2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies (TQCEBT) | 979-8-3503-8427-7/24/$31.00 ©2024 IEEE | DOI: 10.1109/TQCEBT59414.2024.10545029

Moving Vehicle Registration Plate Detection Using Machine Learning

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***Abstract*: This research investigates the application of machine learning techniques in the detection of moving vehicle registration plates. The study explores the effectiveness of various algorithms in accurately identifying and localizing license plates in dynamic and real-time scenarios. By utilizing image processing and pattern recognition methods, the research aims to develop a robust and efficient system capable of detecting license plates under challenging conditions, such as varying lighting conditions and different vehicle orientations. The proposed approach offers potential benefits for law enforcement, traffic monitoring, and parking management systems. Through empirical evaluations, the study aims to validate the effectiveness and reliability of the machine learning-based approach for moving vehicle registration plate detection, providing insights for future research and development in this field.**

Keywords: NPR, binary filtering, Open CV, easy OCR, imutils

I. INTRODUCTION

The transition from cars to information technology is crucial in today's world. Vehicles can be identified in real-time using license plates, which can be used by external agents or specialized smart devices. Automatic License Plate Recognition is one such information system that uses vehicle image data to improve safety, security, and transportation. This paper focuses on the use of machine learning models to analyze unclear images. The Intelligent Transport Framework (ITS) combines electronics, personal computers, and communications technology to monitor traffic conditions, reduce accidents, and increase diversity. Image-based traffic monitoring is popular for improving monitoring ease and comfort. Vehicle detection, monitoring, and classification are key elements in analyzing various types of traffic. Advanced features have been added to the system, but there is still a need for the fastest, most powerful solution at an affordable price.

II. RESEARCH OBJECTIVES

1. To create a checklist based on the vehicle ID.
2. To Reduce the number of employees.
3. To make it easier to pay for license plate verification and registration.
4. Effective and inexpensive
5. To avoids human error
6. Excellent product due to minimal requirements.
7. More reliable and quicker to respond from staff.
8. It is more secure
9. The system is more optimized also.

A. Scope Of The Work

The proposed work will utilize the Bilateral filtering approach to detect the number plate of vehicles. The dataset will consist of Vehicle images that may be cars or other vehicles also. The goal is to identify and read the text from number plates [6]. The work will involve implementing multiple machine learning algorithms. It involves in importing different types of libraries like pandas and NumPy. Car license recognition method from images using morphological algorithms (easyOCR, imutils*)*

B. Problem Statement

Building a Machine Learning-Based System for Reading Vehicle License Plates Automatically. OCR (Optical Character Recognition) with bilateral filtering is used to identify the license plate. Using machine learning to recognize vehicles streamlines vehicle management, improves accuracy in license plate reading, and provides data for insightful reporting. The text from the license plate will be outputted at long last [7].

III. LITERATURE SURVEY

Number plates are used to identify vehicles in many industries today, however this process is laborious and time consuming due to the need for human intervention. This study proposes using deep learning to automate the laborious human process of vehicle number plate recognition. Vehicle license plates can be read thanks to an Internet of Things (IoT)-based system and the YOLO darknet. The license plate can be recognized with the help of the Gaussian filter, DNN algorithms, SVM, ECHE, and CLAHE methods. Locating a license plate in an image using computer vision and deep learning algorithms for object detection [8].

A. *Related Work:*

For innovations like Automatic License Plate Recognition (ALPR) and Vehicle License Plate Recognition (VNPR), the automobile sector uses machine learning, deep learning, artificial intelligence, and the Internet of Things. This research uses morphological functions, edge testing, and artificial neural networks (ANN) to assess Saudi license plates. A deep learning and support vector machine approach is suggested for driver's license recognition. With respect to OCR for license plate and vehicle recognition, the system has excellent success rates in search, segmentation, and text recognition. Furthermore, a computerized system in Libya that checks license plates use neural network techniques and geo-based elements to achieve an accuracy of almost 94.5%.

IV. METHODOLOGY

The goal of the paper is to streamline the process of verifying license plates by linking all smart systems together. We propose a system that can do license plate enquiries while cutting down on human resources and quality control expenditures. Bilateral filtering, OpenCV, morphological transformations, and segmentation error are used in our proposed approach. An optimal model has been proposed.

Once the dataset is compiled, we may pick any image from it and duplicate its location. The model is then constructed using a number of machine learning methods. License plate texts are then predicted using this approach.

A. *Model Description*

Building a machine learning model to recognize the number plate requires several steps:

1) *Image Acquisition:*

Image acquisition is the conversion of analog images into digital form, typically done using a camera or scanner. It is used for research papers, experimental data, and printing photographs. The process begins with raw image processing, which is crucial before any further work. The best part is that all you need is your camera, and the input parameters are created during image capture.

