Real-time Egyptian License Plate Detection and Recognition using YOLO

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***Abstract*—Automatic License Plate Detection and Recognition (ALPR) is one of the most significant technologies in intelligent transportation and surveillance across the world. It has many challenges because it affects by many parameters such as the country's layout, colors, language, fonts, and several environmental conditions so, there isn't a consolidated ALPR system for all countries. Many ALPR methods have been proposed based on traditional image processing and machine learning algorithms since there aren't enough datasets, particularly in the Arabic language. In this paper, we proposed a real-time ALPR system for the Egyptian license plate (LP) detection and recognition using Tiny-YOLOV3. It consists of two deep convolutional neural networks. The experimental results in the first available publicly Egyptian Automatic License Plate (EALPR) dataset show the proposed system is more robust in detecting and recognizing the Egyptian license plates and gives mean average precision values of 97.89% and 92.46% for LP detection and character recognition, respectively.**

***Keywords*—Automatic license plate recognition; Egyptian license plate; Tiny-YOLOV3; CNN; eALPR dataset**

I. Introduction

Numerous applications, including traffic surveillance, automatic toll collection, parking, and theft prevention, depend on the automatic detection and recognition of licence plates [1]. The main objective of ALPR systems is to detect the location of the license plate in the vehicle image and recognize its characters and digits without involving massive human resources, and saving processing time.

The ALPR problem has been investigated over the last decades by many researchers, and several methods have been presented. However, the ALPR is still active due to several difficulties that are related to digital image processing, including the diversity of lighting, camera angles, distance from the camera, scales, complex backgrounds, etc. In addition to the license plate layout, each country defines a special plate structure, background, color, language, font type, and size, which differ from country to country. The majority of ALPR proposed methods are outside the Middle East (e.g. United States, China, Brazil, Taiwan, and Europe) [2]–[5].

Most of the previous works are based on traditional image processing techniques such as binarization, edge-based, character-based, color-based, texture-based, and template matching approaches, which are based on hand-engineered features. With the rapid development of the deep learning, the prediction performance of many computer vision tasks such as image classification, segmentation, and object detection has been greatly improved [6]. Many approaches have used deep Convolutional Neural Networks (CNN) to obtain state-of-the-art accuracy. However, the main drawback of deep learning models is that they need big datasets for the training stage. so, few deep learning works were presented in the Arabic region due to the lack of a publicly available dataset, especially for Egyptian license plates.

You Only Look Once (YOLO) [7] inspired models have made significant advancements in object detection problems. So we decided to use it in our proposed system. YOLOV3 [8] is the enhanced of YOLO and YOLOV2 [9] real time object detection algorithm that uses a model with 53 fully convolutional layers on the other side, Tiny-YOLOV3 is a light model focused on a speed / accuracy trade-off that uses eight convolutional and six max-pooling layers. Hence, Tiny-YOLOV3 is quicker but less accurate than YOLOv3.

In this paper, we propose a new real-time system for Egyptian license plate detection and recognition based on the Tiny-YOLOv3 object detection deep learning model. It consists of two stages : the first stage is responsible for detecting the license plate location from the input vehicle image and the second stage is recognizing the characters and digits from the detected license plate. The proposed system is used to evaluate the EALPR dataset that the first public Egyptian LP dataset.

our main contribution can be summarized as follows:

- A new real-time system for Egyptian license plate detection and recognition based on the Tiny-YOLOv3 deep learning model for both stages.
- Evaluation of the proposed system on the EALPR dataset, including 2450 vehicle images and more than 12,000 Arabic digits and characters.

The paper is organized as follows. We briefly review ALPR related works in Section II. Section III introduces the EALPR proposed system. We report the experimental results in Section IV, and finally, we present the conclusions and future work in Section V.

II. Related Work

ALPR is challenging because it depends on several factors, including the plate country's design, colors, environment, language, and texture. Both license plate detection and character recognition could be done using the object detection techniques. There are two approaches of object detection features, hand-engineered features (Haar, HOG, SIFT, SURF, ... etc.) and deep neural networks features based on convolutional neural networks (YOLO, SSD, Faster-RCNN, RefineDet, ... etc.). We briefly review some previous related work to the ALPR problem.

