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Determine The License Plate of the Vehicle in Violation of a Specific Speed

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Abstract:

The problem of detecting cars that violate the speed limits set by a certain country or region is a matter that needs to find an effective way to solve it in order to help the traffic police in this matter, which is very important, Automatic License Plate Detection (ALPD) is a critical technology for effective traffic management. It is utilized in a variety of applications including. toll payment systems, parking, and traffic control, a convolutional neural network (CNN)-based technique for high-accuracy real-time car license plate detection is presented in this paper. Many modern approaches for detecting car license plates are used under specified conditions or with significant assumptions. When the car license plate is assessed photographs as a result of manual capture by traffic cops or camera deviation, there is a degree of rotation, they perform poorly. Thus, a new framework for multi-directional car plate detection according to a Region-based Convolutional Network method (R-CNN) that is faster. A number tests have shown that the suggested method surpasses in terms of accuracy and computing cost, existing state-of-the-art approaches. The accuracy rate in detecting vehicle license plates reached 98%.

Keywords: LP detection, Deep Learning, RPN, Faster R-CNN.

List of Abbreviations	
Abbreviation	Meaning
AI	Artificial Intelligence
ALPD	Automatic License Plate Detection
ALPR	Automatic License Plate Recognition
ANPR	Automatic Number Plate Recognition
CNN	Convolutional Neural Networks
DNN	Deep Neural Network
FC	Five Convolutional
FP	False Positive
GTX	Giga Texel shader eXtreme
KLT	Kanade Lucas Tomasi
LP	License Plate
LPR	License Plate Recognition
ME	Maximizing Expectations
R-CNN	Region- Convolutional Neural Networks
ROI	Region of Interest
RPN	Region Proposed Network
TP	True Positive

1. Introduction:

Automatic car license plate detection and recognition are used in intelligent transportation systems identification is critical. It offers a wide range of possible applications, from security to traffic control. It has attracted a lot of research interest in recent years[1]. Most existing algorithms, on the other hand, only operate well in controlled environments or with advanced image capturing devices. In an uncontrolled setting, reliably detecting license plates remains a difficult challenge. The challenge comes from the highly complicated backgrounds, such as general lettering on shop boards, windows, guardrails, or walls, as well as random photographic situations, such as lighting, distortion, occlusion, or blurring. The detecting approach yielded accurate bounding boxes. A neural network that is deep is created that takes an image as input and transforms it generates photographs offense number plates with high efficiency and accuracy[1]. In this work, the Faster R-CNN algorithm was based on focusing on a specific area of interest, because it gave the best results in determining the license plates of vehicles violating a specified driving speed by the traffic department for a specific street or place, after trying both the R-CNN algorithm and the Fast algorithm. R-CNN, algorithm based on both algorithms outperformed the two approaches in the work so it was used to recognize car number plates violating safety requirements. Goal of license plate detection is to use bounding boxes to locate license plates in a picture. Existing approaches can be divided into four categories. [2][3]and[4]: color, texture, and edge-based and based on a character Because license plates are usually rectangular in shape, they have a certain aspect ratio and have a higher edge density. Edge information is commonly employed to recognize license plates, more so than everywhere else in the image. A approach based on edges was used in [5]. designed for the identification of plates Maximizing Expectations (ME) Edge clustering, which extracts regions, was used. With a complex arrangement of angles and forms that resemble plates as well as the license plates of license candidates. Proposes a novel line density filter strategy for connecting places with a high density of edges and removing sparse regions in each binary edge's row and column picture. Although edge-based techniques are rapid to compute, they can't be employed on complex images because they're sensitive to unwanted edges[6].

