the tracked vehicle. Developing an efficient ALPR system that works on video stream has many challenges, the motion could blur the image due to the object movement,

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E-mail address: salah.alghyaline@wise.edu.jo

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additionally, when we move from one frame to another, the same license plate could have different views, therefore ALPR system gives many predictions for the same plate, and many false LPs are generated. The false detected LPs require additional time to check the identity of these plates by retrieving their information.

The paper aims to develop a new and efficient ALPR approach for Jordanian license plates. The proposed approach is based on deep learning to solve plate detection and recognition problems. New efficient CNN architectures are proposed in plate detection and recognition stages. The new CNN architectures are based on YOLO3 CNN architecture. The YOLO3 CNN architecture is modified to a shallow CNN architecture to detect and recognize small objects (characters of license plate), the number of layers is small compared with YOLO3, which in turn reduces the running time. Many predictions are generated for a specific vehicle over a series of frames, some of these predictions are incorrect, therefore another technique based on the Edit distance approach and the LPs frequency is proposed to cluster similar LPs. The proposed clustering technique eliminates many incorrect LPs and keeps the correct LPs. Many real video streams from streets in Jordan were used to train and test the new approach and most of these videos are taken from the YouTube website. The experimental results show that the proposed JALPR approach is accurate and fast (works in real-time) compared with the currently existing techniques, which makes the proposed approach applicable to the real-world scenarios.

The main contributions of this paper:

- Proposing a new dataset called JALPR which, up to my knowledge, is the first dataset that includes Jordanian License plates. The dataset is available online and can be used for training and testing any newly proposed ALPR system.
- Proposing a new CNN architecture for License plate detection and recognition. The license plate characters are too small compared with the frame size; therefore, the proposed CNN modified the YOLO3 CNN architecture to a shallow network to detect small objects.
- Proposing a new technique to cluster similar recognized LPs and select the best ones, which significantly reduce the number of false recognized LPs.
- Reviewing the main contributions in ALPR during the last few years.

2. Related work

License plate recognition remains one of the challenging and important tasks in computer vision. Each country has its specifications for the license plate. Developing accurate and fast object detection techniques is a crucial task for developing a successful ALPR system. The object detection operation could be used for both plate detection and character recognition. There are two kinds of features for object detection, the hand-crafted features (SIFT, HOG...etc.) and the deep learning features (based on CNN). During the last few years, deep learning-based object detection techniques significantly outperformed the hand-crafted based techniques (Redmon and Farhadi, 2018; Ren et al., 2017; Redmon et al., 2016a). Tian et al. (2015) proposed a two-stage approach to recognize the Chinese license plate. Preprocessing operations are applied to the input image, after that, the initial segmentation is performed by applying template matching on a bank of the harrow-shaped filter. A* path-finding technique is used in the second stage of segmentation to segment connected characters. Yousef et al. (2015) proposed ALPR for Jordanian plats, they used templets matching of SIFT features for detecting and finding the location of the vehicle plate. The similarity between the stored templates and the candidate object was used for LP recognition. Alhaj Mustafa et al. (2018) used connected components and Canny edge detection to detect the Jordanian LP location, the horizontal and vertical histograms of the detected plate are used to segment the plate into different parts. Finally, the Artificial Neural Network (ANN) is used to classify different segmented objects into different labels. Ng et al. (2015) proposed ALPR for Malaysian license plates. This approach is based on SIFT templets matching for locating and recognizing the license plate content. Laroca et al. proposed an ALPR technique based on CNN. They created a new license plate dataset called UFPR-ALPR collected from Brazilian vehicles. Fast-YOLO and YOLO2 models are used for vehicle and plate detection. The CNN in Jung (2017) is applied for character segmentation. Li et al. (2017) used one shared CNN with a single pass for plate detection and recognition, the CNN model was trained and tested on Chinese license plates from China and Taiwan. Hou et al. (2018) proposed ALPR for Chinese plates, the model includes two CNNs, the first network is similar to YOLO2 CNN and based on YOLO framework to detect the plate location, whereas the second network used a modified version of VGG-16 CNN and based on Caffe framework for plate recognition. Wang (2017) proposed ALPR for Chinese license plates, the plate detection stage implemented using Single Shot MultiBox Detector (SSD) (Liu et al., 2016) framework, whereas a vertical projection technique is proposed for character segmentation. Kim et al. (2017) proposed ALPR for Korean plates, the approach is based on the Multi-Tasking Learning, the CNN includes a sequence of 9 convolutions and 3 pooling layers, the network is shared between plate detection and recognition of the characters of the plate. OpenALPR (''OpenALPR,'' 2020) and Sighthound (''Sighthound,'' 2020) are popular commercial software for ALPR, they support many countries' license plates. They were used by many ALPR approaches such as: (Silva and Jung, 2018; Laroca et al., 2018; Redmon et al., 2016b). According to Silva and Jung (2018) OpenALPR and Sighthound represent a good reference to state-of-the-art, and they can be used as black boxes to compare the performance of the proposed methods with them. Most of the commercial software does not provide any information about their architecture. OpenALPR is an official partner to NVIDIA and Amazon in many projects that are based on LP recognition (Silva and Jung, 2018).