In [10], proposed a smart vehicle control system based on ALPR. The proposed method is color-based and extracts the region of the license plate based on some of the predefined colors like yellow and white, and applies histogram algorithms and morphological operations for rapid detection. This method uses a back-propagation neural network for character recognition. A total of 350 vehicles are used for testing the method and achieving a high success rate.

In [11], presented an ALPR system for the Egyptian license plates. A total of 221 images of classic Egyptian vehicle license plates were used in this study. The proposed method accuracy for plate detection is 78% using edge detection and morphological operations, 85% using the illumination model of YCbCr and wavelet transform, 85% for character segmentation, and 74% for character recognition.

In [2], developed an end-to-end deep learning system for Brazilian license plate detection and recognition in unconstrained scenarios. The developed system is based on deep convolutional neural networks (CNN). The authors used the public available Brazilian datasets. The accuracy of the license plate detection is 99%, and the recognition is 93%.

In [5], presented a two stages method for license plate detection and recognition. In the first stage, the author detected the vehicle region using a faster R-CNN method and in the second stage, they used the same algorithm with hierarchy sampling method for plate detection in the vehicle region. The proposed method is evaluated by Caltech dataset and achieved 98.39% as the precision rate.

In [3], proposed a real-time end-to-end ALP system based on the state-of-the-art YOLO object detection. They presented a fully annotated public dataset called FPR-ALP for Brazilian license plates. Fast-YOLO, YOLOV2, and CR-Net are used for plate detection and recognition respectively. The recognition accuracy of the system is 93.53% higher than both the commercial Sighthound and OpenALPR solutions.

III. Proposed System

A. System Overview

In Fig. 4, we show the main stages of the proposed ALPR system. The development of real-time object detection techniques is an important step for building a reliable ALPR system. We use two object detection models for license plate detection and recognition. The input to our proposed system is the vehicle image, whereas the output is the recognized license plate characters and digits. Tiny-YOLOV3 is the backbone architecture for both stages LP detection and recognition.

B. ELAPR Dataset

In this section, we introduce a new dataset for the Egyptian license plate called (EALPR). We scrap the EALPR dataset images from websites such as Instagram pages [12]–[15] and Facebook Marketplace [16] using web scraping Tools [17], [18]. It has 2,450, and 12,160 characters images including many types of vehicles such as cars, buses, trucks, micro-buses, and mini-busses. Fig. 1 shows the characters and digits statistics. The vehicle images are captured using different cameras, at varying times, lighting, and background. Fig. 7 shows samples from EALPR. It is publicly available on https://github.com/ahmedramadan96/EALPR.

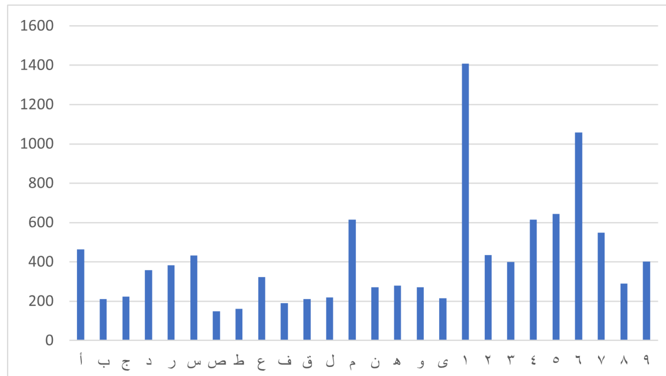


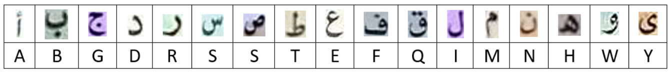
Fig. 1. Characters and Digits Statistics in the EALPR Dataset.

The Egyptian License Plate (LP) uses the Arabic digits and characters which is varying in several countries that use Latin letters such as Europe, Brazil, US, ... etc. It has a dimension 16 (height) X 40 (width) with aspect ratio 1:2 approximately [19]. its layout is divided into 3 regions: the country region contains the Egypt word in Arabic and English format, the character region includes plate characters, and the number region contains plate digits. Fig. 2 shows the Egyptian LP structure. It uses 10 Arabic digits and 17 Arabic characters. Fig. 3 illustrates the used license plate Arabic characters, digits, and their corresponding English format.

Fig. 2. Egyptian License Plate Structure.

