MULTI DATASET BASED LICENSE PLATE RECOGNITION USING YOLO DETECTORS

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ABSTRACT

Detecting the licence plate is the most reliable and economical technique for identifying cars. The methodologies and approaches vary based on several parameters, including but not limited to: picture quality, the vehicle in fixed places, lighting circumstances, and single images. The variations in licence plates across different countries and states must to be able to handle it as well. Additionally, the technique must be able to function properly when there are many characters in the collected photos that have different plate sizes. This endeavor's aim is developing and creating a software for Licence Plate Recognition (LPR), which may be used for e-challan, in car parking, and vehicle identification for smart garage applications through a design by thinking approach. The main focus will be recognising and identifying several automobiles with licence plates from a single picture. Two processes make up the suggested system: plate number identification and identification. The plate number identification procedure identifies the number plate from the photograph, and the segmented plate is then sent to the plate recognition phase in the second phase to determine the characters and numbers.

Keywords: First Keyword, Second Keyword, Third Keyword.

I. INTRODUCTION

Using the licence plate, an image processing technology called licence plate recognitionmay identify the vehicle. The goal is to create an efficient, authorized automated vehicle identification system using the licence plate. The system is installed to monitor safety at the point of entrance into places that are very restricted, including war zones or the vicinity of important government offices, like the Supreme Court or Parliament. This is a system that anybody may use for security reasons. Your phone will be installed with an open-access Android application. After that, all he has to do to get the information he needs on any automobile is to capture a picture of the licence plate and analyse it to extract the required data. This system must be implemented since it is very important. Prior to taking a photograph of the car, the designed equipment detects the vehicle for defensive reasons. The area of the car's number plate is extracted by segmenting the photo into an image. The Optical Character Recognition (OCR) process is used to recognise characters. The obtained information can be then cross-referenced with records to provide unique facts such as location, licencing location, and the owner's name. The structure is developed and emulated in Python then verified on actual picture results.

Simple Licence Plate Recognition (LPR) systems have poor detection accuracy in real-world applications [1]. The accuracy of these systems has been impacted by a number of external factors, including sunlight, headlights from passing cars, number plates with inappropriate designs, and a large variety of number plates. On the other hand, the software and hardware associated with the camera are of limited quality. However, LPR systems are now considerably safer and more widely used due to recent developments in hardware and software [2,3]. These systems are being used by an enormous number of people worldwide, it is expanding rapidly, and it is capable of performing an increasing number of jobs autonomously across various market niches. A result-dependent side programme may correct faults and can provide an almost per- fect system, even if the recognition rate is not 100%. For example, this side programme may disregard certain ignorable faults in the two recognitions to compute the car's parking duration from the time of entering to exiting the parking lot. By cleverly integrating, LPR's drawbacks may be addressed and; dependable, fully automated systems can be created [4, 5,6].

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An LPR system's typical setup is shown in Figure 1. The licence plate scanner software functions as an interface between a series of cameras and a Windows back- ground programme on a PC. The software processes the camera photos it gets to retrieve the licence plates of the moving automobiles. The findings are then shown by the programme, which also has the ability to transfer them via serial communication to other components of the system, such an LED display or camera. After that, it uses the network to deliver this data to either the local database or an external database.