2. Related Works:

There are some researches that presented methods and techniques and suggested methods for identifying vehicle license plates, such as, Christos-Nikolaos E et al [7] utilizes in photos or videos, algorithms of License Plate Recognition (LPR) consist of three steps: 1) segmenting a license plate region; 2) extracting characters from a number plate region; and 3) character recognition. There Due to variety of plate formats, this work is rather difficult. During image acquisition, as well as the non-uniform outside lighting circumstances. As a result, most tactics only work in certain situations. limited circumstances, such as fixed illumination and a limited vehicle speed, pre-determined routes, and static backdrops Numerous for LPR in still photos or video, approaches have been developed. The goal of their research is to categorize and evaluate these sequences. Processing time, computational power, and other factors are all important considerations. When available, the recognition rate is also addressed. And also, Diogo C. Luvizon et al [8] offer an innovative approach for estimating vehicle speed from footage collected on city streets. There Text detection is used by the system. find passing license plates for vehicles, which are then utilized choose steady tracking features. For perspective distortion, following that, the tracked characteristics are filtered and corrected. The vehicle acceleration is calculated by comparing the features that were tracked trajectory to known real-world measurements. For license plate detection, the system accuracy was attained of 0.87, and 0.92 is a recall of in studies conducted on movies collected under real-world situations. In the same context, Tarun Kumar et al [9] provides an effective and unique method for detecting and measuring the speeds of moving vehicles. This method identifies tracks cars traveling through the surveillance zone, as well as keeping a record of their whereabouts. In each frame, the relative positions of the cars are shown are used to track the cars. This data could be utilized in an ANPR system (Automatic Number Plate Recognition) to determine crucial frames where speed limits are broken. There method has an average detection accuracy of around 87.7%. And HIL`RIO SEIBEL et al [10] Design and develop a framework based on SR and automatic license-plate recognition (ALPR) approaches let forensic investigators interpret an event of interest by identifying license-plate characters in low-quality real-world traffic films acquired by cameras not built particularly for the ALPR task. Foundation uses an innovative methodology to locate, track, and identify a target license plate, handling necessary criteria to locate a desired license plate. Its alphanumeric must be aligned, super-resolved, and recognized. As outputs, the customer receives a rectified and super resolved license plate with more detail, as well as a series of license-plate characters. In the super-resolved image, it was immediately recognized. in addition to designing and developing a unique SR method for projecting individual license plates onto a corrected then filling in the missing pixels on the grid Using painting techniques to compare the various algorithms in the framework (five for tracking, two for post-processing, seven for reconstruction, three for registration, and two for recognition), as well as provide explanations on the benefits and drawbacks of each option. They are tests reveal can SR definitely improve the number of characters properly detected, showing that the framework is an important step toward providing forensic specialists and practitioners with a solution to the license-plate recognition challenge in difficult acquisition scenarios. And Gabriele Guarnieri et al [11] describe an algorithm for perspective correction that works for multi-frame super-resolution and frame averaging in their paper. The KLT algorithm is used in the tracking method, important for dealing with low-quality input photos. This robust registration technique has been used to develop a quick multi-frame super-resolution technology. The strategy was successfully compared to an ad-hoc solution for super resolution improvement of license plate images as well as the L1BTV reconstruction-based method.

3. Object detection:

There are many methods that are used for object detection, which depend mainly on determining a specific area of interest and using artificial intelligence techniques, including:

3.1 Object detection with a Faster R-CNN:

Convolutional neural networks (CNNs) are a type of deep learning network model for image recognition. Object detection and image classification R-CNN, which is based on CNN, is a rapid neural network. R-CNN for object detection, and Faster R-CNN [8] have been developed. Fast R-CNN network with Region Proposal Network (RPN) network are two separate networks. RPN in R-CNN Quick, the network takes the place of Selective Search. The entire item Faster R-detection CNN's modules are housed in a deep convolutional neural network that is unified Using a network structure, the detection is improved faster and more exact[12], as shown in Fig. 1.