In Table 1, I highlight some of the proposed ALPR in Jordan. Compared with the previously proposed approaches in the literature, to my knowledge, the proposed approach represents the first end-to-end Jordanian ALPR that processes video stream in real-time. The CNNs architecture used by the state-of-the-art object detector YOLO3 is modified to be used in the proposed approach to detect small objects like license plates and character recognition. To my knowledge there is no benchmark or dataset to evaluate any proposed Jordanian ALPR approach, therefore this paper proposes a new dataset to evaluate and show the efficiency of the proposed approach. The proposed dataset is used to compare the proposed approach with other ALPR approaches. The proposed approach detects many vehicles at the same time and the temporal information in addition to the spatial vehicle information used to make the final recognition result. The proposed approach works in real-time, up to 40 frames per second (FPS). Moreover, the proposed approach

3. The proposed method

This section presents the proposed Jordanian ALPR approach. Fig. 1 shows the main stages of the proposed JALPR approach. The proposed approach is a fully automated ALPR approach, which is different from most of the existing ALPR approaches in and outside Jordan. The spatial and temporal video features are used in the proposed ALPR. As it is shown in Fig. 1 the dataset (JALPR) is built through collecting videos from the YouTube website (discussed in

Table 1
comparison of some proposed ALPR systems in Jordan.

Methods	Database	Image Conditions	Total Rate	Processing Time	Real-Time	Video-based ALPR	Plate format	References
Templet matching of SIFT features	46 images	–	70%	4 s for each image	No	No	Jordan	Yousef et al. (2015)
Connected components and Canny edge detection. Artificial Neural Network is used to classify	240 images	1188 × 960 pixel	90%	–	No	No	Jordan	Alhaj Mustafa et al. (2018)
Proposed approach	187,200 Images/ 104 min/12 videos	1920 × 1080 1280 × 720pixel	87.05%	30–40 FPS.	yes	yes	Jordan	This Paper