2) *Image de saturation:*

Image de saturation removes color from images, resulting in black and white images. High contrast and low contrast images are black and white, while dark tone images have different appearances.

3) *Image Thresholding:*

Image thresholding divides grayscale images into binary regions, with pixels above the threshold considered white or 1 in the output image. Success depends on the width and depth of the valley character.

4) *Model Selection:*

Choose an appropriate algorithm for the task of background blurring and noise reduction, such as a Bilateral filtering algorithm.

5) *Morphological Transformation:*

Morphological transformations are elementary procedures that use the structure of pictures to produce binary representations. Erosion and growth are two facets of morphology, with variations like open, close, and gradient. In the design phase, one pixel from the original image is swapped for one from the final product, with the outcome determining the new pixel's value.

B. *Model Evaluation:*

After building and fine-tuning the model, it's essential to evaluate its performance. The evaluation step to test the model on a separate test dataset and computing metrics such as accuracy, precision, confusion matrix. These metrics help to assess the model's effectiveness in detecting number plate. By evaluating the model's performance, we can identify potential areas for improvement and fine-tune the model further to enhance its accuracy and effectiveness in detecting license plates.

C. *Model Fine-tuning:*

Fine-tuning the model involves adjusting its parameters or testing different algorithms to improve its performance, and repeating the evaluation step if necessary. This step is crucial as it helps to optimize the model and improve its accuracy. Contingent upon the consequences of the assessment, the model might should be tweaked by changing its boundaries or attempting an alternate calculation to accomplish improved results. By repeating the evaluation step, we can assess whether the changes made to the model have improved its performance. Overall, fine-tuning is a necessary step in the model development process to ensure that the model is as accurate and effective as possible.

D. *Registration Plate Detection Model:*

Registration plate detection is a process that recognizes text from a vehicle's number plate. The model uses a dataset of images with number plates and uploads a single image to detect the text. The image undergoes several methods, including gray scale conversion, image de saturation, noise-free filtering, and image thresholding. The model creates a rectangle structure around the text, segmenting the background to make it readable only from the registration plate. The image undergoes morphological transformation and character recognition to read the text.

1) *Image acquisition and image desaturation:*

ANoIR enabled the camera for far infrared photography. Then the blind picture is added to the system. It can read images by changing color to grayscale, called image desaturation. This is done to reduce the complexity of the work, because grayscale images are easier to save than color images. OpenCV has an almost perfect ability to convert color images to grayscale. License plate recognition starts with taking a photo from a photo, preferably a surveillance camera. The image acquisition process determines the quality of the captured image of the license plate that the search process should use. The resulting images are better and more accurate.

One way of preprocessing is to prepare the image to better extract features. This can be considered as the stage of editing car pictures and pictures made for pattern recognition. The decision of the first strategy to acquire of the traffic image depends on the type of use for which the image is used.

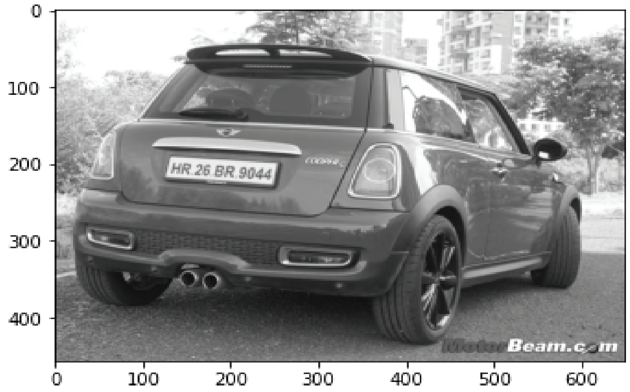


Fig. 1. Desaturated image

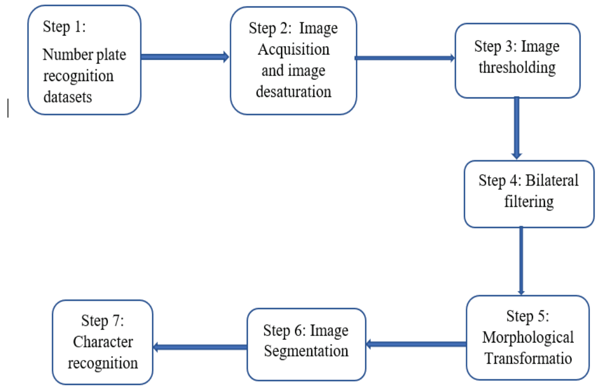


Fig. 3. Model

2) Image Thresholding:

For effective license plate recognition, the suggested method makes use of bilateral filtering, morphological modification, segmentation error, and picture thresholding using OpenCV. By streamlining picture representation and concentrating on important regions, this integrated strategy improves automated license plate reader accuracy and efficiency.