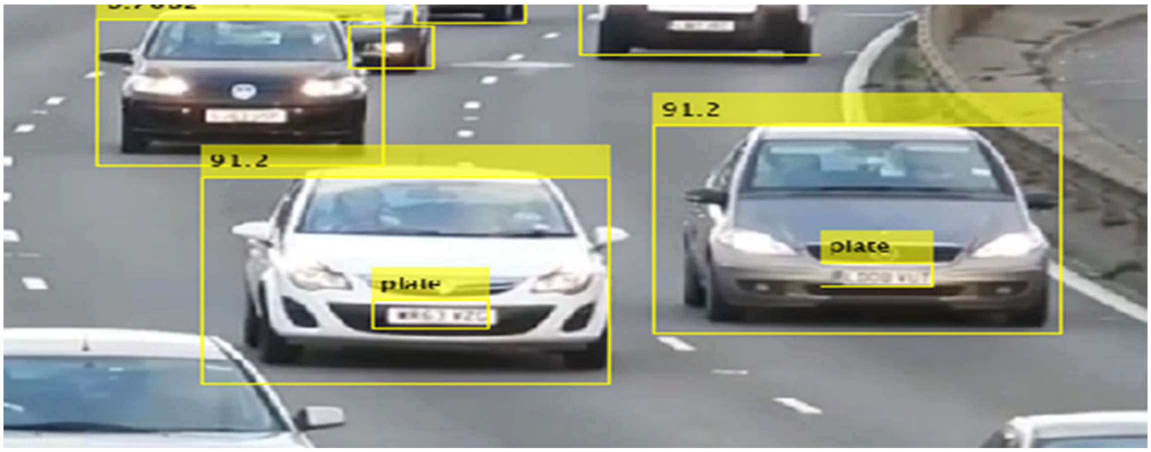

Fig. 1: Cars license plate detection[13].

3.2 Region Proposed Network (RPN):

The RPN is a one-of-a-kind neural network that consists of two parts: a convolution layer and two fully connected layers. A sliding window is one that opens by sliding. Convolution on the feature graph of the last layer to generate some frames of candidates There are two sorts of data in each candidate frame: object's location and probability. Vector with many dimensions formed by multiplying two or more variables. The feature graph and the sliding window are delivered to two layers of network, the cls layer (classification layer) is one, and the reg layer (border regression) is other. Fig. 2 depicts the RPN network's structure[12].

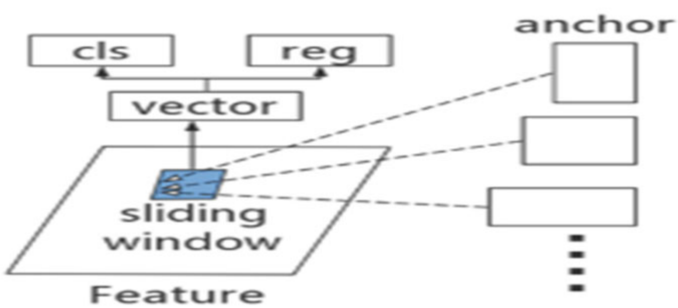

Fig. 2: the RPN network's structure[12].

4. Deep Learning:

Machine learning is a branch of Artificial Intelligence (AI) and computer programming that concentrates on using data to make decisions to replicate how people learn in order to improve accuracy over time. It also refers to the creation of fully automated devices that are guided solely by creation and execution a collection of algorithms and before-defined rules[14]. Machine learning algorithms use data and a set of pre-defined rules to execute and give optimal outputs. In recent years, a strategy has been created that has produced excellent results in a variety of issues, affecting the computer vision community. Deep learning is the name given to this method. The distinction between traditional machine learning algorithms and deep learning algorithms is known as "feature engineering"[14].

4.1 Convolutional Neural Networks:

A grid topology is used in CNN, which is a specialized type of DNN. It consists essentially of a set of filters that are applied to various areas of input data was structured in order to create an output map. LeCun et al. [78] proposed CNN as an answer to the categorization problem posed utilizing computer vision using straightforward pooling, rectification, and contrast normalizing techniques, CNN made training more tractable. Convolutional networks aided the development of deep learning and it is an example of how information and insights acquired can be applied [15].

Convolutional layers, pooling layers, and fully Connected layers are three primary layers that make up a CNN architecture (FC). Several filters are used to ensure that the input picture and the output of the previous layer are not jumbled. After applying a nonlinear activation function (also known as nonlinearity) on the output values of such an operation, the output values are pooled. Produces exactly same number of feature space subsequently used as input for the next layer [16].

4.2 The GoogLeNet Model's Architecture:

GoogLeNet [17] is a Google-proposed CNN that won the ImageNet contest for classification and detection tracks in 2014. GoogLeNet has a unique inception module that combines sparsity and multiscale (convolving with different filter sizes) information into a single block. A schematic of GoogLeNet is shown in Fig. 3.

