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doi:10.15199/48.2022.08.16

Smart vehicle height detection for limited height roads

***Abstract**. Traffic congestion has become more prevalent in metropolitan areas, necessitating the reorganization of roads and their management through Computer vision technologies. One of the techniques is to determine the height vehicles allowed to use the road, and identify the license plates of vehicles an efficient traffic monitoring system has been proposed. the proposed system works by detecting objects (vehicles) and use the laws of area to calculate vehicle heights, as well as license plate detection using the yolov4 and yolov5 networks.*

Streszczenie.** Zatory komunikacyjne stały się bardziej powszechne w obszarach metropolitalnych, co wymaga reorganizacji dróg i zarządzania nimi za pomocą technologii wizji komputerowej. Jedną z technik jest wyznaczanie wysokości pojazdów dopuszczonych do ruchu oraz identyfikacja tablic rejestracyjnych pojazdów, zaproponowano skuteczny system monitorowania ruchu. proponowany system działa na zasadzie wykrywania obiektów (pojazdów) i wykorzystuje prawa powierzchni do obliczania wysokości pojazdów, a także wykrywanie tablic rejestracyjnych za pomocą sieci yolov4 i yolov5.* (Inteligentne wykrywanie wysokości pojazdu na drogach o ograniczonej wysokości***)

Keywords: Plate number, object detection, YOLOV4, YOLOV5.
Słowa kluczowe: wykrywanie obiektów, pomiar wysokopści obiektu

Introduction

Many researchers have worked tirelessly to improve student performance by employing deep learning techniques like object detection, face recognition. Researchers may use this approach (altimetry) to detect and measure objects, as well as increase the performance of an algorithm, according to a literature study utilizing deep learning techniques. This stand-alone technology is gaining a lot of popularity these days [1]. In terms of the license plate, smart transportation and monitoring systems have advanced in recent years as a result of the numerous benefits that technology has brought into our everyday lives through its different applications. Real-time tracking of traffic offenders and the recovery of a stolen car are both possible using vehicle number recognition technology. Additionally, car movement data are automatically saved, and parking tickets are managed. However, detection and identification of number plates has significant limitations, as an instance plate irregularities and inadequate lighting owing to ambient lighting [2]. Degradation and fading are other concerns with license plate recognition and identification, in addition to the aforementioned challenges. A license plate recognition system's detection of license plates remains a difficult challenge. It is linked to the success of both character segmentation and character mapping and recognition, and has an influence on both [3]. This research paper is divided into different sections, the first part describes a method for real-time detection of object (vehicle), The second portion explains how to measure the height of objects (vehicles) in real time, and the third section explains how to identify and implement vehicle license plates in real time [1]. The goal of this paper is to design system accomplishes part of tasks the road is monitored in real time by closed circuit television (CCTV); the proposed system works by detecting objects (vehicles) in the event that the driver of the vehicle (with an unauthorized height) is on the road. The system uses a set of libraries available in Python, and uses a pre-trained YOLOV4 network to detect compounds, and we used deep learning of neural networks (yolov4-yolov5) to make detection of vehicle numbers, where the above-mentioned neural networks were trained on a data set containing (2180) images For license plates divided into two groups, the first set is the training data set (70%) of the data, and the second set is the Val/test data (30%), after the above-mentioned neural network training process is performed. The proposed work was tested using a data set containing (2118) images (license plates) Therefore, the network algorithm (yolov4) achieved a vehicle classification accuracy of up to (96.32%) and we obtained results in training the network algorithm (yolov5) with an accuracy of up to (99.12%).

