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A Real Time Vehicle's License Plate Recognition System Using YOLOv5 Model and Transfer Learning: A Case Study of Afghanistan

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ABSTRACT:

Due to numerous applications, particularly in Intelligent Transportation Systems (ITS), Automatic License Plate Recognition (ALPR) has remained an active study area for years. Due to a variety of factors, it has always been difficult to detect license plates on moving vehicles and identify the characters on them. These scenarios include varying lighting and weather, unavoidable data, acquisition noises, and other difficult situations like the requirement for real-time performance in state-of-the-art (ITS) systems. The efficient deep learning-based ALPR method shown in this work reliably recognizes license plates (LPs) even when trained on a small dataset. We take actual traffic pictures from Kabul city Afghanistan, then label the LPs within various frames. To increase the number of training and testing samples, data augmentation techniques are used. To teach the recently published YOLOv5 object detecting framework to recognize the LPs and the alphanumerics, we employ the transfer learning approach. By using Convolutional Neural Networks for transfer learning, it has been demonstrated that it is possible to recognize LPs more quickly than before. Performance for the intended model was 0.994 mAP.

Keywords: Deep Learning, Afghani License Plate, Automatic License Plate Recognition, License Plate Detection, You Only Look Once Version 5 (YOLOv5).

I. Introduction

Due to the growing demand for reliable intelligent surveillance and security systems in current technology societies, license plate recognition is a crucial topic. Intelligent Transportation Systems (ITS), which have various uses including automatic toll collection, traffic law enforcement, private access control, border control, and road traffic monitoring, have become a need for the idea of smart cities. Traffic monitoring systems, navigation and vehicle tracking, toll collection, parking lot control systems, and the detection of stolen cars are all key applications for ALPR that depend on the process of recognizing license plates.

Every vehicle has a distinctive license plate (LP), which may act as the primary key in a database storing data on the car without the need for other well-known technologies like external cards, tags, or transmitters.

Because ALPRs rely on complex computer vision algorithms to detect and identify license plates, there is still an opportunity for improvement in both their accuracy and their capacity to handle various LP kinds. This is clear from the fact that realistically available solutions continue to fall short in their ability to withstand difficult real-world situations because they impose environmental restrictions such as a set background, camera placement, distance, and angle [1].

ALPR systems typically consist of three stages: LP detection, character segmentation, and character recognition. Complex situations might lead to performance degradation for ALPR systems. Occlusion, varied license plate layouts, and languages, varying license plate sizes and width-to-height ratios, noisy or unclean input photos, and diversity of lighting and weather conditions are a few of the major challenges. The layout of the typical vehicle license plates in Afghanistan uses plates with dimensions of 420 x 175 millimeters (mm), 16.5 x 7 inches (in) in black on a white background for private vehicles. The plate is divided into three sections and is in turn displayed in Arabic/Persian characters at the top, and in Latin at the bottom. The first section of characters in Afghan license plates identifies the province, with a three-letter code, and in the next section the range of the digits is 1 to 9, and the number 0 is not used which shows the number plate, and in the last section of characters identifies grade (registration plate), which depends on the type of vehicle. Furthermore, considering the type and usage of the vehicle, the background color of the license plates may vary. Figure.1 shows some of the typical Afghani vehicle license plates. It should be noted the layout designed for motorcycles and Rickshaws are completely different, and recognizing them is not the purpose of this manuscript. These variations make the LPD and CR processes in Afghani vehicle license plates a formidable challenge.

In this paper, we propose a deep learning-based solution for the detection and recognition of Afghani license plates in videos of real-world traffic. The objectives of this research are listed below:

- Municipalities use ANPR to monitor incoming and outgoing traffic.
- Traffic classification is required in environmental zones.

- Around airports, the traffic is monitored to detect patterns as an anti-terrorism measure.
- A number plate can be used to flag vehicles (blacklist matching) or control entry to private areas because each one is unique (whitelist matching).
- Car categorization can typically identify a fake number plate.
- Suspicious trends in the use of highway parking lots may indicate criminal activity, among other things.

II. Literature review

Various techniques have been proposed in the literature for LP detection, segmentation, and recognition. Many have addressed LP detection as a general object detection problem for real-time LP detection and recognition.

Figure 1: Different types of Afghani vehicle license plates.