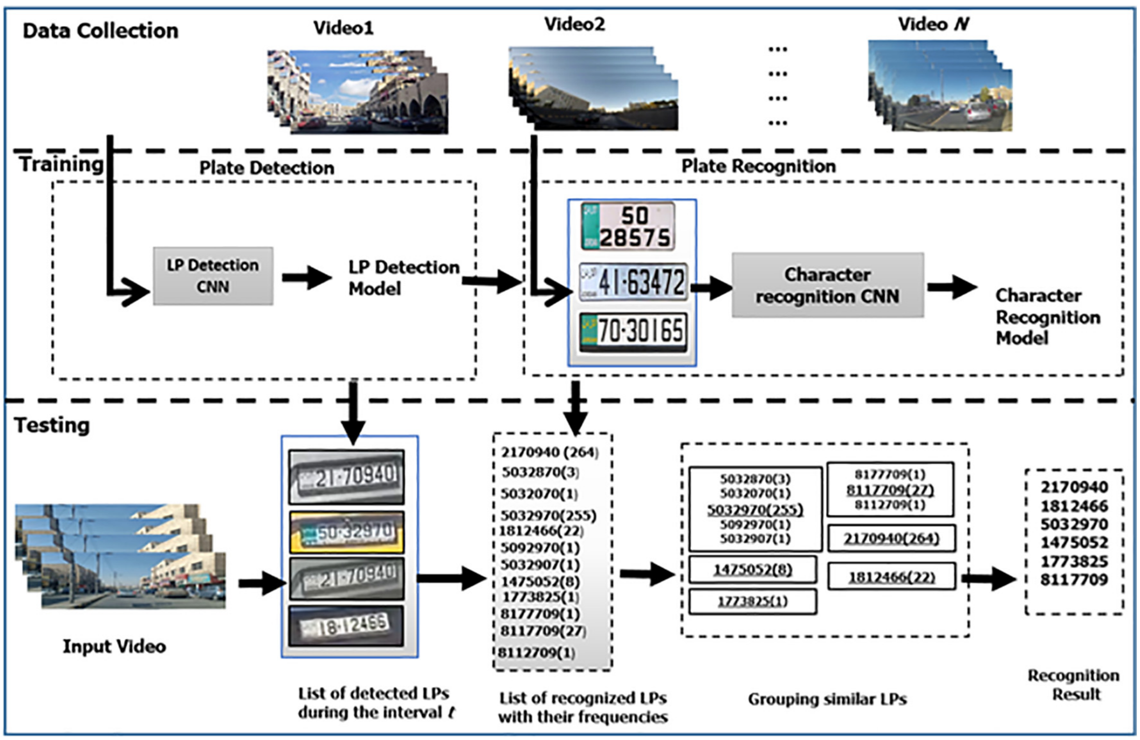

Fig. 1. Main Steps of the Proposed JALPR Approach.

detail in Section four). After that, two training stages are performed to build License plate detection and recognition models. In the testing stage, the license plate detection and recognition models are used to detect and recognize LP in a new video stream. The LP recognition process is performed at each frame; therefore, many incorrect predictions will be generated for the same LP. The similarity and the frequency of predicted LPs are used to eliminate the wrong predictions and keep the correct predictions. For simplicity, the proposed approach is summarized in three main stages: License plate detection, character recognition, and finally, license plate recognition. Sub-sections 3.1, 3.2 and 3.3 describes in detail each stage.

3.1. License plate detection

A license plate is an object like many objects in our lives and it can be detected using an efficient object detector. The existing object detectors are designed to detect objects with different sizes and shapes. Most of the existing deep learning-based object detectors use a very deep neural network, and the goal of using a deep network is to detect objects with different sizes. The shallow layers of the network are responsible for detecting the small objects, whereas the very deep layers are responsible for detecting the big objects. We have noticed that the size of the license plate is small compared with the frame size, for example, most of the captured videos are 1920 × 1080 and the dimensions of the license plates do not exceed 250 × 70. The proposed ALPR approach modified the YOLO3 network to detect only the small objects. The number of convolutional layers in the original architecture is 75, whereas the used convolutional layers in the proposed approach are 15. This number of convolutions showed a good result to detect the license plates and the reduced number of network layers make the license plate detection stage fast compared with the original architecture. YOLO3 uses 9 anchor boxes for each grid cell and they are responsible for the variety of license plate shapes and the aspect ratio of the plate dimensions. According to Jordan Public Security Directorate (Public Security Directorate, 2019), the Jordanian license plates have four shapes: 520 × 114 mm, 340 × 220 mm, 305 × 155 mm, and 240 × 135 mm, therefore the proposed approach reduced the number of anchor boxes from 9 to 3 anchor boxes. This number of anchor boxes showed a good result to detect the Jordanian license plate accurately and to reduce the running time to achieve a real-time LP recognition. In license plate recognition, it is useless to detect very small plates because the plate content will not be clear enough to make accurate character recognition. Reducing the number of convolutional layers and the number of anchor boxes will detect the license with enough size for the recognition stage. Table 2 shows the proposed CNNs architecture for the license plate detection stage. The dimensions of the input image are 832×832, these dimensions experimentally showed better accuracy results compared with 416×416 dimensions. The architecture is modified to detect one class label ("plate"). The shortcut layer output can be obtained by adding the content of the mentioned layer with the layer that comes before the shortcut layer. For example, the output of layer 4 is obtained by adding the output of layer 1 with layer 3. The filters in layer number 19 were obtained by applying the following formula filters = (classes + 5) $\times$ 3), whereas the class number is one ("plate"). Fig. 2 shows some of the detected license plates using the proposed method.