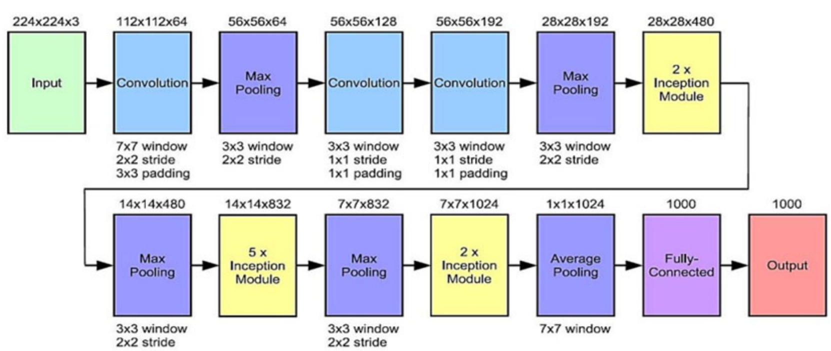

Fig. 3: The GoogLeNet architecture is depicted in this diagram[18].

It functions similarly to a tiny network within a larger network. There are 22 layers and 40 million parameters in the GoogLeNet architecture. This network had the lowest top-5 error rate of any network. The network was successful in achieving the optimum results. It is a search engine, non-sequential CNN with the ability to extend in width and depth without putting the computer under undue strain[19]. The GoogLeNet is a search engine that allows you to find information quickly. In terms of depth, the network does not focus on digging further into the network. The presence of multiple layers rather. In a way, this block increases the breadth of each layer rather than the height. Three max-pooling, two convolutional, and nine inception modules are included in the depth. Make this design from scratch. Each of the inception modules additionally includes max-pooling and convolutional layers[20].

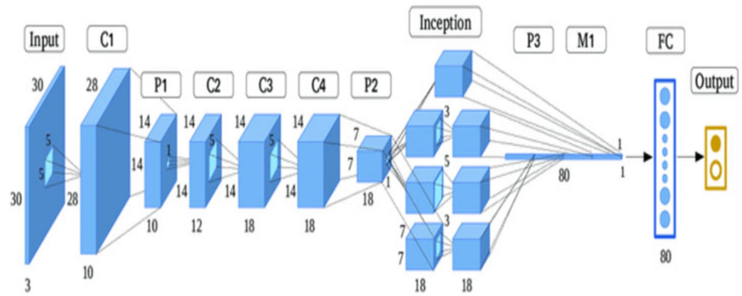

Fig. 4: The GoogleNet layers[21].

GoogLeNet uses a parallel workflow to process its data. Several auxiliary classifiers are incorporated in the intermediate layers. Auxiliary classifiers are used to improve the lower layers' discrimination capacity. Each layer of this module can use convolutional and pooling methods. In AlexNet and VGGNet, for example, each level employs either a convolutional or a pooling procedure. The module's key feature is that filters of various sizes are used in a single layer as an outcome, patterns obtained are of varying sizes, and the data is more thorough. The bottleneck layer, a 1x1 convolutional layer, serves two purposes: it simplifies computations and reduces the number of parameters in the CNN. In comparison to AlexNet and VGGNet, the GoogLeNet network includes less parameters. It has 12 times fewer parameters than the AlexNet model from 2012, yet it can learn more detailed feature presentations. Table (1) lists the GoogLeNet architectural layer details [21].

Table 1: Details of the GoogLeNet architecture's layers[17].

Type of Layer	Patch size/ stride	Output size	depth	#1x1	#3x3 reduce	#3x3	#5x5 reduce	#5x5
convolution	7x7/2	112x112 x64	1					
max pool	3x3/2	56x56x64	0					
convolution	3x3/1	56x56x192	2		64	192		
max pool	3x3/2	28x28x192	0					
inception (3a)		28x28x256	2	64	96	128	16	32
inception (3b)		28x28x480	2	128	128	192	32	96
max pool	3x3/2	14x14x480	0					
inception (4a)		14x14x512	2	192	96	208	16	48
inception (4b)		14x14x512	2	160	112	224	24	64
inception (4c)		14x14x512	2	128	128	256	24	64
inception (4d)		14x14x528	2	112	144	288	32	64
inception (4e)		14x14x832	2	256	160	320	32	128
max pool	3x3/2	7x7 x832	0					
inception (5a)		7x7x832	2	256	160	320	32	128
inception (5b)		7x7x1024	2	384	192	384	48	128
avg pool	7x7/1	1x1x1024	0					
dropout		1x1x1024	0					
dropout (40%)		1x1x1024	0					
linear		1x1x1000	1					
SoftMax		1x1 x1000	0					

4.3 R-CNN:

To get around the issue of selecting a large number of regions, it presented a method that uses a limited search to extract only 2000 sections from the image, dubbed "region suggestions." As a result, instead of attempting to identify a vast number of locations, you may now focus on just 2000. The targeted search algorithm described below is used to create these proposals[22].