Dataset annotation is required for object detection YOLO models. After collecting EALPR dataset we manually annotate the vehicles, characters, and digits using Ybat tool [20] as shown in Fig. 5, and 6. Ybat provide the start and end coordinates (x_{min},x_{max}), (y_{min},y_{max}) respectively for each rectangle. The four values of YOLO bounding boxes is calculated using

a. Plate Arabic Digits and Latin Digits.



b. Plate Arabic Characters and Latin Characters.

Fig. 3. a. Plate Digits b. Plate Characters in Arabic (First Row) & English (Second Row).

equations (1)-(4)

$$b_{\mathrm{x}} = \frac{x_{\min} + x_{\max}}{2 \times w} \tag{1}$$

$$b_{\mathrm{y}} = \frac{y_{\min} + y_{\max}}{2 \times h} \tag{2}$$

$$b_{\mathrm{w}} = \frac{x_{\max} - x_{\min}}{w} \tag{3}$$

$$b_{\mathrm{h}} = \frac{y_{\max} - y_{\min}}{h} \tag{4}$$

where b_x,b_y,b_w,b_h representing the center point of the rectangle, width, and height, respectively.

C. *License Plate Detection Network **(LP-Net)***

LP-Net is responsible for taking the raw vehicle image as input and detecting the location of the plates. The plates are cropped based on the bounding boxes using OpenCV [21] and passed to the character model. A license plate is an object that may be detected using object detection algorithms. The main function of object detection algorithms is to detect the object locations at different scales (shapes and sizes). Deep learning object detection techniques work effectively in a variety of environments and with a large dataset. LP-Net is the same original Tiny-YOLOV3 network. Tiny-YOLOV3 consists of 8 convolutional and 6 max-pooling layers in the feature extractor block. The network architecture is shown in Table I. It uses small kernel sizes 3×3 and 1×1 for the convolutional layers and 2×2 for max-pooling layers. We changed the input image size from 416×416 to 608×608, which resulted in higher accuracy. We also changed the final convolutional layer to predict only one class label ("license_plate"). YOLO predicts bounding boxes using A anchor boxes (we choose A = 3) with four values (b_x,b_y,b_w,b_h), confidence, and C class probability, therefore the number of filters is 18 which is defined in Equation (5)

$$\#Filters = (Classes + 5) \times Anchors \tag{5}$$

TABLE I. Tiny-YOLOV3 Architecture

Layer	Type	Filters	Size/stride
0	Conv	16	3×3/1
1	Max		3×3/2
2	Conv	32	3×3/1
3	Max		3×3/2
4	Conv	64	3×3/1
5	Max		3×3/2
6	Conv	128	3×3/1
7	Max		3×3/2
8	Conv	256	3×3/1
9	Max		3×3/2
10	Conv	512	3×3/1
11	Max		3×3/2
12	Conv	1024	3×3/1
13	Conv	256	3×3/1
14	Conv	512	3×3/1
15	Conv	33	3×3/1
16	Yolo loss		
17	Route 13		
18	Conv	128	3×3/1
19	Upsampling		×2
20	Route 19,8		
21	Conv	256	3×3/1
22	Conv	33	3×3/1
23	Yolo loss		

D. *Character Recognition Network **(Char-Net)***

The main function of Char-Net is to detect the plate digits and characters and recognize them using deep object detection CNN. The input for this network is the cropped license plates that were detected from the previous network. We accept all cropped (LP)s with an aspect ratio of 1:2 and reject the small plates. Also, It has the same architecture of Tiny-YOLOV3 as shown in Table I with some changes. All plates are resized to be 384×192 to prevent the vanishing gradient in CNN layers. The architecture is changed to detect 27 digits and characters that are used in the Egyptian license plates. Fig. 3 show all used digits and character classes. The number of filter in the last convolutional layer is 96 which calculated using Equation 5

IV. Experimental Results and Evaluation

A. *Experimental Setup*

All experiments were performed on a personal computer with Windows 10 64-bit, Intel(R) Core(TM) i7-9750H 2.6GHZ CPU, 16GB memory, and NVIDIA GeForce GTX 1660Ti GPU. The proposed system is implemented using the darknet deep learning framework and OpenCV library. The YOLO implementation is available here [22]. As previously mentioned, the EALPR dataset vehicle images are collected from social networks with different environments and conditions. For plate and character networks, we resize the input image to be 608×608 and 384×192 respectively. 80% of the dataset is selected randomly for training our proposed system and the remaining 20% is used for testing purposes. In the training stage, we use the pre-trained Tiny-YOLOV3 model to initialize the network's weights. Both the plate and character networks were trained for 5000 epochs and 6000,54000 max batches respectively with a batch size of 64 images. We use the Leaky RELU activation function. The momentum is set to 0.9, the weight decay to 0.0005, and the learning rate started with 0.001 used for both networks. Table II summarizes all training parameters for both models.

