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AUTOMATIC LICENSE PLATE RECOGNITION FROM VEHICLE IMAGES UNDER CHALLENGING CIRCUMSTANCES

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Abstract--There are several uses for automatic license plate recognition (ALPR) in intelligent transportation systems (ITS). The bulk of traffic-related applications, including vehicle identification, traffic monitoring, parking enforcement, and access control, use ALPR as their primary method. Different methods have been developed to recognize license plates. Due to a number of factors, the process of reading number plate information and character recognition has proven to be difficult. These include multiple or mixed license plates, various lighting and weather situations, and blurry images from moving automobiles, among other things. Here is a strong approach that can identify characters without significant distortion and detect multiple or mixed license plates. To capture all the representative data, a Gaussian filter with a contrast-limited adaptive histogram equalization enhancement approach is used. The suggested technique concurrently detects and classifies license plates and characters using two completely convolutional detectors with a single stage.
Keywords--License plate recognition, intelligent transportation systems, Gaussian filter, mixed license plates, convolutional neural network.

I. INTRODUCTION

Automatic license plate recognition systems have received a lot of attention due to recent developments in intelligent transportation systems (ITS). ALPR (automatic license plate recognition) systems are used to regulate security measures in constrained spaces like parking lots, collect toll payments, and restrict access and exit in vehicle parks, military bases, and protected sanctuaries.

Today's utilisation of intelligent transportation systems (ITS) is widespread, and they are garnering a lot of interest globally. ITS has gained public interest due to the need for traffic monitoring and current developments in autonomous object tracking [1]. Information and communication technologies (ICT) are combined with transportation networks to improve their sustainability, efficacy, and safety. Road safety, congestion relief, and real-time traffic information are all benefits of ITS. Examples of ITS include toll booths, traffic lights, automatic speed limiters, vehicle-to-vehicle communication, and driver assistance systems. ITS isutilized to carry goods, manage public transport, monitory the environment, and offer emergency services [2]. Better resources and information are made available by intelligent transportation systems (ITS) to assist people in making better decisions. A more efficient and sustainable transportation system will arise from researching people about the transportation needs. Intelligent transport systems depend on license plate recognition (LPR).

Additionally, ALPR technologies are commonly utilized in specific industries to reduce fraud and improve security. For instance, they might be helpful while looking for vehicles involved in theft or other crimes. This activity needs a lot of manpower and resources, with the exception of ALPR systems. In addition, it is difficult for people to remember or read the license plate of vehicles in motion, and the use of physical aids in these processes may lead to misinterpretations.

The information on the license plate is output by an ALPR system when it gets a stream of video or images as input, often as text [40], if the frame includes an image of a vehicle. These gadgets have a camera for photographing vehicles. Depending on the needs of the system, those images can be in colour, monochrome, or infrared. The license plate can be located and retrieved using a variety of methods, including object detection [3], [4], [5], [6], image processing [7], [8] and pattern recognition [9], [10].
The effectiveness of an LPR system, depends on the image quality of the LP. Therefore, image enhancement is important in LPR systems. Poor image quality leads to inaccurate recognition results. Several issues can lead to poor image quality including noisy channels, noisy images, and noisy image capture sources.

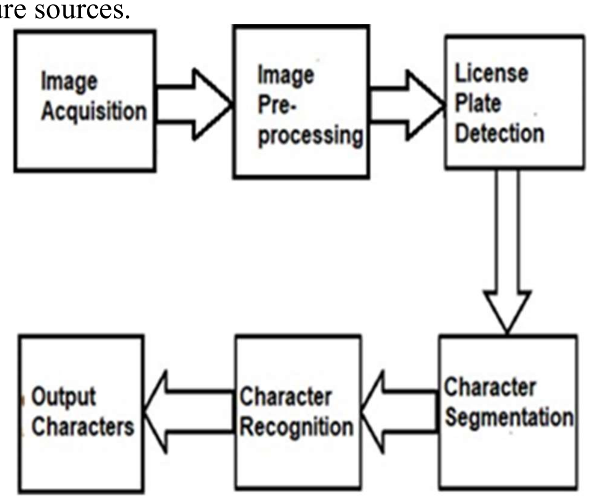

Fig. 1 General Block Diagram of LPR

A. Problem Specification

1). Blurred images from fast-moving vehicles 2). Multiple or mixed license plates
3). Recognizing license plates under changing environmental and weather conditions.

4). Variation of license plates across different regions 5). Rotation and occlusions of license plates

II. RELATED WORK

The majority of ALPR methods currently in use treat license plate detection and recognizing characters as two separate tasks that must be finished in that order. You only look once (YOLO-2), mask region based convolutional neural network (Mask R-CNN) and faster region based convolutional neural network (Faster R-CNN) are some examples of commonly used convolutional neural network (CNN) based algorithms that use objects detectors to identify LPs [11] - [15]. The independent sequential tasks produce a sub-optimization problem for training error accumulation. LP detection and character recognition tasks can cooperate by giving each other context and detailed information, and they can be carried out simultaneously to boost performance.