3) Bilateral Filtering

The bilateral filter is used in the highlight extraction technique to reduce noise while breaking down visual characteristics. The system improves digital document conversion, repair, and search by using OCR and Imutils in Python with OpenCV; morphological transformation supports geometry analysis.

Fig. 2. Morphological transformation of image

4) Image Segmentation:

We discuss the detection of oriented number plates in overturned vehicles, which may not be in the correct introduction. The image is segmented into parts for identifying objects or relevant information. Two segments are identified and cleaned of local noise using bilateral filtering. The license plate is then divided into an independent set of characters for Optical Character Recognition testing. Character recognition is also tested visually. Authentication is used to mitigate attacks based on the identifier's information. The final output is the text read from the vehicle registration image, using bilateral filtering to reduce noise and improve accuracy.

E. Dataset Description:

With the development of deep learning, recent ALPR systems use big data. However, collecting enough license plates is difficult and costly. There are certain requirements for the datasets used in automatic license plate recognition (ALPR) that change from country to country and area to region. Therefore, data produced for one study may not be of much use in another. In addition, some studies use synthetic data instead of real plates, and encouraging results are produced. However, benchmark data must be available to represent real-world situations and issues in order to be used as a benchmark and to be able to compare different ALPRs. In addition, many studies use traditional data for evaluation and comparison, and some of them do not contain images of a complex world. This section describes ALPR's requirements for real-world data to provide guidance for future operations.

F. Experiments And Results

1) Install And Import Dependencies:

easyOCR is a python library for easily extracting text from images.

Imutils library is used to do process the images.

So, we have to install these libraries before going into the development.

```
16s
!pip install easyocr
!pip install imutils
```

Here there are many libraries, each have respective properties. CV2 is a python library that is used to read the pictures or images that user upload.

Matplotlib is similar property with CV2 and it is used to detect the borders of the object or and images also.

NumPy is used in case of working with arrays or any sequential structures.

```
[2] import cv2
    from matplotlib import pyplot as plt
    import numpy as np
    import imutils
    import easyocr
```

2) Loading The Dataset:

After importing libraries let's move to the datasets. For any machine learning model dataset is more essential one so, here I use the dataset of vehicle containing registration number plates.

cvtColor is used to convert the image into gray scale.

imread () method is used to read the input. It can be any image or any data also.

imshow () method will display the output.

Here the output is grayscale image of the vehicle with dimensions also.

```
[3] img = cv2.imread('/content/img1.jpg')
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    plt.imshow(cv2.cvtColor(gray, cv2.COLOR_BGR2RGB))
```

3) Applying Filter:

Bilateral filtering is an algorithm that can able to reduce the noise from the image. It is most important in this paper. Because, less the noise more the accuracy or clarity in output image.

Canny is used to find where an image's borders are. By combining the techniques of bilateral filtering and canny it, we can lessen the overall amount of noise in the images and bring out the clarity of the boundaries

```
bfilter = cv2.bilateralFilter(gray, 11, 17, 17) #Noise reduction
edged = cv2.Canny(bfilter, 30, 200) #Edge detection
plt.imshow(cv2.cvtColor(edged, cv2.COLOR_BGR2RGB))
```

findContours() function will take three parameters. The first argument is the image that should be the gray image. The second is the retreval mode and the third is the approximation mode.

```
keypoints = cv2.findContours(edged.copy(),
                             cv2.RETR_TREE,
                             cv2.CHAIN_APPROX_SIMPLE)
contours = imutils.grab_contours(keypoints)
contours = sorted(contours,
                  key=cv2.contourArea,
                  reverse=True)[:10]
```

approxpolydp() function is used to detecting a shape with a precision.

```
location = None
for contour in contours:
    approx = cv2.approxPolyDP(contour, 10, True)
    if len(approx) == 4:
        location = approx
        break
```

```
location

array([[[122, 219]],

       [[246, 227]],

       [[252, 200]],

       [[132, 191]]], dtype=int32)
```

The np. zeros () function will return a array of given shape and type with zeros.

The boundary of an image is said to have a contour if there exists a line that passes through all points that share the same reference. Shapes may be described, object sizes determined, and hidden objects uncovered with the help of contours.

The findContour() method in OpenCV is useful for contour detection and extraction. As such, thresholding, Sobel edges, etc., are necessary only for binary pictures.

It will compute bit-wise AND of the underlying binary representation of integers present in input arrays.

```
mask = np.zeros(gray.shape, np.uint8)
new_image = cv2.drawContours(mask, [location], 0,255, -1)
new_image = cv2.bitwise_and(img, img, mask=mask)
```

Now, the morphological transformation and segmentation of image is done. It will the display the picture of number plate of vehicle by making background as dark.