Related works

The authors of this study, moshin and et, proposed an ELMAN Neural network-based approach for detecting Iraqi license plates, one for numbers and the other for provincial names. The processing included the use of the Median filter, the Sobel operator, and picture banalization. For vertical and horizontal projection, picture segmentation was employed, and a collection of images was examined. Their total number of photos was around (21) and the technique hada success percentage of (85%) and (76%), respectively [4]. Author XIN LI presents a method for establishing license plate finding utilizing an SVM classifier and bounding boxes that may be determined using shift mean in this work. performance and analysis of HOG The system was tested with various cell and block sizes, and the findings revealed that variations in illumination and license plate patterns, among other things, had an impact on the algorithm. A 96.0 percent accuracy rate was reached [5]. Artificial neural networks are used to recognize chassis numbers using OCR. Sunil K. Tsaka Nadkar, Parul Shah, Nikita Golecha, and Ketan Ladd are the authors. The vehicle's license number was determined using a new technique created utilizing a 3-layer Artificial Neural Network based on Optical Character Recognition in this study (ANN). Most commonly used image processing techniques are used to pre-process captured photos, Recognition has been given to more images of this figure. This technology has a modest level of accuracy and does not identify plate numbers collected from various angles [6]. Using a neural network, an Iraqi license plate recognition and localization system has been developed. Safaa S. Omran and Jumana A. Jarallah are the authors. An automated license plate recognition method is used to recognize three types of Iraqi license plates in this article. The Resilient Back propagation (RP) technique with two hidden layers Back Propagation Neural Network (BPNN) is used for segmentation and recognition. This approach worked well in distinguishing three kinds based on plate size, but it was only applicable in Iran [7]. Rayson et al. suggested a novel YOLOv2-based CNN model that is resilient in real-time. In the case of both vehicle and VLP detection, their goal was to detect just one class. They found the car first, then the VLP. The number of filters is reduced and the speed is raised as a consequence of this method. Both Fast YOLO and YOLOv2 were used in the study effort of SSIG and their recommended UFPR-ALPR, which outperformed two commercial ALPR systems. They got ALPR with all correct and accuracy of 64.89 percent and 78.33 percent, respectively, at 35 frames per second and a time of 28.3022 milliseconds. [9]. The Indonesian license plate is suggested by Ebnazvi et al. The recognition system is made up of two processes: detection plate item and getting to know number. construct an object panel The YOLOv4 transfer learning model is used to create the detector. Meanwhile, the YOLOv5 transfer learning model is used to create the number Recognition. The YOLO model, which is the most recent current object detector, is employed in this work. With a translation accuracy of up to 89 percent, Detection of license plates with an accuracy of 87 percent to categorize letters on car license plates [10]. Salma and el, the suggested system uses YOLO object detection to determine the number plate region (you only look once) At a threshold of 0.50, I received a MAP score of 94.3 percent for YOLOv3 and 99.5 percent for YOLOv4, whereas our framework's average accuracy score was discovered to be 73 percent [11].

Proposed System Assumption and Design

To train the model, the problem could be overcome by applying several methods of object detection and vehicle pick-up. Using image of automobiles and other vehicles with license plates, but we focus on the usage of YOLOv4s - YOLOv5s to identify the existence of a number pad in a given image, as well as confidence that the identified spot is a number plate. the height of the cars will be discovered by calculating the height of the vehicle at a certain position using the area law [12] [8].

The proposed system will do the following:

1-Configuring the system, and inserting the video from camera to the system.
2- Choosing the target region ROI (Region of Interest).
3- Enter the target area into YOLOv4.
4- Vehicle detection.
5- Return the car's location coordinates(x-y-w-h).
6- Calculating the height of the mechanism using the laws of area.
7-if vehicle height Sending a warning to the driver.
8-train network YOLOV4 –YOLOV5 algorithm on the custom data to detect plate number vehicle.

The system works in full, where the system starts and then works to calculate the height of the vehicle. If the height of the vehicle is higher than the permissible limit, we move to the stage of determining vehicle plate numbers based on the Yolo algorithm, which trained.

Implemented module

1- measuring the height of vehicle

The finding of the composite's components is the first step, the object detector's main purpose is to teach the vehicle detector, which will only create pictures of automobiles, whether or not there is a car there. The YOLOV4 network, which had previously been trained, was employed. It is one of the quickest object identification algorithms, specialized to the rapid detection of the model to be produced from CCTV video pictures [13]. To create a deeper and more complicated network, they employed a thick block. There are numerous convolutional layers after batch and ReLU normalization, followed by convolution [14]. Furthermore, by linking numerous thick blocks with transitional layers, a dense network is generated. The dense block input feature maps are then divided into two pieces using a partial cross section (CSP), one of which travels directly to the next transition layer and the other passing via the dense block [15]. Because just one portion goes through the thick block, the computing requirements are decreased [16]. They extracted Backbone features, which enhance CSP connections, using CSPDarknet-53 and Darknet-53 from earlier YOLOv3. Because it enhances the receptive field, describes the most essential characteristic, and causes no delays, CSPDarknet-53 adopts spatial hierarchical clustering (SPP) as a solution [17].

