INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 06 ISSUE: 06 | JUNE - 2022 IMPACT FACTOR: 7.185 ISSN: 2582-3930

Real-time Automated License Plate Recognition using R-CNN

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***Abstract*—** The extraction of vehicle license plate information from a picture or a succession of photographs is known as automatic license plate recognition (ALPR). Many applications, such as electronic payment systems (toll payment, parking fee payment), and highway and arterial monitoring systems for traffic surveillance, can use the extracted data with or without a database. The ALPR takes pictures with colour, black-and-white, or infrared cameras. The quality of the acquired photographs is critical to the ALPR's success. As a real-world application, ALPR must process license plates swiftly and successfully in a variety of environments, including inside, outdoors, day or night. It should also be generic enough to handle license plates from other countries, provinces, or states.

Domain – **Deep Learning**

Keywords – **ALPR, ANPR, R-CNN, Neural Networks.**

I. INTRODUCTION

ALPR is a technique that reads vehicle registration plates using optical character recognition on images. Due to their applicability in intelligent transportation systems that have been deployed in several countries for duties such as traffic law enforcement and traffic monitoring, these systems are receiving increasing interest. ALPR systems are also used to control security measures in restricted locations, manage access and exit in car parks, and even search for missing vehicles or vehicles linked to crimes.

The two-stage detection technique Region-Based Convolutional Neural Network (RCNN) is used here. The RCNN model uses a process called Selective Search to extract information about the region of interest from an input image.

The majority of ALPR systems are designed to be used outside. However, changing ambient and climatic conditions make detecting and recognising licence plates problematic. Lighting changes, snow or fog weather conditions, and day and night are all things to think about. Additionally, there may be issues with the cameras and licence plate variations. For example, dust and vibrations in the camera can produce a blurry image, making detection harder and resulting in inaccurate output.

Recent ALPR systems make use of massive datasets, thanks to advances in deep learning techniques. Obtaining a significant number of license plate images, however, is difficult and expensive. ALPR datasets, for example, require sophisticated parameters depending on the country or area where the system is implemented.

Abbreviations and Acronyms

ALPR – Automatic License Plate Recognition

R-CNN – Region-Based Convolutional Neural Network

YOLO - You Only Look Once

SVM – Support Vector Machine

IoU – Intersection over Union

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II. PROPOSED SYSTEM:

A. Working Principle :

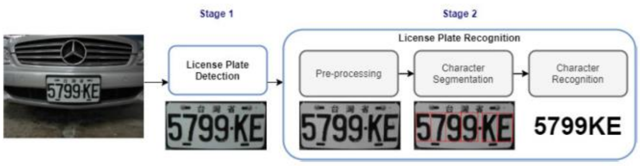

Fig.1. Main Stages of ALPR System

The working of an ALPR system is categorized into two stages.

Stage 1:

License Plate Detection – Using RCNN & Selective Search.

Stage 2:

- Preprocessing
- Character Segmentation
- Character Recognition

Stage 1: Region-Based Convolutional Neural Network(RCNN)

R-CNN, or Region-Based Convolutional Neural Network, is a form of machine learning model used for computer vision applications, particularly object detection. A two-stage detection technique is used. The first stage finds a selection of image regions that could contain an object. The object in each region is classified in the second stage. The R-CNN model uses a process called selective search to extract information about the region of interest from an input image. The rectangular boundaries can be used to illustrate the region of interest.

Fig.2. Working of R-CNN

Figure 2 represents the boundary boxes which use Region-Based Convolutional Neural Networks (R-CNN) to detect the license plate on the back of a vehicle.

B. Feature Extraction:

We extract a 4096-dimensional feature vector from each region proposal using the Caffe version of the CNN described by Krizhevsky et al. To compute features, a mean-subtracted 227 227 RGB image is passed through five convolutional layers and two fully connected layers. To compute features for a region proposal, we must convert the image data in that region into a format that the CNN can recognize (the CNN's architecture requires constant-size inputs of 227 227 pixels). For our arbitrary-shaped areas, we chose the simplest of the several possible modifications.

C. SVM for Object Classification:

This step includes learning a separate linear SVM (Support Vector Machine) classifier for each class, which detects the presence or absence of an object belonging to that class.

Inputs: Each region proposal's 4096-d feature vector.

Labels for training: During training, all region proposals with an IoU overlap of less than 0.3 with the ground truth bounding box are regarded as negatives for that class.

Stage 2 produces a set of positive object suggestions for each class based on the CNN features of 2000 area proposals after training the SVM (of every image).

D. Bounding box regression:

We implemented a bounding-box regression step to learn corrections in the anticipated bounding box location and size in order to improve localization performance.

$$\begin{aligned} P^i &= (P^i_x, P^i_y, P^i_w, P^i_h) \\ G &= (G_x, G_y, G_w, G_h) \end{aligned} \quad (1)$$

$$\begin{aligned} t_x &= (G_x - P_x)/P_w \\ t_y &= (G_y - P_y)/P_h \\ t_w &= \log(G_w/P_w) \\ t_h &= \log(G_h/P_h). \end{aligned} \quad (2)$$

$$\begin{aligned} \hat{G}_x &= P_w d_x(P) + P_x \\ \hat{G}_y &= P_h d_y(P) + P_y \\ \hat{G}_w &= P_w \exp(d_w(P)) \\ \hat{G}_h &= P_h \exp(d_h(P)). \end{aligned} \quad (3)$$

$$d_\star(P) = \mathbf{w}_\star^{\mathrm{T}} \phi_5(P)$$

$$\mathbf{w}_\star = \underset{\hat{\mathbf{w}}_\star}{\operatorname{argmin}} \sum_i^N (t^i_\star - \hat{\mathbf{w}}_\star^{\mathrm{T}} \phi_5(P^i))^2 + \lambda \|\hat{\mathbf{w}}_\star\|^2 \quad (4)$$

III. RESULTS & DISCUSSION

A. Selective Search:

In the field of object detection, Selective Search is a region proposal algorithm. It's made to be quick and recallable. It works by calculating hierarchical groupings of related regions based on colour, texture, size, and shape compatibility.