The creation of complete ALPR networks that use a single integrated deep neural network to carry out LP detection and recognize characters, has increased recently [16]. These algorithms have several issues because they always combine an RNN-based sequential model with a region-based convolutional neural network: 1) The Recurrent Neural Network (RNN) based portion of the network has a higher computational cost, making it difficult to optimize the network's detection portion; 2) The commonplace nearby object detectors, like the faster R-CNN, and YOLO-2 (you only look once), are anchoring-based, relying on a number of previously established anchor boxes.

The quantity, dimensions and aspect ratios, of bounding rectangles (anchor boxes) affect how well these object detection networks perform. In addition, anchor boxes require challenging calculations for intersection over union (IOU) rated using ground-truth boxes as boundaries.

A. Without deep learning, ALPR

There are two groups of ALPR techniques now in use: character-first and license plate first procedures are two different methods [26]. Customary ALPR is a two-step process, includes borders, colors, create and run a texture to detect LP positions. Next, cut out characters and extract features. Recognize each character using a machine learning classifier. Adding a line density filter region based on edge density from the binary image is suggested in [17]. The expectation-maximization approach used in [18] to cluster the edges for LP detection. In [19], development of LP detection method analyze pixels via color geometric templates strip search. Wavelet transform is used in [20]. Develop the image's horizontal and vertical features and utilise empirical modal decomposition analysis (EMD) for LP position decisions. These methods are good for LPs that have a good function but are overly susceptible to complex images. The character first approach looks for the character region. Create an image and group those regions that follow the semantics of the graph for building LPs. Graphic semantics include foreground and background colors, orientations, and features in size, location, etc. In [21], the candidate characters are extracted using the maximum stable external region (MSER), and conditional random field (CRF) models are built on the candidate characters to reflect relationships with the candidate characters. In [22], the probabilistic Hough transform is used to recognize characters and LPs by combining the stroke width transform (SWT) and MSER.

B. Deep learning-based ALPR

IncreasinglyALPR to produce great accuracy, the task turns to detecting and recognizing LPs using CNNs. Numerous of these techniques are built on the conventional couple-step procedure. Detection networks based on common object detection methods (YOLO-2, SSD-based and faster R-CNN) are used for LP detection, and recurrent neural networks are used as recognition networks for OCR. In [14] ,the author proposes a complete one ALPR scheme runs with three subnetworks for character recognition, LP detection, and vehicle localization. Character recognition is performed using a modified YOLO network, and vehicle detection is performed using a YOLO-v2 [23]-based subnetwork. A real-time ALPR system is presented in [13] that makes use of a CR-NET network [24] for character segmentation and recognition and a network based on YOLO for detecting vehicles and license plates . In [25], searches for character areas in digital pictures using a convolutional neural network (CNN)-based character detector, clusters them using edge data to create LPs, and utilises connectionist temporal classification (CTC) with RNN to recognize.

TABLE I
COMPARISON OF SYSTEMS FOR RECOGNIZING LICENSE PLATES

References	Technique	Advantages	Disadvantages
[27],[28]	Edge-based approaches	Faster, Simple	Susceptible to undesirable edges, unsuitable for use with complicated and blurry images
[29],[30]	Colour based techniques	Sturdy against deformation and rotations	Dependent on variations in illumination.
[31],[32]	Texture-based approaches	Sturdy in the LPs with regard to boundary deformations	Computationally complex,work poorly in the License plates with complex backgrounds and illumination changes.
[33],[34]	Character based methods	Can be used for rotated plates	It takes a lot of time and is not appropriate for images with additional texts.
[35],[36]	Using statistical classifiers	Efficient, accurate, and resistant to environmental changes.	Computationally complex
[37],[38]	Deep Learning based methods	Efficient, environmental change resistance	Resource intensive and computationally difficult.