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2- Choosing the target region ROI (Region of Interest).
3- Enter the target area into YOLOv4.
4- Vehicle detection.
5- Return the car's location coordinates(x-y-w-h).
6-Calculate the number of pixels in the given rectangle.
7- Calculating the height of the vehicle using the laws of area.
8- input image to CNN algorithm training on custom data.
9-if vehicle height Sending a warning to the driver.
10-Taking a picture of the vehicle and making a detection of the vehicle plate number using the yolov4-yolov5 algorithm, which we trained on data dedicated to vehicle numbers.

2- plate number detection

After completing detection process, the image is entered into the neural network yolo to perform a plate number detection. Two types of transfer learning convolutional neural networks (YOLOV4s-YOLOV5s) were trained on the data of images of plate number for vehicle.

2.1- YOLOv5s

YoloV5s is YoloV5's lighter sibling. Other subversions, such as YoloV5m, YoloV5l, and YoloV5x, improve accuracy but slow down object detection and increase the model's training time. YoloV5s was chosen to be deployed since speed is an important factor in traffic monitoring. As a deep learning framework, PyTorch is used in this version. The model requires two crucial files to be customized to the project's requirements. The first one does. The path where the test and train photos are saved is contained in the YAML extension. In addition, information on the number of courses and their names will be included in this file [18]. The YOLOv5 network is divided into three sections: the backbone for feature extraction, The neck for merging of features, and the output for object identification. The backbone network is a convolutional neural network that uses repeated convolution and pooling to generate feature maps of various sizes from the input picture [19]. In the backbone network, feature maps are created in four levels. They are 152 x152 pixels, 76x 76 pixels, 38x 38 pixels, and 19x 19 pixels in size. To gather more contextual information and reduce information loss, the neck network connects feature maps of various levels with feature maps of various sizes [20]. In the fusion process, the feature pyramid structures of FPN and PAN are used. The FPN structure sends strong semantic qualities from the top feature maps to the bottom feature maps. The PAN structure also transmits significant localization features from lower to higher feature maps at the same time. The integration of the two structures strengthens the neck network's feature fusion capability. Each of the three feature fusion layers revealed creates three scales of new feature maps with dimensions of 76x 76x 255, 38x38x 255, and 19x19x 255, where 255 specifies the number of channels. The smaller the feature maps are, the larger the picture region that each grid unit in the feature map corresponds to. This means that the 19 x19x 255 feature maps work well for detecting large things, while the 76x 76x 255 feature maps work well for detecting little objects. Using these updated feature maps, the output network component performs item recognition and categorization. [21].

2.2 YOLOv4s

We employ YOLOV4s with rapid detection speed, and the specific YOLOv4 network design is separated into three components. Three layers can get an effective initial advantage by using the core feature extraction network. We can utilize MobileNet [22]., which is as lightweight as a backbone Extraction network characteristic, because YOLOv4's original core network, CSPDarkNet53, has deep network layers and we require that Lightweight detection network design. This preserves MobileNet's benefits without sacrificing YOLOv4's original accuracy. The enhanced feature function Grid extraction is used in the second half to extract improved features to take advantage of Enhanced. We may make use of the Enhanced feature extraction network by Extract better features, acquire three more strong feature layers by combining the three most effective core feature layers. A removable deep casing can be utilized to replace the usual 33% convolution in the improved feature extraction lattice for a lighter lattice design. The number of network parameters is drastically decreased as a result, and the retrieved features are unaffected. The prediction network's role in the third group is to obtain the prediction result utilizing the most efficient feature layer. Parts 1 and 2 can be improved more readily than the other two. Part 3 doesn't need any substantial changes because it's balanced.3 x 3 rolls and 1 x 1 roll are combined [23].

2.3 IOU

The statistic Intersection over Union is used to determine how accurate an item detector is on a particular dataset. This assessment measure is commonly used in object detection challenges, such as the popular PASCAL VOC challenge [24].

IOU = Combined Region / Overlapping Region.

2.4 dataset

We used vehicle license plate image data and an image dataset for a vehicle plate number category. the total amount of data we utilized to train our license plate recognition algorithm (2118) image was the model with YOLOv4. 70 %of the percent of the photos were utilized as train data and 30 % as test/validation data. Fig 3 shows some of the data set's examples. We gathered image of cars and license plates for vehicles from various neighborhoods of Mosul, Iraq, at random, it's worth noting that the data includes a variety of other license plates. We established a label for the photos and prepared a TXT file for train, test, and Val after that flowchart in Fig 1 depicted step training model on custom data system [25].

