License plate detection using YOLO v4

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Abstract---Automatic License Plate Recognition (ALPR) is a sizzling topic in the disciplines of intelligent transportation systems and image recognition. The real-time object detector YOLO (You Only Look Once) - darknet deep learning framework is used in this article to detect car number plates in parking lots in real time. The YOLOv4 deep learning technique was utilized in this proposed strategy to automatically recognize a car's number plate from a video stream. An OCR technique is applied to extract the number from the image of the number plate. The system detects license plates with an accuracy of around 89%.

***Keywords*---**convolutional neural network, object detection and recognition, YOLO, deep learning.

Introduction

License plate detection and recognition (LPDR) is used in a variety of recent surveillance and transportation systems, including traffic monitoring, highway toll collection, and parking lot access and exit management. Extensive research has been conducted in order to develop a quicker or more accurate LPDR. License Plate (LP) detection, text segmentation, and text recognition are the three important steps of LPDR systems. As depicted from the steps given earlier, failing to detect the LP would certainly result in a failure in the next phases, therefore early steps require better accuracy or near-perfection. Numerous methods look for the vehicle first, then the LP, which results in faster processing better results. However, snow, fog, rain, uneven angles and other such uncontrolled conditions still act as major glitches for license plate (LP) detection. Most LPDR articles validate their methods using very small datasets, implying that they may only operate well under specific conditions. In these situations, a properly trustworthy LPDR system should perform admirably. We used a dataset from the Google open image collection to help us better benchmark LPDR techniques.

Related Work

There are many different strategies for detecting license plates. In research study by (Xu*et al.*, 2018) there is an architecture named Roadside Parking net (RPnet) to detect and recognize license plates in a single pass. Similarly, to detect and recognize LP, authors in (Laroca*et al.*, 2018) devised a two-stage approach for character segmentation and recognition.

(Laroca*et al.*, 2021), (Du *et al.*, 2013), (Sarfraz *et al.*, 2013),(Anagnostopoulos *et al.*, 2008),presents a method for locating a car with a certain license plate on noisy CCTV video material captured by non-dedicated, medium-to-low resolution cameras operating in low-light situations. Authors in (Donoser, Arth and Bischof, 2007) show that without the use of any learning method, an effective approach based on analysis of Maximally Stable External Region (MSER) detection findings allows for the localisation of license plates in single photos where tracking and character segmentation are done at the same time. In two ways, our approach builds on previous work: publicly available datasets and existing LPDR methods. We have further separated works for LP detection and LP recognition.

Datasets for LPDR

The majority of LPDR datasets collect photos from traffic monitoring systems, toll booths, and parking lots. The photographs are always taken in bright sunlight or with additional light sources, and the angle of LPs is appropriate. We have collected images with different variations, angles and light. The dataset was collected from google open images dataset which has different variations of images.

The quality of dataset plays a very important role in the accuracy of the model. The model training is done with lots of variation in the images. The deep Learning model needs a huge amount of data to effectively train the model. The Images collected in our dataset are of good quality and it shows a required corpus size to train the YOLO model.

Fig. 1: Example of Images of Datasets Having Appropriate Lighting and Angles

Fig. 2: Our Dataset with Different Angles, Lightings, Distance and Variations

LP Detection Algorithms

Traditional methods, neural networks methods, and YOLO methods are the three types of LP detection algorithms. We have used the YOLOv4 method for the detection of LPs from videos and images which will be further explained in the next section.

Materials and Methods

The term 'You Only Look Once' is abbreviated as YOLO. Unlike image classification this algorithm doesn't just detect an object in an image instead it detects the object in an image along with the position of the object in real time. The YOLO algorithm detects objects in real time using convolutional neural networks (CNN). A single algorithm run is used to work on the full image. Subsequently, CNN Algorithms are used to form several class probabilities and bounding labels around all objects.Several modifications of the YOLO algorithm exist. YOLO and YOLOv3 are two examples of these modifications. We used YOLOv4 which is the latest version of YOLO algorithms.The three strategies used by the YOLO algorithm are Intersection over union (IOU), Bounding box regression, and Residual blocks.

Residual Blocks

In Residual blocks technique, the image is separated into several grids. Let's consider the dimensions of each grid as N x N. The graphic below shows how a grid is created from an input image.

Fig. 3: Dividing Image into Grids

In figure 3, there are multiple grid cells that are of the same size. The algorithm will work through each grid cell and will detect each object that appears within its boundaries.

Bounding Box Regression

A bounding box is an outline barrier in a photograph that calls attention to a certain object. Every bounding box in the image will have the following features:

- Width
- Height
- Bounding box center
- Class (For example car) - represented by letter c

We can see an example of a bounding box in figure 4. The red outline represents the bounding box.