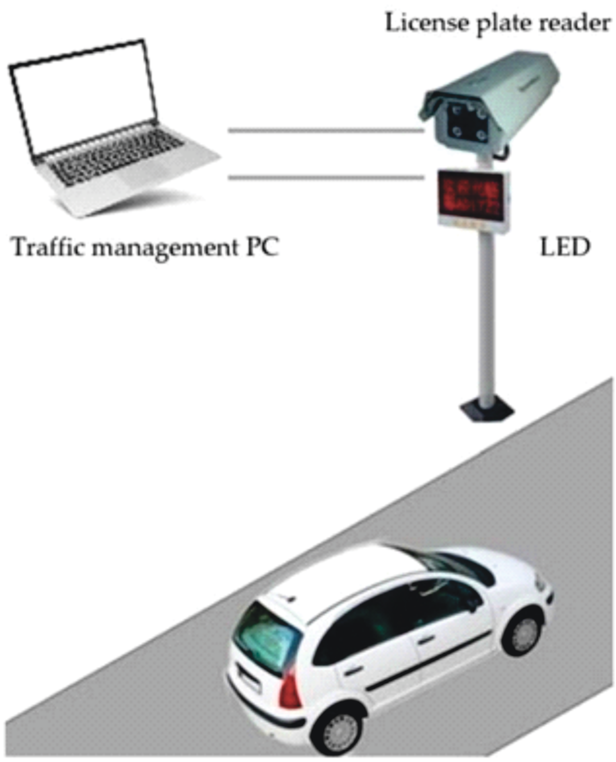

Figure 1 : General Setup for License Plate Recognition

II. EXISTING RESEARCH

In order to determine the effectiveness of any Licence Plate Recognition (LPR) system, research on Licence Plate Detection (LPD) methodologies has advanced significantly in recent years, as briefly discussed in the following ways.

In [7], scientists created a brand-new technique for accurately locating and categorising licence plate areas and characters at the same time. An assembly layer is creat- ed in this work to integrate the characters that produce licence plate strings. When applied to actual cars with licence plates in several states, this method produces positive outcomes. In [8], pixel-to-pixel investigation is used to address the LPD issue. Researchers combined the SIFT-based SVM classifier with the intelligent classifier Adaboost. In [9], the Adaboost classifier is given the segmented licence plate's HOG- based characteristics in order to find licence plates.

The established approach in [10] primarily uses colour transformations and changes in different colour spaces via segmentation and filtering methods to overcome licence plate identification problems. The suggested method in consists of three stages to find a vehicle licence plate. First, an approach based on Sliding Concentric Windows (SCWs) is presented to extract potential areas, and then the HSI-color model is used to identify those potential regions. Using a position histogram, the potential areas are finally broken down to identify the characters on the plate. While Kim et al. suggested a fixed color-pairs-based licence plate placement approach for analysing the letters in it and backdrop areas, Kim et al. combined colour and appearance information in the process of identifying complicated licence plates. Through colour pixel analysis, a modified template-matching technique is provided. In order to distinguish between the context and the specifics in the plates, fully Convolutional Neural Networks (CNNs) were used. A three loss layer architecture was then used to achieve accurate plate identification.

In order to identify licence plates on photos in the realm of exceptionally effective video compression, YOLO V3 small object detectors are presented. A new com-pressed domain licence plate database, consisting of pictures taken employing an industrial LPR system, is reported in this study. In comparison with several of the approaches tested there, this study offers superior detection results with a minimum of two degrees scale less information. Additionally, used a Deep Convolutional Neural Network (DCNN) and Long Short-Term Memory (LSTM) on photos to handle the licence plate detection issue. A technique for locating Chinese licence plates by colour detection and segmentation is covered. A technique for detecting licence plates combines a hierarchical sampling strategy with the Faster-RCNN. Character segmentation and deep learning are used to identify licence plates. The developed licence plate identification technique uses a line density filter method in conjunction with picture downscaling.

To find the licence plates, the researchers used a conditional random field model with a component-based technique. A CNN-based detection method for rotational licence plate recognition is shown. Meanwhile, located licence plates in a variety of settings by using the core visual word notion and the bag of words. The issue of object identification is addressed by a method based solely on the CNN method, which uses distributed calculations across complete pictures. Lastly, a recent development in the field of licence plate identification is shown, where authors suggest an intelligent system for detecting and recognising licence plates that makes clever use of neural networks and a hybrid wide learning system.

Only some of the many methods that have been published in the subject of LPD are included in the above description. But due to problems including relatively small licence plate regions, different background clutters, multiple plates within a single picture, and uneven lighting, robust and accurate licence plate identification is still a challenging process. As a result, our approach is among the most recent developments in the field of research that seeks to find licence plates under challenging conditions, such high or low brightness, reflected glare, and numerous licence plates per picture on multiple datasets.

Morphological operators were shown by Cheokman et al. to pre-process the picture. Following preprocessing, each character was recognised using the template matching method. It was given out for the Macao-style automobile license plate. The Support Vector Machine (SVM) technique was used in conjunction with scaling and cross validation to eliminate outliers and identify the obvious parameters. Character recognition using the Support Vector Machine (SVM) approach yielded a greater precision rate than the Neural Network (NN) system.