Data augmentation

To boost performance and avoid leakage, increasing image data is a common strategy. The Keras libraries' Picture Data Generator class allows use to image data augmentation to suit models. The Generator turns file image into preprocessed tensor that may be immediately input into the train dataset to train a model using different picture rotation, scale, crop, and flipping parameters [26].

Experiment Analysis and Results

1- Dataset

The collection contains roughly (2118) photos of plate number vehicles. Data is dispersed at random and categorized into three categories: training, test, and verification.

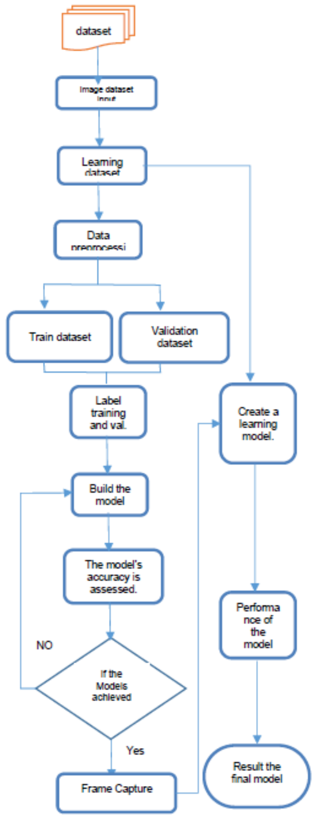

Fig 1: train model on custom data system is depicted in this flowchart

2- Python language

(python 3.9), Tensor Flow, and Keras are all utilized with Python. To explore the convergence of convolutional neural networks, the Matplot program was used to create a loss curve and an accuracy curve using experimental data

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3- Hyper parameters

Several in the configuration of the training model, several hyper parameters are employed, and they are applied to all models. These hyper parameters are used to train each model, with the best results kept for future comparison and analysis of each model's performance, such as:

- Epoch: 100
- Image size 416*416
- learning rate (α): 0.00001
- Optimizer: Adam
- patch size is 16

5- Training models

Training Models on custom dataset of To recognize number plates in photos, we utilized YOLO v5s, a smaller variant of YOLO v5. Because YOLO v5 allows for detection from video streams, it may be used in actual cameras for panel detection. Here are some YOLO v5s statistics. Many characteristics, such as mAP (meaning precision accuracy), recall, and accuracy, must be considered when evaluating the correctness of any model. Parameters like object loss and categorization loss can also be investigated. It's also possible to examine parameters like object loss and categorization loss.The accuracy of the training model that we trained using custom yolov5s data achieved mAP_0.5 results is around (99.12) percent, and the precision parameter (98.64) and recall for Yolo (99.83) grow with each period when the model is taught. As indicated in the fig4.trained. The level of loss at the conclusion of the period. The suggested model yields a high classification rate and a low loss rate, as can be observed.

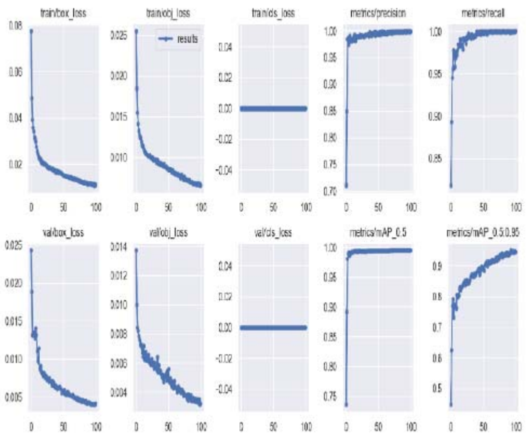

Fig.2.depicts YOLOV5s performance.

Fig.3 depicts the YOLOV4s accuracy curve, which indicates that accuracy rises with the start of training and then rises with each age until it reaches a constant state. This network's outcomes are around mAP@0.5 (96.32) percent, precision coefficient (87.62), and Yolo Recall (97.53), with a rapid decrease in the loss rate.