Fig. 4: Bounding Box Around a Car

To forecast the height, width, center, and class, YOLO uses a single bounding box regression as shown in the image given in figure 4.

Intersection Over Union

The concept of intersection over union (IOU) illustrates how boxes overlap in object detection. IOU is used to create a final result box that completely surrounds the object. Each grid cell calculates the confidence scores of each bounding box. If the observed and actual bounding boxes are the same, the final value IOU is given as 1.This method removes the irrelevant bounding boxes which do not cover the whole object.

Fig. 5: Two Bounding Boxes Around the Number Plate

There are two bounding boxes in figure 5, with 0.89 and 0.67 probabilities. YOLO makes sure that the two boundary boxes are of the same size.

Combination of Three Techniques

We have divided the image into various grid cells and each cell estimates the class to which that object belongs. We have used a single convolutional network based IOU which removes the overlapping redundant grids and then we get the final outcome where each bounding box will represent a particular object.

Implementation and Result

The collection includes 4,500 images collected from typical traffic in an urban setting. The photographs were taken with three different cameras and are in the PNG format. We divided the dataset in 3 parts - 60% (for training), 30% (for testing) and 10% (for validation). We used the YOLOv4 algorithm for prediction of license plate position in a video or image.
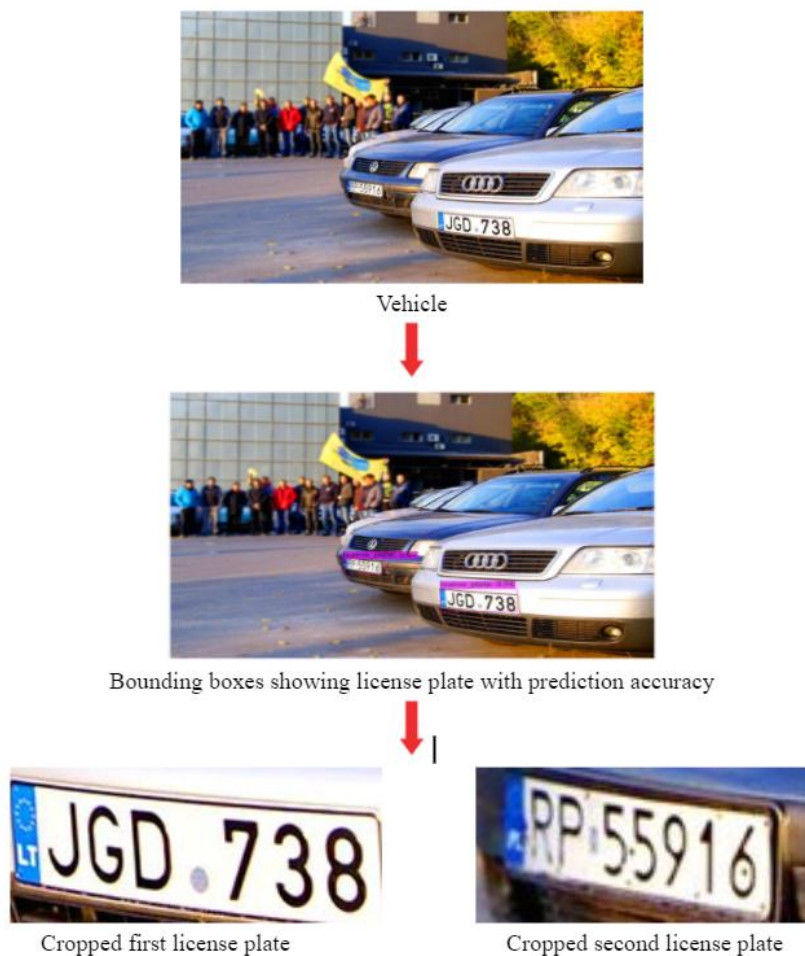

Vehicle

Bounding boxes showing license plate with prediction accuracy

Cropped first license plate   Cropped second license plate

Fig. 6: Steps to Predict the License Plate From a Video or an Image

Conclusion

In this paper, we present a large-scale and diverse license plate dataset, as well as a robust real-time end-to-end LPDR system based on the cutting-edge YOLOv4 object detection algorithm. Our System is capable of achieving a full detection rate of **89%** in the google open image dataset which can be further improved by generating more reliable images and improving the algorithm. We plan to investigate new CNN architecture in the future to better optimize our algorithm and boost accuracy. We also believe that the proposed LPDR technology is capable of tracking down a car in any country.

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