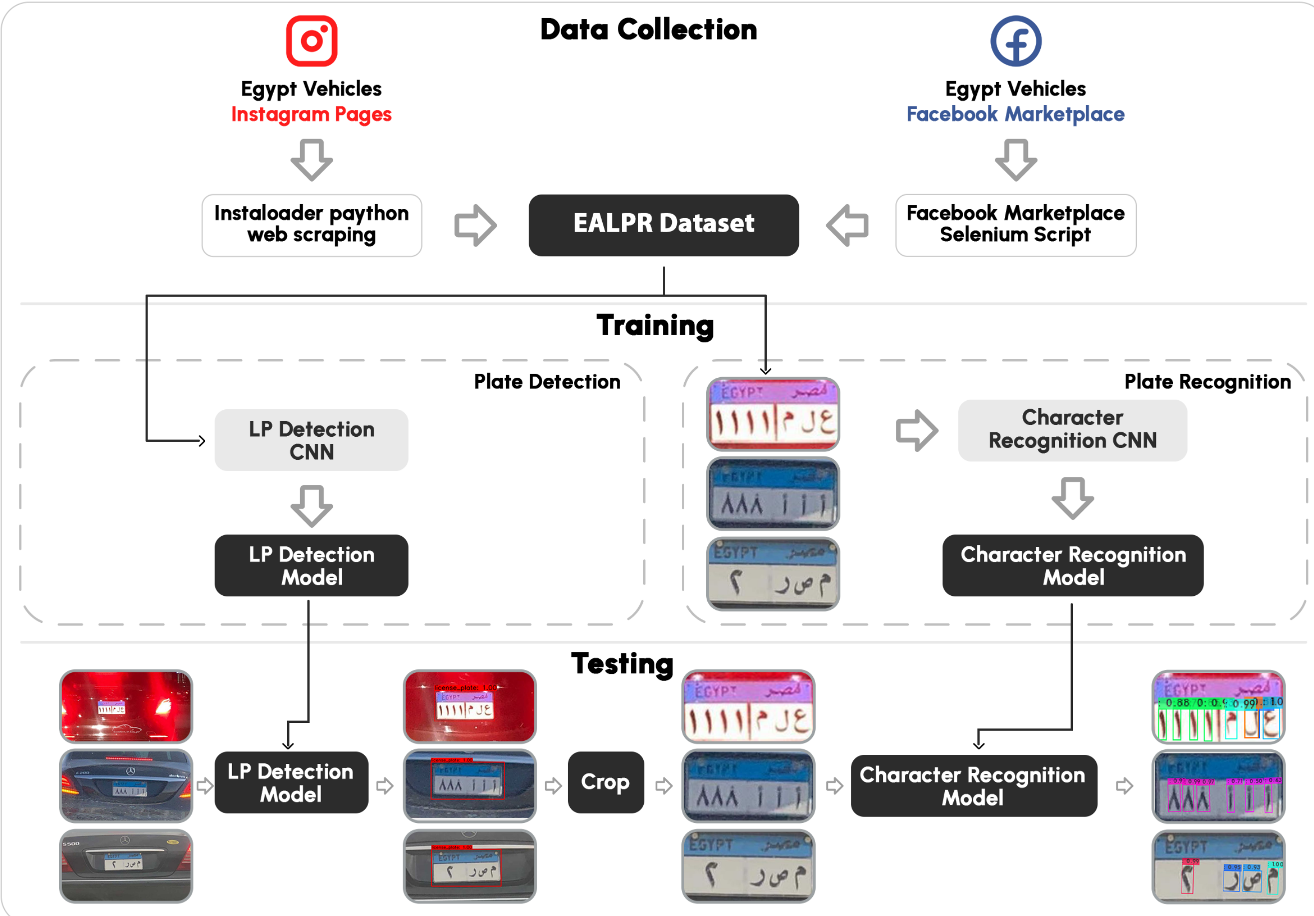


Fig. 4. Main Stages of the Proposed EALPR Approach.