To get accurate findings, we're employing Multi-level Segmentation. This method will produce the best results for various license plate variations such as rotation, tilt, and so on.

Considering an input image with two different objects, initial segmentation is performed. Then Region of Interest is depicted, where no objects are detected. Using the Greedy Algorithm, after a few segmentations one object is detected. After performing segmentation again, finally, two objects are detected which are highlighted using green rectangular boxes. The greedy Algorithm finds two smaller similar regions and combines them into a larger region. It repeats the process again and again until the best result is obtained.

These similarities can be of many types such as Color Similarities (using channel histogram of R, G, and B – 25 bins each), Size Similarities Texture Similarities (using Gaussian derivatives) and so on.

B. Pre-processing - Thresholding:

An image processing approach that generates a bitonal (aka binary) image by applying a threshold value to the original image's pixel intensity. It's most typically used on grayscale photographs, although it can also be used on colour ones.

Pixels with a bit value of zero are transformed to black, and pixels with a bit value greater than zero are turned to white (a bit value of one).

Example:

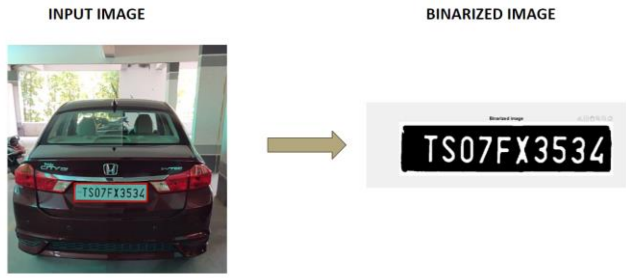

Fig.3. The transition of an input image to a Bitonal Image

Any input image given will be converted to a Bitonal (Binarized) image in a black and white format as depicted in Figure 3. It helps in making the upcoming processes easier, for instance, Character Segmentation.

C. Character Segmentation: K-Means Clustering:

K-Means Clustering divides the unlabeled data into distinct groupings. K specifies the number of predetermined clusters that must be produced during the procedure; for example, if K=2, two clusters will be created, and if K=3, three clusters will be created, and so on. Here, each character in the License plate is a cluster.

D. Character Recognition: Optical Character Recognition (OCR):

Optical Character Recognition is a set of computer vision activities that convert text from a digital image into machine-readable text.

OCR works by dividing up the image of a text character into sections and distinguishing between empty and non-empty regions.

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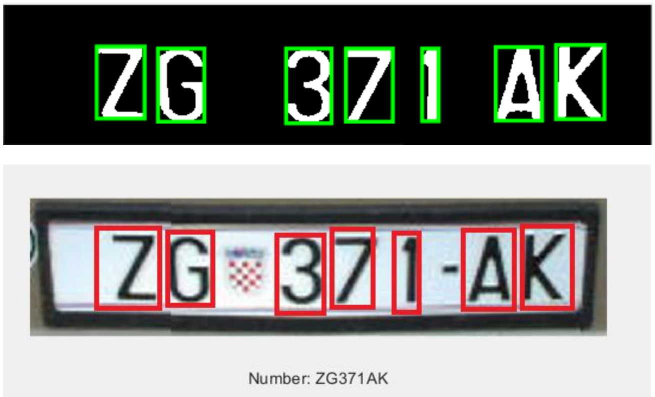

The above images represent how OCR distinguishes and obtains the characters, and converts them into text.

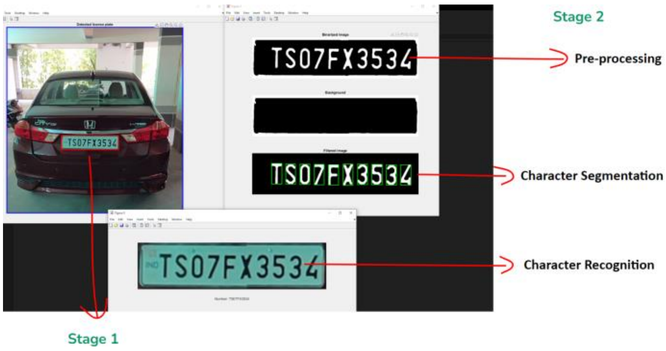

Fig. 4. Final Output

Using MATLAB, the final output is obtained as shown in Figure 4.

Input image of a car is given, and using R-CNN and Selective Search, the back & license plate of the car is identified. Later it segments the characters and is recognized using OCR. Finally, the license plate digits are printed as text.

IV. CONCLUSION

We were able to collect the license plate information using R-CNN and Selective search. ALPR systems are useful for traffic surveillance as well as other uses like finding and retrieving missing automobiles. The precision of ALPR is the main concern. When compared to other approaches like Bi-LSTM, R-CNN produces one of the most accurate results. Multi-level Segmentation, a subtle approach that aids in detecting the back of a car and its license plate more effectively, is also applied here. Technology advances with the passage of time. Because of its widespread use, the ALPR system is a must-have for every country on the planet.

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