Selective Search [22]:
1. Create the initial sub-segmentation; create a large number of prospective regions.
2. Recursively combine comparable sections into larger ones using a greedy approach.
3. Create final candidate region suggestions using the generated regions.

Problems with R-CNN[22]

1. It is classifying to 2000 area ideas every image to train the network, which might take a lot of time.
2. It can't be used in real time since every test image takes about 47 seconds to generate.
3. A fixed algorithm is the chosen search algorithm. As a result, no learning takes place at that point. This may result in the creation of poor candidate region suggestions.

4.4 Fast R-CNN:

Fast Region-CNN was created to address some of short comings of R-CNN in order to create a faster object detection system. The method is comparable to the R-CNN algorithm. Instead of feeding the CNN the region proposals, we give the CNN the input image to produce a convolutional feature map. We select the region of proposals from the convolutional feature map, warp them into squares, then restructure them into a fixed size using a ROI pooling layer so that they may be fed into a fully connected layer. We employ a softmax layer to forecast the class of the proposed region as well as the bounding box offset values from the ROI feature vector. Because You shouldn't have to provide convolutional neural network 2000 area suggestions each time; "Fast R-CNN" is faster than R-CNN. Rather, the convolution procedure produces a feature map, which is performed once per picture[23].

4.5 Faster R-CNN:

To find region proposals, both algorithms (R-CNN and Fast R-CNN) use selective search. Selective search lowers network performance because it is a slow and moment procedure. As an outcome, a method for detecting objects was created that bypasses the selective research methodology and allows the model to learn region ideas. Similar to Fast R-CNN, the image is input into a convolutional network, which produces a convolutional feature map. Rather than using a selective search strategy on the feature map to discover the region proposals, a separate network is used to anticipate the region of interest. The projected region proposals are then molded using a ROI pooling layer to classify the image within the region proposal and anticipate the offset values for the bounding boxes[24].

5. Proposed Approach:

In this section, the proposed methodology is described in detail here. The proposed technique is divided into three stages: primary, second, and third. The primary stage is mostly made up of Get the car image from the sequence of video frames. In the second stage includes Entering the image of the car into the network of the Faster R-CNN algorithm to determine the area of interest, which is the license plate of the car and last third stage includes Obtaining a copy of the license plate of the violating vehicle and storing it in the violations file, as show in fig. 5.

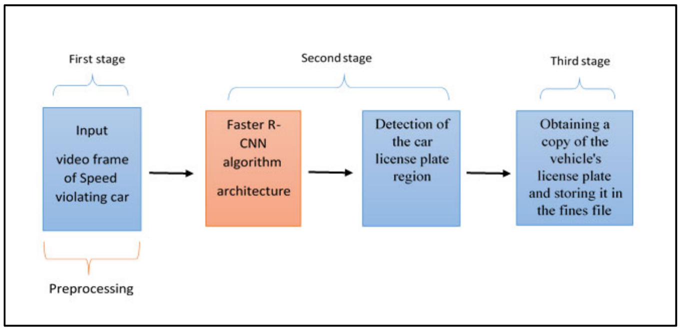

Fig. 5: Block diagram of proposed approach.

5.1 Preprocessing:

The first step, which is preprocessing, consists in obtaining the frame of the vehicle violating the specified speed from the video sequences that are being processed. This frame is the main entrance to the next step to make it easier to find the vehicle license plate place.

5.2 Vehicle license plate detection:

In this step, which is the core of the work for this research, advanced techniques from artificial intelligence and convolutional neural networks are used, specifically, The R-CNN Faster algorithm was utilized and applied using googlenet technology.