Fig. 5. Vehicle Plate Annotation.

B. Evaluation Metrics

The proposed system is evaluated using the mean average precision (mAP) value. The mAP value depends on precision and recall metrics [23] which are described in Equations (6) and (7).

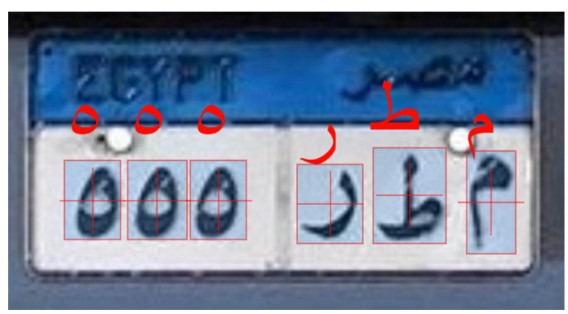


Fig. 6. Plate Characters Annotation.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

where True Positive(TP), False Positive(FP), and False Negative(FN) means the number of correctly detected (plates

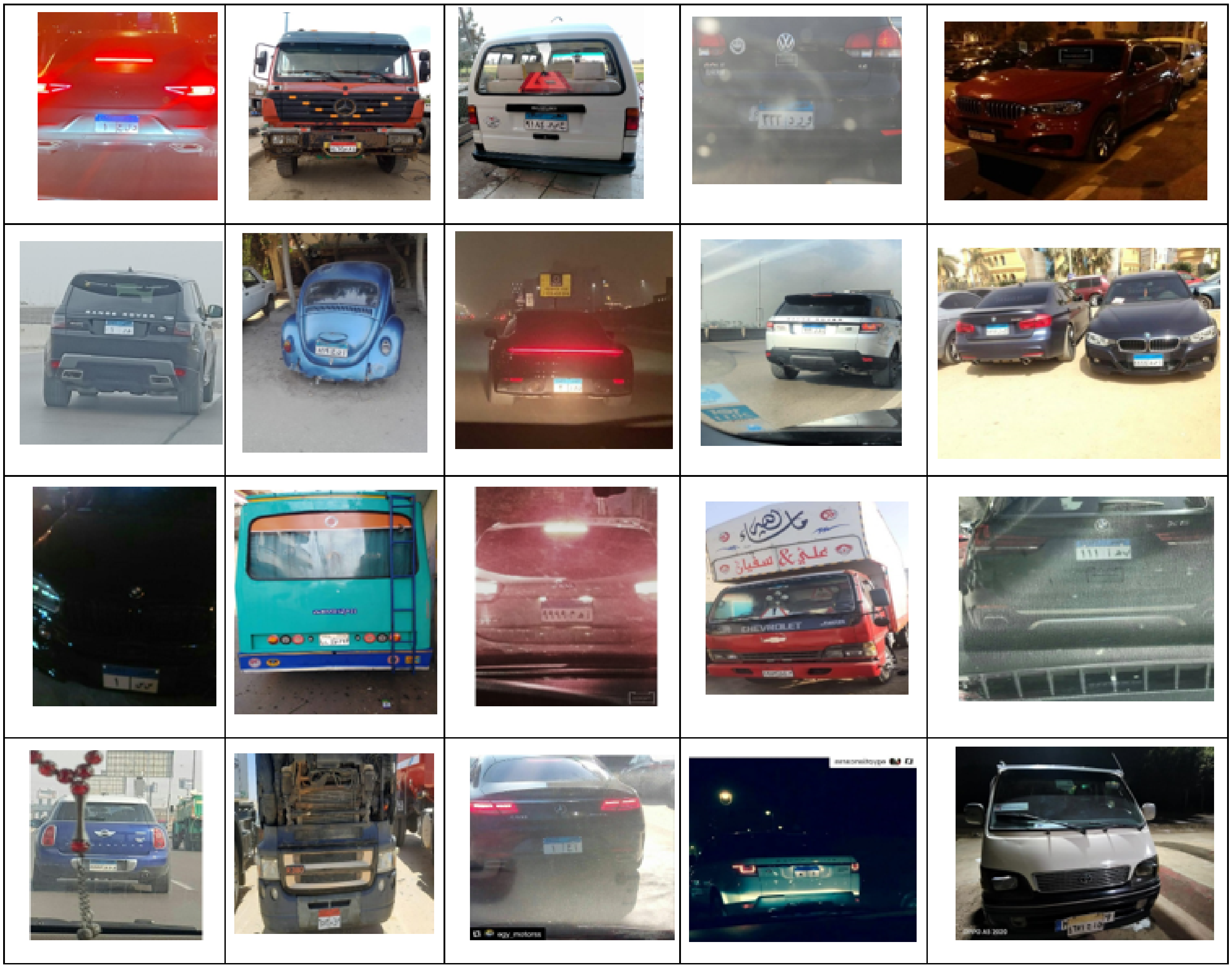


Fig. 7. Sample Images from EALPR Dataset.

TABLE II. TINY-YOLOV3 TRAINING PARAMETERS FOR LP-NET & CHAR-NET

Parameter	Value
Framework	Darketnet
Image Dimensions	608×608 (LP-Net) and 384×192 (Char-Net)
Channels	3
Activation Function	Leaky RELU
Policy	steps
Epoch	5000
Max batches	6000 (LP-Net) and 54000 (Char-Net)
Batch size	64
Subdivision	16
Learning rate	0.001
Decay	0.0005
Momentum	0.9

and characters), the number of negative correctly detected (plates and characters), and the number of not detected (plates and characters), respectively. Object detection correctly depends on the Intersection over Union (IoU) value that measures the similarity between the ground truth, and the predicted bounding box. We choose IOU = 0.5. The average precision (AP) is described in Equation (8) as the area under precision and recall values. AP is the standard evaluation way for object detection networks.

$$AP = \int_0^1 P_{(\mathrm{R})} dR \tag{8}$$