3.2. Characters recognition

This stage accepts a set of license plates for different vehicles in the street as input. Then, it outputs the license plate number for each plate separately. The locations and the dimensions of the license plates are obtained for each frame as described in the previous stage. Immediately after detecting the set of plates for the current frame, the detected plates are cropped from the original frame and used in the character segmentation stage. The dimensions for the cropped plates are ranged from 227×64 to 60×30. The dimensions for the cropped plates are small and will be vanished after a few CNN layers, therefore, the proposed approach resized all the detected plates to 352×160. Table 3 shows the proposed CNNs architecture for the character recognition stage. The dimensions of the input image are 352×160. The CNNs are modified to detect ten classes of characters ("zero",

Table 2
The Proposed CNNs Architecture for the License Plate Detection Stage.

Layer	Stage	Number of filters	Filter size	Conv. Stride	Size of the output image
0	Conv	32	3×3	1	$832 \times 832 \times 32$
1	Conv	64	3×3	2	$416 \times 416 \times 64$
2	Conv	32	1×1	1	$416 \times 416 \times 32$
3	Conv	64	3×3	1	$416 \times 416 \times 64$
4	Shortcut Layer: 1				
5	Conv	128	3×3	2	$208 \times 208 \times 128$
6	Conv	64	1×1	1	$208 \times 208 \times 64$
7	Conv	128	3×3	1	$208 \times 208 \times 128$
8	Shortcut Layer: 5				
9	Conv	64	1×1	1	$208 \times 208 \times 64$
10	Conv	128	3×3	1	$208 \times 208 \times 128$
11	Shortcut Layer: 8				
12	Conv	256	3×3	2	$104 \times 104 \times 256$
13	Conv	128	1×1	1	$104 \times 104 \times 128$
14	Conv	256	3×3	1	$104 \times 104 \times 256$
15	Shortcut Layer: 12				
16	Conv	128	1×1	1	$104 \times 104 \times 128$
17	Conv	256	3×3	1	$104 \times 104 \times 256$
18	Shortcut Layer: 15				
19	Conv	18	1×1	1	$104 \times 104 \times 18$
20	YOLO				

Fig. 2. Samples of LP Detection Using the Proposed Approach.

"one, "two", "three", "four", "five", "six", "seven", "eight", and "nine"). The filters in layer number19 obtained by applying the following formula filters = (classes + 5) × 3), whereas the classes number is ten.

3.3. License plate recognition

The frame rate of the most used videos is about 30 FPS. This means that there are plate detection and character recognition at each frame, therefore the same vehicle could have many prediction results. The predicted characters in each LP are reordered and aggregated based on their locations in the LP (x and y coordinates). The different interpretations for the same vehicle number occur due to many noise factors such as the distance from the camera, view angle, sunlight, shadow, dust, etc. Due to the previous factors, the recognition result includes the true LP with many false-positive LPs (incorrect license plates). It has been observed during the experiment that most of the false positive LP numbers have high similarity with the true LP numbers. The similarity is above "4/7" whereas "7" is the maximum number of characters in the Jordanian LPs. Reducing the false detected plates will reduce the time for retrieving license plates information from the database and only the true LPs information will be retrieved. Two techniques are used to remove the false detection results, the Longest Common Subsequence (LCS) and Edit-distance (EDIT). However, EDIT showed better performance compared with the LCS technique, therefore EDIT is adopted in the proposed approach. EDIT is used to measure the similarity of two strings. Let's say we have two predicted license plates numbers L1 and L2. The EDIT (L1, L2) between the two predicted LPs L1 and L2 is the minimum number of edited operations (insertion, substitution, deletion) to transform L1 to L2. Additionally, a set of arrays is used to save the basic information about the newly detected plate. Table 4 shows samples from the collected information about the detected LPs at time t. The shaded rows represent a set of predicted LPs numbers that are related to the same vehicle. The proposed approach discovered that they are similar (their EDIT <=3), and added them to the same group. The plate with the id = 1 has the highest plate_count (i.e. 255), therefore the proposed approach picks the plate with the id = 1 and ignores the rest of the plats inside the same group and considers them as false positive LPs. The LP recognition decision is made after missing the license plates immediately, this is done by applying the following condition *current_frame- end_frame*[*id*]) > *threshold_time*, where *threshold_time* is the time after missing the license number(*threshold_time* is set to 30 s during all experiments). The set of arrays includes the following information about each predicted LP:

ID: The prediction id.