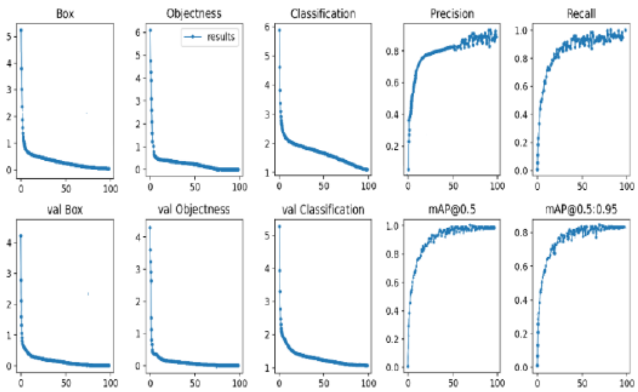

Fig.3.depicts the YOLOV4s Performance curves.

After the system is completed and implemented, we explain some pictures of the system's work during implementation, where it shows a detection work for a vehicle whose height is to be measured, and the vehicle's height was about 387.2 cm. Iraqi as shown in fig.6

We conducted tests with several models to check the accuracy of two types of yolo convolutional neural networks using image size 416 * 416, which we trained on a single CLASS to detect vehicle numbers and with the presence of custom data (2118) images and the results are shown in Table 1.

Table 1. show of result training accuracy

Models	MAP_ 0.5	precision	Recall	Epoch no.	Time (hour)
YOLOV4s	96.32%	87.62%	97.53%	100	78.41
YOLOV5s	99.12%	98.64%	99.83%	100	96.28

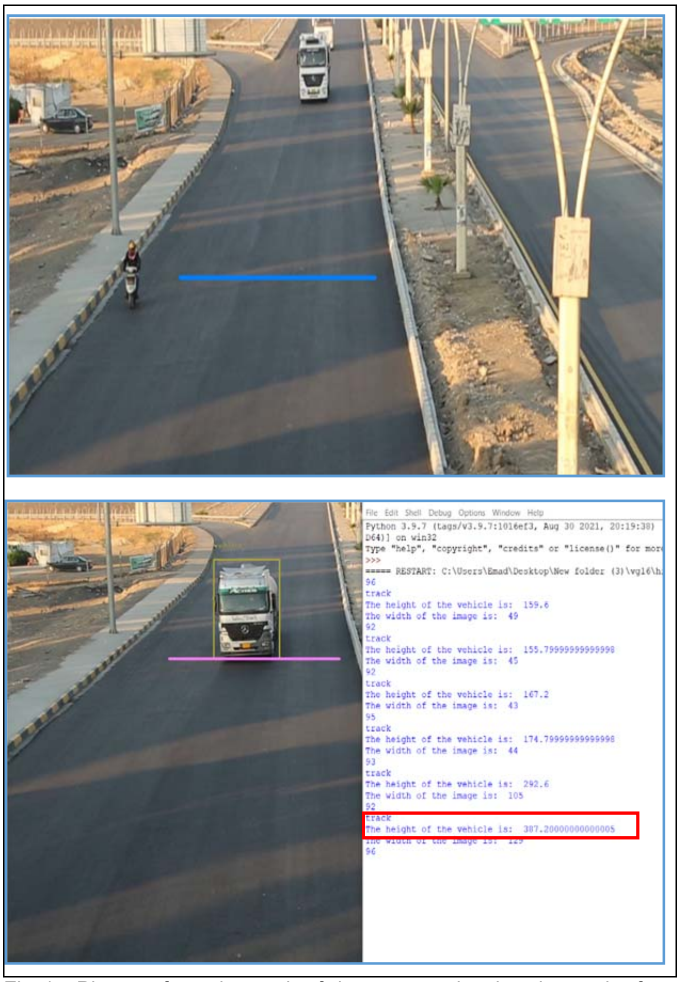

Fig 4: Pictures from the work of the system showing the work of detecting measuring the height of vehicle limited 387.2cm.

Conclusion

focuses this paper on calculating vehicle height to estimate the height permitted to travel under a bridge or via a traffic tunnel, as well as identifying the offending vehicle's license plate number and recognizing cars and license plates using the yolo algorithm. Neural networks were employed in this study (YOLOV4s and YOLOV5s), as a result of which the network algorithm achieved (YOLOV5s) mAP 0.5 results of around (99.12 percent), and obtained result training the network algorithm (YOLOV4s) which achieved mAP 0.5 results (96.32). In terms of accuracy and size, YOLOV5s grids were determined to be the most successful for vehicle license plate recognition and further work will be required to create a new data set with a greater size and the same amount of photos for each vehicle type. On the other hand, a dataset with varying image orientation and illumination to replicate the actual environment and license plate identification would be preferable.

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