where $P_{(\mathrm{R})}$ is the precision over recall. The mAP value is the average of all classes of AP.

C. Results Analysis

We evaluate the Performance of LP-Net and Char-Net using the mean average precision with the threshold value = 0.5. After training both networks with 5k epoch. The mAP of Let-Net is 97.89 %, while the Char-Net Performance is 92.46% to predict the bounding boxes with the ground truth. Fig. 8 and 9 show the results obtained from the experiments on both networks. In Fig. 8, the model result is the bounding boxes for each LP and LP class inside the vehicle image, while in Fig. 9 the result is the bounding boxes for each character and its class inside the detected license plate.

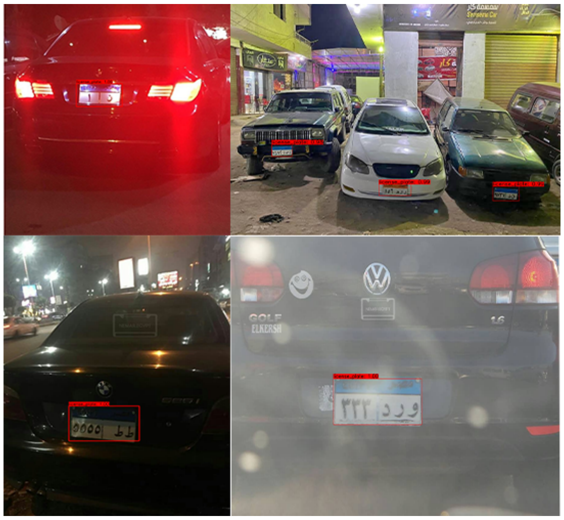


Fig. 8. LP-Net Results.

Fig. 9. Char-Net Results.

V. Conclusion

In this study, We present a real-time Egyptian license plate detection and recognition system. The proposed system is a pipeline of two deep convolutional neural networks. It can be deployed on GPU-less computing devices. The tiny-YOLOV3 model is the backbone for both networks. Also, We evaluated it on the publicly available Egyptian License plate (EALRP) dataset. The accuracy of the proposed system is 97.89% and 92.46% for license plate detection and character recognition, respectively. We suggest collecting more samples for the dataset with many variations and Implementing other YOLO model versions or Attention vision transformers to improve the accuracy of the proposed system.

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