Plate number: The current predicted LP number.

Plate_count: The count of this plate number during the last n seconds.

End_frame: The last appearance of the LP (Frame number).

Visited: Has two values: "1″ indicates that this plate is checked with other LP in the same group and was used in the recognition decision. "0" this plate was not checked for LP recognition.

Plate_group: The group of the LP, similar plates will have the same group id, Edit-Distance is used to measure the similarity between different LPs.

Max-group: The plate number with the highest count in each group.

Algorithm 1 summarizes the details of the proposed JALPR.

Algorithm 1: *Jordanian Automatic License Plate Recognition* (*JALPR*) *Algorithm*

```
JALPR (Video)
Input: Video
Output: a List of recognized license plates
Create first_LP_list, second-LP-list and final-LP-list
LP_id = 0, Group-id = 0
For each new frame f
  Detect all plates' pictures in f, crop and add them to the list Cropped_LP
  For each Cropped_LP in f
  Recognize the plate's characters
  Arrange characters according to their × and y coordinates
  Add the concatenated Characters to the set first_LP_list
  End For
  For each LP number × in first_LP_list
    IF length[x] > length_threshold
      IF × does not exist in second-LP-list
        Add × to second-LP-list
        LP_id = LP_id + 1, Plate_number[LP _id] = x,
        Plate_count[LP_id] = 1, end_frame[LP _id] = current_frame
        Visited [LP_id] = 0, Plate_group[x] = null
        For each y in second-LP
          IF Edit-Distance (y,x) < sim_threshold
          Plate_group[x] = Plate_group[y]
          Exit the for loop;
          End IF
        End For
        IF Plate_group[x] = null
        Group-id = Group-id + 1, Plate_group[x] = Group-id, Max-group[x] = LP_id
        End IF
      Else
        Suppose that × exists in second-LP-list with the old_id position
        Plate_count[old_id] = Plate_count[old_id] + 1
        end_frame[old_id] = current_frame
        For each y in second-LP-list
          IF (Plate_count[old_id] > Plate_count[y] and Plate_group[old_id] = Plate_group[y])
          Max-group[y] = old_id
          End IF
        End For
      End If
    End IF
  End For
  For id = 0 to LP_id
    IF (current_frame- end_frame[id]) > threshold _time)
      IF Max-group[id] = id and Visited [id] = 0)
        Add Plate_number[id] to Final-LP-list
        group_id = Plate_group[id]
        For id2 = 0 to LP_id
          IF Plate_group[id2] = group_id
          Visited [id2] = 1
          End IF
        End For
      End IF
    End IF
  End For
End For
```

Table 3
CNN Architecture for the Proposed LP Characters Recognition Stage.

Layer	Stage	Number of filters	Filter size	Conv. Stride	Size of the output image
0	Conv	32	3 × 3	1	352 × 160 × 32
1	Conv	64	3 × 3	2	176 × 80 × 64
2	Conv	32	1 × 1	1	176 × 80 × 32
3	Conv	64	3 × 3	1	176 × 80 × 64
4	Shortcut Layer: 1				
5	Conv	128	3 × 3	2	88 × 40 × 128
6	Conv	64	1 × 1	1	88 × 40 × 64
7	Conv	128	3 × 3	1	88 × 40 × 128
8	Shortcut Layer: 5				
9	Conv	64	1 × 1	1	88 × 40 × 64
10	Conv	128	3 × 3	1	88 × 40 × 128
11	Shortcut Layer: 8				
12	Conv	256	3 × 3	2	44 × 20 × 256
13	Conv	128	1 × 1	1	44 × 20 × 128
14	Conv	256	3 × 3	1	44 × 20 × 256
15	Shortcut Layer: 12				
16	Conv	128	1 × 1	1	44 × 20 × 128
17	Conv	256	3 × 3	1	44 × 20 × 256
18	Shortcut Layer: 15				
19	Conv	45	1 × 1	1	44 × 20 × 45
20	YOLO				

Table 4
Sample Data from LP Information Tracking.