Tourani et al. 2020 [1] presented a real-time License Plate Detection (LPD) and Character Recognition (CR) system for Iranian vehicle license plates, using the YOLOv3 object detector, incorporated with the (DNN) Deep Neural Network, the networks are trained using the realistic condition data collected from practical systems installed as surveillance applications, with the addition of various data augmentation techniques, so that they are robust under different conditions. The proposed system achieved an average end-to-end recognition rate of 95.05% on 5719 images.

Laroca et al. 2021 [2] presented a real-time end-to-end ALPR system using the YOLO object detector, incorporated with the following two CNNs: one used for vehicle detection in the given input image and the other used for LP detection in the detected vehicle. The networks are trained using images from several datasets, with the addition of various data augmentation techniques, so that they are robust under different conditions. The proposed system achieved an average end-to-end recognition rate of 96.9% across eight public datasets (from five different regions) used in the experiments, the given technique is not adequate for real-world ALPR applications.

Shohei et al., 2019 [3] used a two-stage YOLOv2 model for accurate LP detection in night scenes, which helped overcome the YOLOv2's problem of not being able to detect smaller objects like an LP, which is typically just around 1% of the whole frame. The first stage detects the vehicle and the second stage detects its license plate. Despite achieving good accuracy in the night-time, it not only wrongly detected some signboards as LPs but also faced difficulty in detecting distant LPs.

Liu et al. 2014 [4] used a YOLOv3 detector, which divides the image into rectangular regions. Each region predicts bounding boxes around potential objects and class probability to calculate the confidence value. For higher precision, non-maximal suppression is applied to the Intersection over Union (IOU), a ratio of the overlap between the predicted and the annotated (ground truth) bounding boxes. Despite being fast and accurate, the model is biased towards the object's size in an image. The objects encountered with bigger sizes while training cannot be detected accurately if they appear as a smaller size while testing.

Izidio et al. 2020 [5] trained a CNN model on synthetic LP images using an Adam optimizer and transfer learning and fine-tuned it with actual LP images to allow the network to adjust for the real world. The use of transfer learning helps to save time by fetching better performances from pre-trained models on the custom dataset.

Hui Li et al. 2016 [6] used a recurrent neural network with long short-term memory to recognize the sequential features extracted from the whole LP, avoiding segmentation. However, it requires a large number of labeled LPs for training, limiting its use as a practical ALPR solution in real-world circumstances.

Silva et al. 2018 [7] used a CNN to detect and rectify distorted LPs, before passing them to the recognition module. It provided good recognition results, but the dataset used for testing did not represent very challenging scenarios.

Hui li et al. 2018 [8] used an end-to-end CNN approach to avoid separate training of the detection and training models and to reduce the intermediatory errors of separate models.

Masood et al. 2017 [9] used a sequence of CNNs to perform the recognition task under different variations in the background, LP sizes, fonts, and other factors, which increased the accuracy, and computational complexity as well.

III. Problem formulation and methodology

The characteristics of the license plates are crucial to the identification procedure. In developed countries, the size, color, font, face, that is, the size, color, and spacing between each character as well as the number of lines and the height and width of the letters are all closely followed. Many nations around the world have used this specific approach to establishing license plate standards. But in Afghanistan, the license plate is quite different from international LP, it is in turn displayed in Arabic/Persian characters at the top, and Latin at the bottom. These variations make the LPD and CR processes in Afghani vehicle license plates quite difficult, a simple of the Afghani license plates with variations in shape, script, etc. is shown in Figure.2.

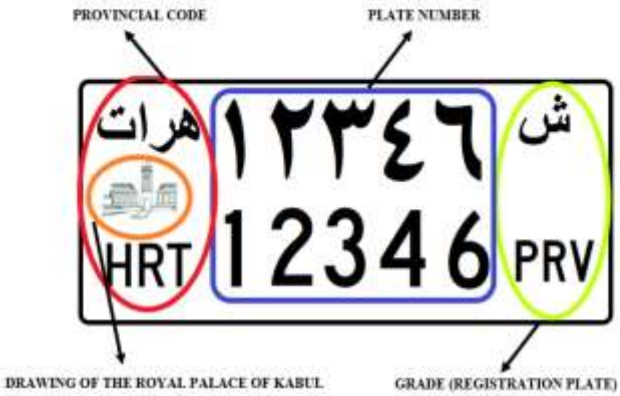

Figure 2: Afghani License Plate.