A webcam was recommended by Prabhakar et al. to take pictures. Using the collected photos, this technology is able to localise number plates in many sizes. Several NNs are used for character segmentation and recognition once the plate has been localised.

A Sobel colour detector was used to identify vertical edges, hence eliminating the ineffective edge. A design association method was employed for identification of the license plate (LP) area. For segmentation, mathematical morphology and linked component analysis were used. Using the neural network's radial basis function, Chirag Patel suggested mathematical morphology and using connected element evaluation to identify as well as divide letters.

The number plate detection system located the plate by using the colour of the characters and the backdrop of the plate. The column sum vector was used for segmentation. The character recognition process made use of artificial neural networks (ANNs).

The technique described is used to recognise Chinese licence plates. The image of the licence plate transforms into a binary picture, and the noise is eliminated. Subsequently, the feature is removed from the picture and its resolution is adjusted to 8 by 16. The back-propagation neural network is utilised for recognition after normalisation.

In order to find the number plate, Ziya et al. suggested utilising fuzzy geometry. They then used fuzzy C-Means to segment the plate. The segmentation approach achieves a 94.24% segmentation accuracy by employing blob labelling and clustering. The number plate was located in using linked component labelling, thresh- old, and gabor filter. Following segmentation, a self-organizing map (SOM) neural network was used for character recognition. A two-layer Marko network was used for character recognition and segmentation. Similar number plate detection studies have been described.

In order to extract characteristics from an RGB picture and convert it to a binary image, Maulidia et al. provided a technique that measured the accuracy of Otsu and KNN. The process of transforming pixels into binary form in pattern recognition included feature extraction. The Otsu approach was used to extract features, and KNN categorised the picture by contrasting the training and test data from the image's neighbourhood. The test data were identified by classifying them using a technique that employs the learning algorithm. Without changing the threshold value, the Otsu approach was created using a binary vector to facilitate pattern identification. To achieve binary segmentation, the distribution of the image's pixel values was adjusted. KNN categorization worked very well for identifying the vehicle's licence plate. Nevertheless, the authors failed to give the system's capacity to recognise adverse weather conditions.

III. METHODOLOGY

Together with the experimental results related to the YOLO detector, we describe in this study a completely computerised workflow for ALPR which is independent of a previously set guideline. The following subsections provide a detailed explanation of every model of feature acquisition in our proposed application along with a breakdown of the datasets that were utilised.

A vehicle type classifier utilising ResNet50 was used in the experiments, which used the cutting-edge darknet architecture, the v4 technology for later phases while a YOLO v2 technology is employed in the initial phase.

3.1 Datasets

A strong overall ALPR system must use many datasets to capture a wide range of changes, including illumination, backdrops, vehicle sizes, and camera angles. An ALPR system will function better in the real world if it can perform well over a variety of datasets. The majority of earlier studies concentrated on and displayed their findings using a single dataset. A few datasets are used, which causes the LPs to be biased towards those nations. As a result, all processing stages will either be biased or fail to produce sufficiently significant changes in the LP. The datasets must be made publicly accessible in order to guarantee repeatability and to remove any doubt regarding the parameters used in comparisons made by other researchers. Eight publicly accessible sets of data frequently used in research are listed. 5 datasets accessible to the masses are utilised in this article. Open-ALPR EU, English LP, Caltech Cars, UFPR ALPR, and AOLP were the datasets that were utilised.

3.2 Pipeline of Proposed Work

The YOLO algorithm to serve the initial phase, namely a YOLOv4 tiny algorithm with the YOLO v2, comprise every level of the pipeline. The selection of YOLO was based on its present status as the fastest detector available without compromising too much on accuracy. Several suggested approaches in this field also employ it due to its pace and demand for instantaneous execution. The Figure 2 displays the ALPR's entire workflow.

The whole picture, for instance, from a security camera is the starting point of the procedure; it first passes through the vehicle detector stage (1), which detects all cars. Following cropping, each of the identified cars' vehicle patches is run through two models. To determine what kind of vehicle it is—such as a truck or an emergency vehicle—it first passes through a vehicle classifier. Second, every vehicle patch ex- tends towards the LPD (2), in which the LP is found. As a result, we would now have an LP patch for every vehicle found. The last step, the LP OCR (3), which is a part that finds every character in the LP, is then applied to all those LP patches. The whole LP characters are then created from there. Thus, for each car in the picture, we will ultimately get the vehicle's kind (which may be expanded to include many classes, as well as the make, model, year, etc., if necessary) and its number plate number.