III. PROPOSED METHOD

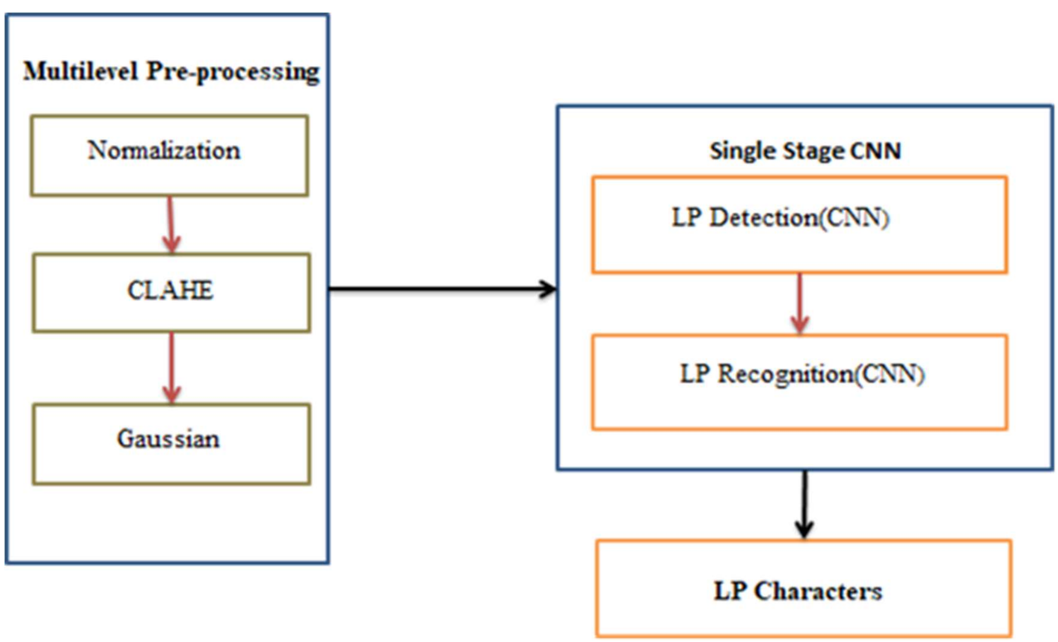

Fig. 2 Proposed method of License Plate Recognition

A. Multi-level Pre-processing

The range of pixel intensity values can be changed by using the normalisation technique in image processing. Normalisation is commonly referred to as contrast stretching or histogram stretching. Smoothing images is more effective when using a Gaussian filter. Three main components make up the CLAHE
[39] algorithm: 1) The generation 2) Histogram equalisation, 3) Bi-linear interpolation. A part or tile of the input image is partitioned. Each tile's histogram equalisation is carried out utilising a pre-defined clip limit. The bilinear interpolation block creates addresses to access the memory location of the input picture pixel values. To capture all the representative characteristics, the suggested pre-processing method is combined with a Gaussian filter and contrast-limited adaptive histogram equalisation (CLAHE) approach. The corresponding histogram features are computed for each level of a license plate image. The recovered features are sent into an extreme learning machine classifier, which then uses them to identify multiclass vehicle LPs. In a multi-level pre-processing stage ofthis procedure, the CLAHE algorithm and a Gaussian filter are applied. First, an LP image is resized and grayscale image created after conversion . A multi-level pre-processing features space is used to generate grayscale images.

B. LP detection and recognition.

Here, an ALPR approach is proposed in which characters are viewed as objects that need to be recognised and categorised while LP detection and recognition are carried out concurrently by a single neural network. By directly anticipating the limits of the boxes and labels of license plate and characters using the region of interest (ROI) pooling and crop processes of object detection, such a technique eliminates the difficult recurrent neural network (RNN)-based recognition process. The following is a list of the study's contributions:

1). Create a single-stage network that is unique for license plate detection and recognition and has two concurrent branches. One for object detection and the other for classification. These subsections directly output the LP class and the LP string by removing redundant and intermediate stages.

2). To support multiple and diverse style LPs the license plate classification is introduced here.

3). LPs with several lines and varying lengths are possible when the LPs are put together utilising the bounding rectangles of the characters and license plates.

For the detection and classification of the license plates and characters, the suggested method makes use of a single- stage convolutional neural network made up of a pair of fully convolutional one-stage detectors for objects [26]. On various specific map layers produced by the core network, these two detectors are applied simultaneously and equally.

Figure 3 shows a comparison of accuracy in predicting for license plate detection between various convolutional neural network (CNN) models including the scratch model, ResNet50, VGG 16 model, and the model applied AlexNet.

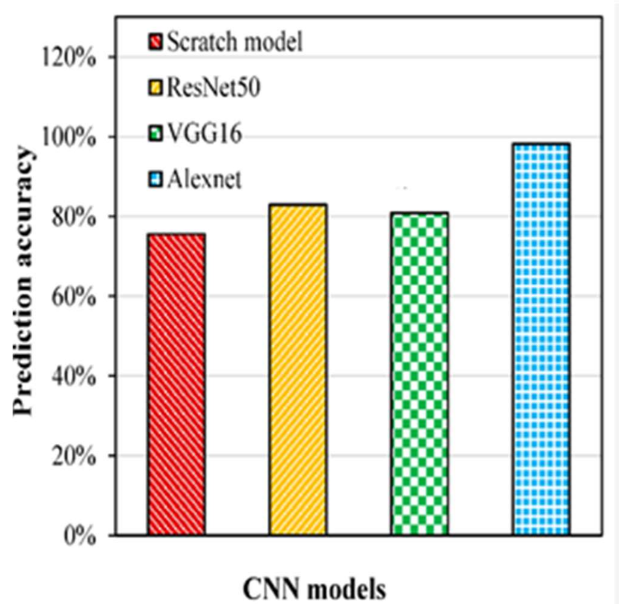

Fig. 3 Comparison of CNNmodels
Source: adapted from [41]

IV. CONCLUSION

A Gaussian filter and the CLAHE algorithm are employed in a multi-level preprocessing stage. During the pre-processing phase more images of training vehicle were added. In the next phase, introduced a single stage CNN for multiple and mixed-style LP identification that simultaneously performs the tasks of object detection and object classification on both LPs and characters. As a result, a one-stage fully convolutional framework without any RNN branches is created that performs LP detection and recognition tasks. Sharing the convolutional feature maps allows the net, which is smaller and requires fewer parameters, to be trained more efficiently and cooperatively for these two tasks.

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