1. Methodology:

Good generalization on complex tasks can be achieved by designing a network architecture that has a certain amount of a priori knowledge about the task. Figure.3 illustrates the machine learning pipeline from model preparation, annotation, and augmentation through LP detection, segmentation, and identification. Following, it will be detailed how this approach differs from other ones now in use and how each stage is implemented.

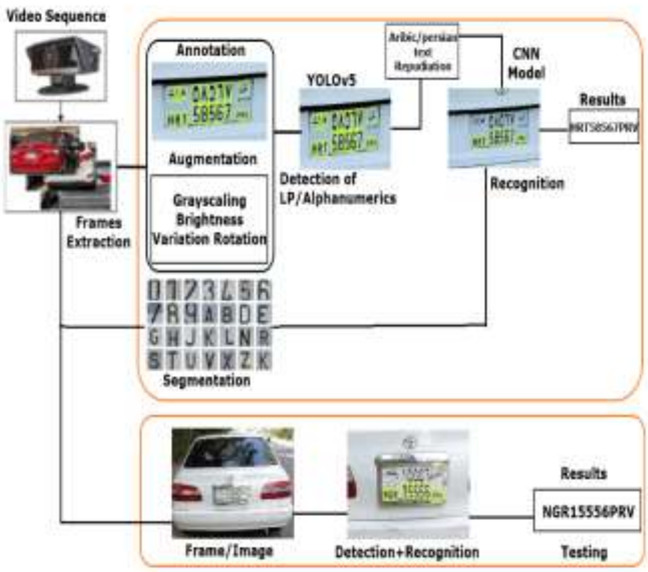

Figure 3: Pipeline for the ALPR system model.

2. YOLOv5 [10]:

Mosaic data augmentation and auto-learning bounding box anchors are features of YOLOv5, which is an upgraded and expanded version of YOLOv4. With an average processing speed of 140 FPS, it can predict objects in images in 0.007 seconds. Additionally, YOLOv3 offers a low mAP (mean average precision) and a high FPS (frames per second). FPS and mAP performance from YOLOv5 are excellent. There are four different varieties of YOLOv5 backbones: YOLOv5s (small), Yolov5m (medium), Yolov5l (large), and Yolov5x (heavy) (xlarge). The backbone and head of each of the four YOLOv5 models are the same, but they differ in terms of the number of channels in each layer and the model depth multiple. Figure 4. displays the results of the performance comparison between YOLOv5 and EfficientDet [11], for s,m,l,x. which, among object detecting methods, performs very well. Performance-wise, the four YOLOv5 models outperform EfficientDet. The s model is the fastest in YOLOv5 but has lower accuracy, while the x model is the slowest but has higher accuracy. In this paper, since real-time processing is targeted, the YOLOv5s model, which is the fastest model among the four models of YOLOv5, is used for LP detection and recognition.

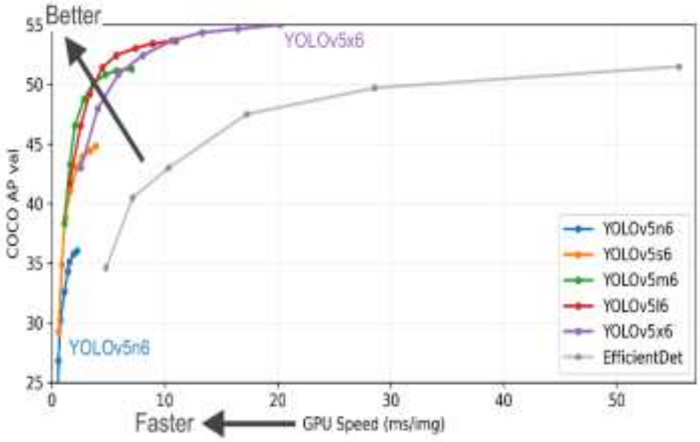

Figure 4: YOLOv5 performance [10].

IV. Results

Figure 5: YOLOv5 detection of license plates.