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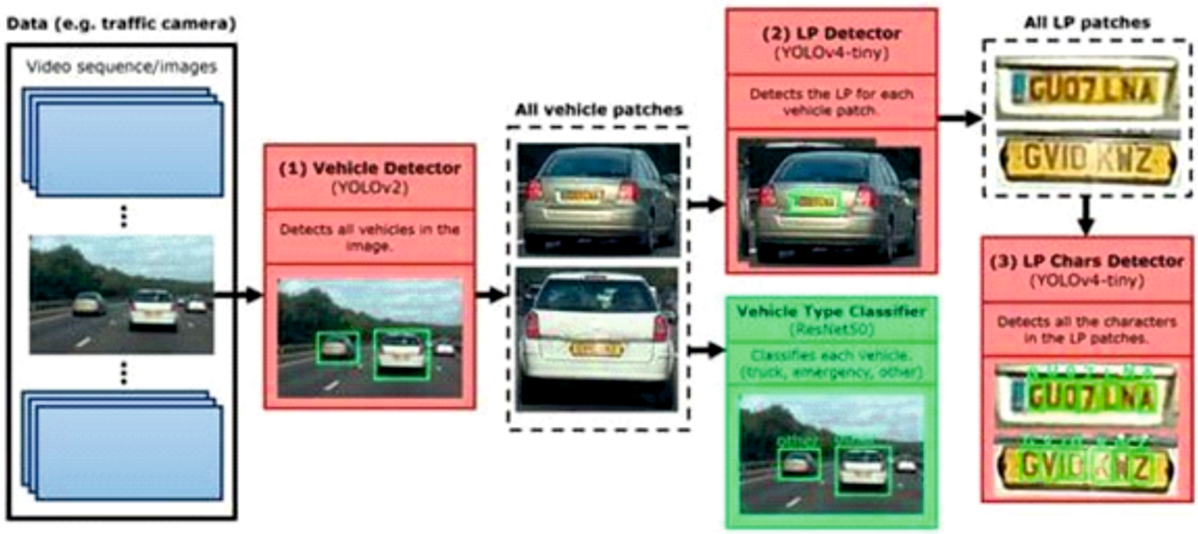

Figure 2 : Pipeline of Workflow

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3.3 License Plate Detection

The LPD phase is a small replica of YOLOv4. The vehicle patches from the complete photographs that have been cropped are the training images. The dataset was twice utilising the negative photos of every sample in order to expand its size and enhance accuracy; this doubled dataset greatly boosted accuracy. Since a vehicle may only have one LP, only identifications that have an IoU greater than 0.65 are included as part of the identification. When multiple identifications occurred, the one with the greatest rating of trust had been chosen.

3.4 License Plate Recognition

With sufficient data, achieving high accuracy is quite simple in the first two steps, which are also significantly

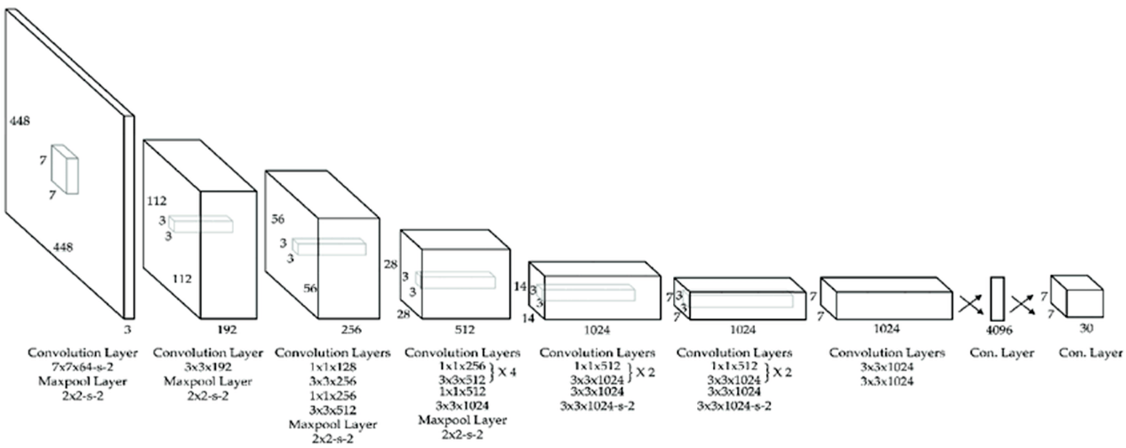

Figure 3 : YOLO v4 Architecture for LPR

simpler and do not present any significant problems. The true test comes in the last phase, when you have to collect every character on the LP in order to finally identify the vehicle.