Faster R-CNN is discussed in this study has been applied. It is strong in the face of various environmental changes and maintains high accuracy. Plate detection systems were created. This method enabled an increase in speed. This algorithm is an extension of R-CNN. It is similar for fast R-CNN where no structure uses the whole image as input, R-CNN structures power selective region to suggest region and then use Region Proposal Networks (RPN) instead of selective search, the algorithm shows feature map generation through single extraction and it is used in this convolution slice window The method is to create vectors with this tens of candidates for (n) 2-dim candidates the probability of a non-sifted object and bounding box coordinates, and to create a region of interest ROI to obtain quantum computation gains, as shown in the following fig. 6.

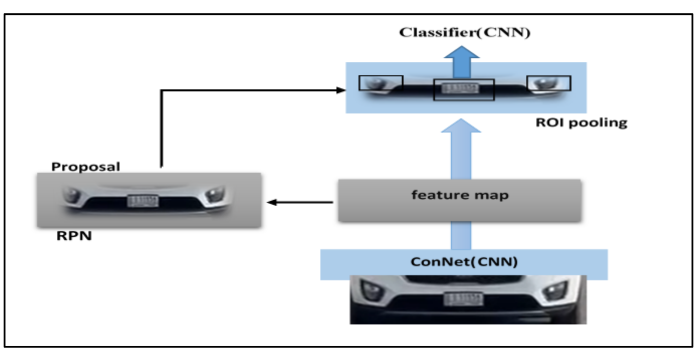

Fig. 6: The structure of the Faster R-CNN**.**

Using Faster R-CNN to detect the license plate in the field of object detection and by applying the googlenet algorithm, the box surrounding the license plate area using the input image as the input image for R-CNN outputs the coordinates and the probability that the license plate is here (true positive) TP with high accuracy and use it as a structure Internal can be detected however the training data and the number of exercises are sufficient if this is not the case FP (false positives) along with TP are shown in this paper.

Algorithm(1): Global System Algorithm
Input: *vehicle video frame*
Output: *A picture of the violating vehicle's license plate*
Begin ***Step one:-*** *Read the vehicle frame.* ***Step two:-*** *load plate_detector_googlenet_258imgs.* ***Step three:-*** *Select one out of every five frames in the video.* *for I Image = 1:5: size(frames,4)* *read (video Reader, I Image)* ***Step four: -*** *Detection car plate region by using Faster R-CNN algorithm and based on GoogleNet* ***Step five: -*** *Save the image of violating vehicle's license plate in fine file* ***End Algorithm.***

6. Results and discussion:

In this paper, the Faster R-CNN algorithm was applied to according to the following information, Car-Plate-Detection using Faster R-CNN in Matlab: Using 258 car plate photos, a Faster R-CNN detector was trained in Matlab on 258 photos. In the test, it was based on 100 images as a test base. The video frames that were relied on as the database of this work, which included 1000 of the vehicles, from which pictures of the license plates of the violating vehicles were taken from the following source (A3 London Motorway Traffic UK HD - rush hour - British Highway traffic_ congestion busy Christmas (1080P_HD).mp4) (https://getsnap.link/WG5NGFpeZWw) [13]. The neural network is googlenet, which was trained in Matlab R2018b for roughly 70 minutes on a GTX 950. Where a network is trained to classify specific object classes, when it defines a network as a Series Network, the function converts the network into a quicker R-CNN by adding a Region Proposal Network (RPN), a ROI max pooling layer, and new categorization and regression layers to facilitate object recognition using an array of layer items or the network name. In this research, number of speeding cars was 100 and they were identified perfectly as show in fig.7, except for two cases that were not well defined, due to occlusion or the presence of text near the license plate of the car that led to its identification instead of the original car license plate as show in fig.8.

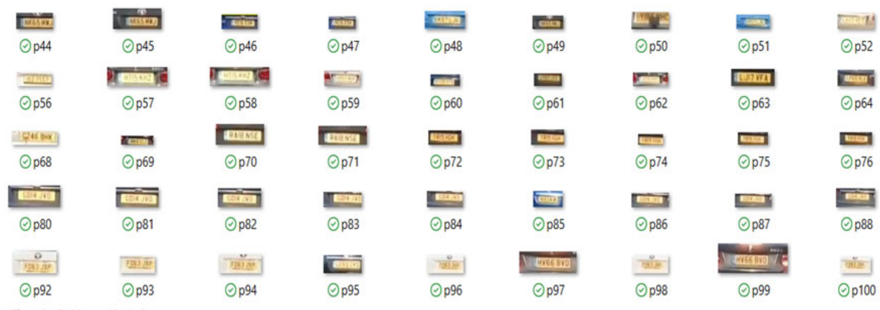

Fig. 7: Some results of identifying and cutting out pictures of speeding license plates in the fines file.