ID	Plate_number	Plate_count	End_frame	Visited	Plate_group	Max-group
0	2,170,940	264	312	1	0	0
1	5,032,870	3	591	1	1	3
2	5,032,070	1	287	1	1	3
3	5,032,970	255	619	1	1	3
4	1,812,466	22	468	1	2	4
5	5,092,970	1	486	1	1	3
6	5,032,907	1	527	1	1	3
7	1,475,052	8	541	1	3	7
8	1,773,825	1	607	1	4	8
9	8,177,709	1	716	0	5	10
10	8,117,709	27	759	0	5	10
11	8,112,709	1	751	0	5	10

4. The JALPR Dataset

There are few published papers about Jordanian license plate recognition and most of them are applied with still images. The Jordanian license plate is composed of a combination of up to seven Arabic numbers (Public Security Directorate, 2019). The plate color for private vehicles is white and the number is written in black color. Nonprivate vehicles could have a squared color area on the left corner of the plate (State-owned plates, Diplomatic, Passenger cars, etc.).

Compared with other countries there is no standard Jordanian license plate dataset. A new dataset was built to train and evaluate the proposed approach. The videos of the dataset were collected from the YouTube website. The JALPR dataset includes 12 videos captured by people during driving in Amman's streets. The captured videos represent real videos from different streets in Amman city during different periods. The camera is mounted on the front of a moving vehicle. The lengths of these videos vary from 01:41 to 25:30 min. The videos format is MP4 and the dimensions are 1920 × 1080 and 1280 × 720, with 30 FPS for most of them. All the dataset videos are available online (YouTube website)[1]. The collected dataset is divided into two groups, videos 1 to 8 are used for training the CNN model, whereas videos from 9 to 12 are used for testing the proposed approach and compare it with other approaches. For evaluation purposes, a list of all true license plates is created for each video. Table 5 shows the main characteristics of the proposed dataset. Samples from the JALPR dataset are shown in Fig. 3. The number of the used images for training the CNN model for the license plate detection stage is 1500, whereas the number of used plate images for training the CNN model for character recognition is 3000 images of 352 × 160 dimensions. The used training videos are split into frames and then the license plates are labeled manually for training the license detection model. The proposed CNN model is used to detect the license plates automatically, and the detected plates are cropped and resized to 352 × 160 dimensions. Some of the detected plates are too small, therefore resizing the plate dimensions to bigger dimensions (352 × 160) compared with the cropped ones makes the labeling and recognition steps easier. The cropped plates are then labeled manually for the character segmentation stage. The character recognition stage is more challenging compared with plate detection.

5. Evaluation of the proposed JALPR approach

The proposed JALPR approach is implemented based on the C language and the OpenCV library. The YOLO3 code available in (Alexey, 2020) is used in the proposed method. The used computer

[1] https://www.youtube.com/playlist?list=PLgXPbStWOTfjhrLUHpZWDtniqXCw4pzs9

Table 5
the proposed dataset for training and testing the proposed ALPR approach.

Video #	Video's Name (as written in YouTube)	Duration (minutes)	Format	Format Resolution (pixels)	Frame Rate (fps)	Number of true license plates
Video 1	Driving in the streets of Amman – Jordan	05:43	mp4	1920 × 1080	30	–
Video2	A drive-through Amman for Jordan Lovers	03:55	mp4	1920 × 1080	30	–
Video3	Amman morning commute to work	25:30	mp4	1280 × 720	30	–
Video4	Driving in Amman Ramadan day from Abdullah Ghosah street to Abodoun	07:44	mp4	1920 × 1080	30	–
Video5	Jordan, Amman, traffic	02:59	mp4	1920 × 1080	30	–
Video6	Riding in Amman Traffic 1	15:34	mp4	1280 × 720	30	–
Video7	Al Madeena street - Amman drive - music included	03:00	mp4	1920 × 1080	30	–
Video8	جولة في عمان	23.20	mp4	1280 × 720	29	–
Video9	Amman Sahab 12 10 2019	06:45	mp4	1920 × 1080	30	129
Video10	صباح الذكريات - شارع قريش وسط البلد	04:55	mp4	1920 × 1080	30	45
Video11	7th circle - Amman drive - music included	02:58	mp4	1280 × 720	30	39
Video12	شارع زهران العريق	01:41	mp4	1920 × 1080	30	11

Fig. 3. Sample frames from the proposed JALPR dataset.