4) Morphological Transformation:

```
plt.imshow(cv2.cvtColor(new_image,
                        cv2.COLOR_BGR2RGB))
```

Here, np. where () function will print the index of elements present in array if the given condition is satisfied.

```
(x,y) = np.where(mask==255)
(x1, y1) = (np.min(x), np.min(y))
(x2, y2) = (np.max(x), np.max(y))
cropped_image = gray[x1:x2+1, y1:y2+1]
```

5) Image Segmentation:

Here, the output is in the form of segmented. It will produce the image of registration plate along with dimensions.

```
plt.imshow(cv2.cvtColor(cropped_image,
                        cv2.COLOR_BGR2RGB))
```

['en'] is an attribute, which means now it can able to detect English text present in the image file.

Readtext() will produce the bytes in the form of string.

```python
reader = easyocr.Reader(['en'])
result = reader.readtext(cropped_image)
result
```

6) Character Recognization:

Here, puttext() is used. Why because, the puttext() will make to write text on any image. In our paper to detect the text from image and to draw it in image the puttext method is used.

Rectanlge() will draw thw rectangle shape around the required space. Here, it draw around the text of number plate to identy by anyone easily.

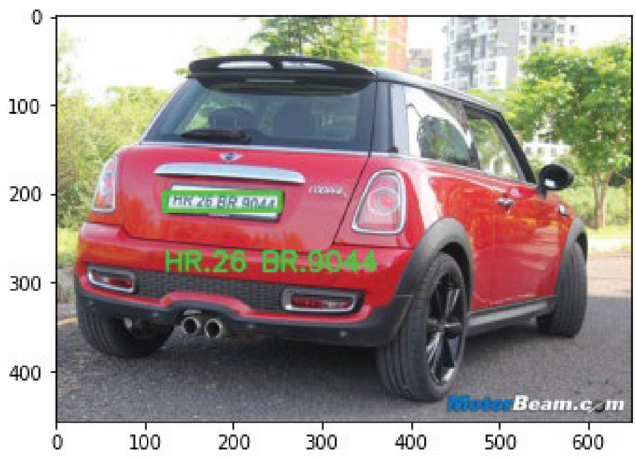
It will make the charator recognization and text read. It will produce the vehicle image with number plate text rounded as rectangle and write text on it.

```python
text = result[0][-2]
font = cv2.FONT_HERSHEY_SIMPLEX
res = cv2.putText(img, text=text,
                  org=(approx[0][0][0],
                       approx[1][0][1]+60),
                  fontFace=font, fontScale=1,
                  color=(0,255,0),
                  thickness=2,
                  lineType=cv2.LINE_AA)
res = cv2.rectangle(img,
                    tuple(approx[0][0]),
                    tuple(approx[2][0]),
                    (0,255,0),3)
plt.imshow(cv2.cvtColor(res, cv2.COLOR_BGR2RGB))
```

G. Result

Below figure is the segmented picture of the registration number plate of vehicle.

And the final output will be



The proposed algorithm for license plate verification is superior to other techniques, particularly for blind and afflicted plates. It can detect skewed input images during adverse weather conditions. To prevent biased outcomes, data from multiple sources is combined. Image-to-image translation methods are recommended for authentic license images. A Python training model is used for license-code detection and recognition, with a red rim surrounding the license space.

V. CONCLUSION AND DISCUSSION

Automatic license plate registration (ALPR) systems require careful feature and technology selection to accommodate various operating systems and hardware. This has examined and reviewed the most up-to-date methodologies and procedures for ALPR solutions. This article provides a comprehensive comparison of relevant studies and identifies data evaluation needs in practice. We also describe the open challenges for ALPR solutions and recommend future research directions.

Numerous applications exist for this software in which the vehicle's license plate number is the principal identifier. For relatively modest uses, such parking lots or traffic lanes, existing applications are ideal. Facial recognition might be added in the future, and the entire system could be linked to databases of criminal histories so that we can identify repeat offenders.

VI. CHALLENGES FACED:

However, developing a general and optimal solution for ALPR is difficult due to environmental and license change factors such as rotation, closure, changing lighting, objects and shadows. Therefore, current ALPR systems do not have a good solution in difficult situations.

We provide a comprehensive and insightful analysis of the state-of-the-art literature on automatic language recognition (ALPR) and highlight some of the specific limitations and challenges in the subject.

VII. FUTURE WORK:

Research on license plate reading technology is needed for the future. In general, ALPR solutions tend to be more resource-heavy, as they necessitate high-priced hardware and constant access to the internet. As a result, it can only be used in places with reliable access to energy and the internet. Therefore, it is crucial for future scientists to develop systems that can function with less power and no internet connection. Since ALPR systems are in high demand, this will facilitate the implementation of solutions in rural areas.

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