(A) (B)

Fig. 8: Failure cases, (A): Determine the shape of car's license plate close to location of original plate, (B): Determine the plate, but it is obscured by the speed tag of the car in front of it.

The result of the discovery of the vehicle license plate in this work, and according to the data set used, was 98% because out of the 100 violating cars, 98 license plates were detected correctly, and only two cars whose plates were not accurately detected, as shown in Table 2.

Table 2: Table to show the accuracy of the results

Images	**Detection of a license plate**	**Accuracy of License plate detection**
Sample1	True	100%
Sample2	True	100%
Sample3	True	100%
Sample4	True	100%
Sample5	True	100%
	. . .	
Sample96	True	100%
Sample97	True	100%
Sample98	False	0%
Sample99	False	0%
Sample100	True	100%
Total performance accuracy		98%

When comparing these results with other research related to the subject of vehicle license plate detection as in the following search where is Vehicle license plate identification is proposed, on the basis of a novel adaptive image segmentation technique (sliding concentric windows) and connected component analysis in conjunction with a character recognition neural network. The algorithm was tested with 1334 natural-scene gray-level vehicle images of different backgrounds and ambient illumination. The camera focused in the plate, while the angle of view and the distance from the vehicle varied according to the experimental setup. The license plates properly segmented were 1287 over 1334 input images (96.5%). The optical character recognition system is a two-layer probabilistic neural network (PNN) with topology 108-180-36, whose performance for entire plate recognition reached 89.1%. The PNN is trained to identify alphanumeric characters from car license plates based on data obtained from algorithmic image processing. Combining the above two rates, the overall rate of success for the licenseplate-recognition algorithm is 86.0%. And also reveals that better performance (90% up to 95%) has been reported, when limitations in distance, angle of view, illumination conditions are set, and background complexity is low, as shown in Table 3.

Table 3: Results of performance accuracy.

Images	SCW settings for license plate segmentation M is mean value	Performance in plate segmentation	Performance in entire plate content	Overall performance for each sample set
Sample set 1	X1=12, Y1=4, X1=6, Y1=2,T=0.5	419/427 (98.1%)	372/419 (88.8%)	372/427 (87.1%)
Sample set 2	X1=12, Y1=4, X1=6, Y1=2,T=0.8	238/258 (92.2%)	208/238 (87.4%)	208/258 (80.6%)
Sample set 3	X1=12, Y1=4, X1=6, Y1=2,T=0.5	303/310 (97.7%)	280/303 (92.4%)	280/310 (90.3%)
Sample set 4	X1=12, Y1=4, X1=6, Y1=2,T=0.8	147/154 (95.5%)	129/147 (87.8%)	129/154 (83.8%)
Sample set 5	X1=8, Y1=4, X1=4, Y1=2, T=0.5 (day),T=0.8 (night)	180/185 (97.3%)	159/180 (88.3%)	159/185 (85.9%)
		1287/1334 **(96.5%)**	1148/1287 **(89.1%)**	
Overall Performance (success in entire content/total images)		1148/1334 **(86.0%)**		

7. Conclusion:

The detection license plate of the car is a so very important process and addition of artificial intelligence techniques and algorithms for this task leads to excellent results and very quickly and thus provides a great service to traffic police departments in their work by facilitating the detection of cars that violate the specified speeds. In this research a model for the detection of vehicle license plates was presented Through the video, where it was proposed to implement the method using three steps. The first stage is mostly made up of Get the car image from the sequence of video frames Second stage includes Entering the image of the car into the network of the Faster R-CNN algorithm to determine the area of interest, which is the license plate of the car and last third stage includes Obtaining a copy of the license plate of the violating vehicle and storing it in the violations file, As for the group of photos that were worked on, there were 100 photos of a speeding violation, and the license plates of these cars were detected, except for two, meaning that the error rate was 2% , This research can be developed in future works by converting the car number to text instead of keeping it as an image only in the violation record.

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