in all experiments is Intel(R) Core i5-8600 k 3.6 GHz, memory 8 GB, and GTX 1080 Graphic Card. To show the efficiency of the proposed approach, two commercial software packages are used for the comparisons. OpenALPR ("OpenALPR," 2020) and Sighthound ("Sighthound," 2020) are well-known commercial software for ALPR and they support many countries' license plates. OpenALPR supported more countries compared with Sighthound. In the OpenALPR system, the Middle East area is selected for all tested videos. Sighthound system used a model that supports different countries and there was confusion between characters "I" and "1", therefore all "I" characters are replaced by "1" because there are not alphabetic characters in Jordanian license plates. "Video9" to "Video12" were used to test the performance of the proposed approach. As shown in Table 6, the overall accuracy shows that the proposed approach has the highest accuracy with 87.05% compared with 80% and 64.73% for OpenALPR and Sighthound software, respectively. The tested videos have different lengths; therefore the number of license plates is increased by increasing the video length. "Video9" represents the longest video, the number of manually (by eye) recognized LPs is 129 plates. The proposed approach outperformed all approaches and recognized 91.47% of them. OpenALPR and Sighthound accuracies on "Video9" are 79.10% and 69.00%, respectively. The proposed approach and OpenALPR have similar accuracies on "Video10" and "Video12". In "video1" OpenALPR correctly recognized 34 LPs (87.20%) whereas the proposed approach correctly recognized 32 LPs (82.10%). The proposed approach outperformed the Sighthound system in all the tested videos. The false recognitions that are generated by each approach are shown in Table 7. The proposed JALPR and OpenALPR produced small numbers of false detections compared with Sighthound. There is a marginal difference between the proposed approach and OpenALPR in most of the tested videos. In the longest video ("Video9") OpenALPR produced 6 false recognitions, whereas the proposed approach produced 7 cases. Fig. 5 shows some of the successfully recognized license plates using the proposed method. Fig. 4 shows a list of the last *N* recognized

Table 6
The recognition accuracy of the proposed JALPR approach and other approaches.

ALPR	OpenALPR	Sighthound	The Proposed approach
Video9	79.10% (102/129)	69.00% (89/129)	**91.47% (118/129)**
Video10	75.56% (34/45)	48.89% (22/45)	**75.56% (34/45)**
Video11	87.20% (34/39)	64.10% (25/39)	82.10% (32/39)
Video12	100.00% (11/11)	81.82% (9/11)	**100.00% (11/11)**
All videos	80.80% (181/224)	64.73% (145/224)	**87.05% (195/224)**

Table 7
False Detection results produced by the proposed JALPR approach and other approaches.

ALPR	OpenALPR	Sighthound	The Proposed approach
Video9	6	25	7
Video10	16	19	**15**
Video11	**17**	22	23
Video12	4	13	**2**
All videos	**43**	79	47

Fig. 4. Samples of the last recognized N plates (N = 4).

Fig. 5. Samples of LP recognition using the proposed approach.

plates using the JALPR approach. It is clear from the results that the proposed approach accurately recognized the plate numbers in difficult scenes. In addition to showing the result to the user into the screen, the proposed approach prints the list of recognized LPs to a text file and crops the images of the recognized LPs in a folder. The proposed method running time is fast, the time rate of frame processing is more than the real-time rate with 30–40 FPS.

6. Conclusion

This paper proposed an efficient real-time ALPR approach for Jordanian license plates called the JALPR approach. Additionally, a dataset called the JALPR dataset is proposed. The JALPR dataset is collected from real-world videos in Jordan streets. The proposed dataset to my knowledge represents the first dataset that includes Jordanian license plates (the dataset available online on YouTube). The proposed JALPR approach modified the YOLO3 CNN architecture to a shallow CNN architecture to recognize small objects. Two CNNs are used to detect the plate and to recognize the plate content. Moreover, a data structure based on a set of arrays is used to track the license plate information, and the temporal information from the last set of frames is used to choose the best license plates and remove many incorrect plates (false positive plates). To test the performance of the proposed approach, two commercial software packages are used for the comparisons. The overall accuracy of the proposed JALPR is 87%, and the accuracies for OpenALPR and Sighthound are 80.80% and 64.73%, respectively.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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