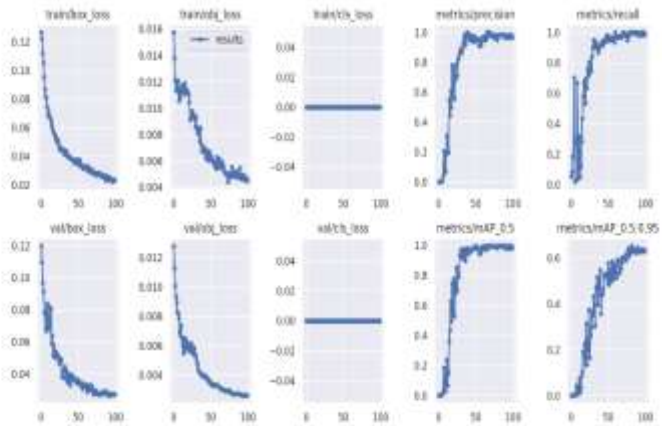

Figure 6: Plots of box loss, object loss, precision, and recall over the epochs for the training and validation dataset.

Table 1: Comparison of the proposed ALPR system with the existing methods, using a custom dataset.

Method	Accuracy
Fast R-CNN **[12]**	0.725
Plate Recognizer **[13]**	0.843
Faster R-CNN **[14]**	0.979
YOLO v.4 **[15]**	0.983
Proposed	**0.994**

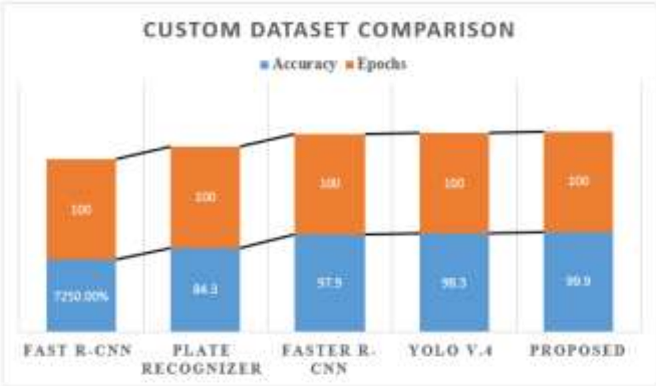

Figure 7: Graph of Comparison of the proposed system with the existing methods, using a custom dataset.

Table 2: The computational efficiency of the proposed system on different benchmark datasets.

Dataset	Iterations per second
Caltech dataset **[16]**	4.71
Media Lab dataset **[17]**	3.73
Indian Vehicle dataset **[18]**	2.30
Proposed	**2.03**

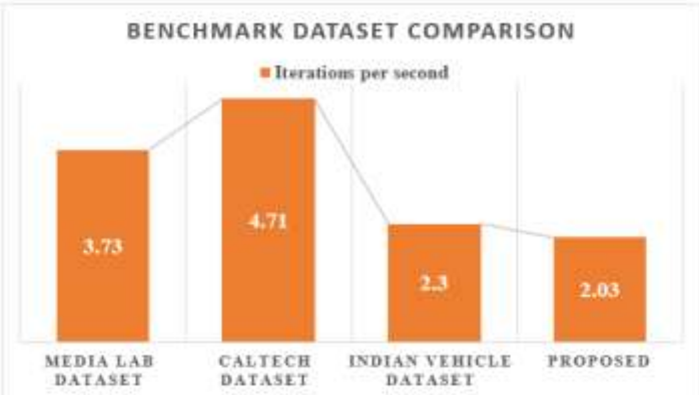

Figure 8: Graph of computational efficiency of the proposed system on different benchmark datasets.

V. Conclusion

To identify the alphanumeric text on each detected plate, this paper presented a deep learning model. The suggested approach is computationally effective and useful in difficult real-world situations. A well-known deep neural network model called YOLOv5 was developed to detect and recognize license plates. It was trained on a dataset of 300 photos. With our limited dataset, we were able to effectively train this network using the transfer learning method for the specific goal of detecting license plates and alphanumeric characters. Due to the bilingual language in these LPs, we trained the model to ignore any candidate alphabets that did not match the primary English text. This improved our system's ability to recognize license plates with high accuracy, and the suggested model did as well overall. The proposed model outperformed existing state-of-the-art methods in the literature by 0.994 mAP.

Future Works:

In our future research, we plan to address the image quality problems by using high dynamic range (HDR) images, which can better capture details in extremely bright and dark regions and hence, further improve the accuracy of the system. One other interesting direction would be to use the discarded

Arabic part to restore the completely degraded English alphanumeric. Also, a large volume of data could be used to fine-tune the models which might lead to better performance.

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