Once again, the YOLOv4 small detector was used in this step. The whole LPR YOLO network design is seen in Figure 3. Only LP patches with widths and heights greater than 20 and 10 pixels, respectively, were deemed to be Lps.

3.5 Character-Recognition

Currently, 1000 instances (100 for each number) make up the neural network training data. This artificial neural network has three layers: a hidden layer with 50 activation units, an output layer with 10 activators to represent numbers 0–9, and an input layer with 1600, the same size as the previous ANN's input layer. The correlating parame- ters are kept after the ANN has been trained and utilised to help the system decide which of the related candidates' characters to recognise as the real ones.

IV. RESULTS AND DISCUSSION

The outcomes of the whole ALPR pipeline are shown here. Only when every step of the pipeline was completed successfully and every LP character was identified cor- rectly is an LP recognition regarded accurate. Therefore, it is deemed to be an incor- rect sample, for instance, if a car or an LP is not found and does not proceed to the following level or stages.

Table 1 shows that highly precise outcomes are produced for training on each dataset while not requiring established guidelines or additional processing on the plates utilising prior understanding of the plates following forecasts. Every crop is fed into the next step in the exact same manner that it was identified at previous stage. It should be noted that we have a rather limited number of FN for the English LP, Cal- tech Cars, UFPR ALPR, and AOLP. In some situations, given a tiny set for testing, regardless of whether it is a single automobile or plate that is misidentified, it has a big impact on the entire recall.

Dataset	TP	FN	Recall
AOLP	214	5	97.98
UFPR ALPR	111 7	68 3	65.06
Caltech cars	13	1	93.06
Open ALPR	12	0	99.69
UFPR ALPR as vid	44	16	74.81
English LP	50	2	95.15

Table 1. Accuracy of The Model for Different Datasets

It should be noted that while the UFPR ALPR dataset is undoubtedly more difficult, it is composed entirely of still pictures from a film. For instance, you would have thirty slightly different shots from the same movie while the car is going. There are 60 videos in the UFPR ALPR test set, and each movie has 30 frames in total. When working with a video stream of that kind, you can, for example, consider a recognition with 100% confidence if the same LP for the same vehicle has been detected three times in a row. This is because you will have many opportunities (frames) to correctly detect the full LP as the car moves across the frame. That example, while the LP may be properly identified with as little as three consecutive frames, the other frames in which the vehicle appears are not important. The recognition result is noticeably higher if we handle the UFPR ALPR dataset in this manner, as shown in Table 1 (UFPR ALPR as vid). The reason this happens is due to the reality that once we are able to recognise the vehicle's plate on three occasions in a row, then we aren't required to perform it again.

It is evident the entire license plate recognition workflow, comprising of the entirety of the phases, is operating at a very high level. Even though the last stage is obviously the least effective, it nevertheless yields very good results by considering each character in the alphabet as a separate class and operating avoiding making any assumptions regarding the plate's history.

V. CONCLUSIONS

A way to execute the license plate recognition job completely autonomous and opti- mised workflow including the 3 steps, without using pre-defined pre/post processing rules or taking use of any previous knowledge of the LP is proposed. This proves that the suggested approach is appropriate and generalizable in a real-time setting. We used the YOLOv4 detector in a darknet framework to conduct our research. YOLO has exceptional plasticity in learning characteristics despite its locations, and we adjust the settings individually at each step to enhance performance.

Multiple data generating strategies were created to increase data samples, and data augmentation techniques were used to cope with lighting and artefacts. Comparing the findings to earlier approaches that addressed the whole ALPR issue, competitive outcomes were obtained. Our approach performs well and yields accurate findings on five distinct publically accessible datasets.

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