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AUTOMATIC VEHICLE NUMBER PLATE RECOGNITION SYSTEM USING TENSORFLOW OBJECTION DETECTION

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Abstract—**The implementation of Automatic Vehicle Number Plate Recognition (AVNPR) technology has proven to be instrumental in various practical applications, including access control, traffic law enforcement, inventory and property management, security system surveillance, parking space allocation, and road traffic monitoring. In this research, we employed the Tensor Flow object detection algorithm within the AVNPR system to enhance the detection of vehicle plate numbers. Our approach utilizes object detection for vehicle license plate localization, demonstrating superior robustness and accuracy compared to conventional methods. Through the training of 203 Nigerian license plate images, our model successfully detected all 40 plates tested, showcasing its efficacy in real-world scenarios. Subsequently, the identified plate numbers, considered as Regions of Interest (ROIs), served as inputs for our Optical Character Recognition (OCR) model, leveraging the Easyocr library. The OCR model exhibited an impressive average accuracy of 93.33% across the 40 tested plate numbers. The extracted text, representing the plate number, was then used to query an SQLite database, providing comprehensive user details, including name, address, plate number, and other relevant information. This research underscores the efficiency and accuracy of the proposed AVNPR system, showcasing its potential for seamless integration into diverse applications that require reliable vehicle plate recognition and subsequent user information retrieval.**

Keywords— **Automatic Vehicle Number Plate Recognition (AVNPR), Optical Character Recognition (OCR), Object Detection, Tensor flow, Object detection**

I. INTRODUCTION

The realm of Automatic Number Plate Recognition (ANPR) systems, as delineated by [1], [2] represents a technological paradigm employing Optical Character Recognition (OCR) on images to extract intricate details from vehicle license plates, thereby establishing their spatial context. These images can originate from diverse sources, including existing closed-circuit television [3], road-rule enforcement cameras, or specifically designed license plate recognition cameras [4].

The inception of this technology in 1976 by the Police Scientific Development Branch (PSDB) in the UK, with its inaugural application in 1979 for detecting stolen vehicles and the first arrest in 1981 [5], marks the genesis of Automatic Vehicle Number Plate Recognition (AVNPR). Since then, it has undergone substantial evolution, transcending its initial role in crime fighting by law enforcement agencies. Presently, AVNPR has found utility across diverse sectors, becoming a vital tool for organizations and individuals alike.

Applications extend beyond law enforcement, encompassing access control in garages and offices [6], electronic toll collection on pay-per-use roads [7], and the collection of statistical data on vehicular movement throughout road networks [8]. This multifaceted evolution underscores the broad spectrum of applications that AVNPR has assumed, reflecting its indispensable role in modern surveillance, security, and organizational management.

II. RELATED WORKS

The fundamental architecture of the Automatic Vehicle Number Plate Recognition (AVNPR) system comprises several key stages, as outlined [9]: camera, vehicle plate localization, optical character recognition (OCR), and a database. The camera employed in AVNPR systems may be stationary, defining a Fixed AVNPR, or mobile, characterizing a Mobile AVNPR (MAVNPR) [10]. In certain regions, MAVNPR units are strategically affixed to police vehicles, as observed in countries like Australia and the UK [11], [12].

Regardless of the camera's mounting configuration, its primary function is to capture images of vehicles traversing specific areas of interest [7], [13]–[15]. This image capture is initiated through sensors or image recognition algorithms, with common examples including infra-red (IR) sensors and motion sensors [6], [16]–[19]. Once the vehicle image is captured and stored, a Digital Image Processing (DIP) algorithm is employed to localize the vehicle's number plate. The DIP algorithm identifies the Region of Interest (ROI), typically a rectangular area of the image containing the vehicle's plate number. Subsequently, the identified ROI is cropped from the image frame and subjected to an Optical Character Recognition (OCR) algorithm, extracting the plate number characters in textual form from the image.

The text output from the OCR algorithm serves as a query to the database, retrieving all pertinent records associated with the number plate user. ANVPR databases often encompass a wealth of information, encompassing pre-stored histories of vehicle usage, owner details, location data, traffic offenses, tickets, and more. These details are frequently leveraged by law enforcement agencies for surveillance, contributing to the mitigation of criminal activities. This comprehensive process underscores the multifaceted functionality of the AVNPR system in seamlessly integrating image capture, processing, and database interrogation for effective vehicle identification and information retrieval.

This section reviews pertinent studies in the domain, with a focus on the research conducted [20], who delved into the Automatic Vehicle Number Plate Recognition (AVNPR) system utilizing MATLAB. In this investigation, the initial step involved resizing the vehicle image to 480*640 pixels to optimize computational efficiency. Subsequently, grayscale and binary image transformations were applied to facilitate the vehicle license plate localization process. Morphological operations on the binary image not only achieved localization but also enhanced specific regions of the image by sharpening. A filtering mechanism was then employed, displaying pixels meeting predefined standards while modifying the background of smaller pixels, thereby improving the binary image representation and eliminating noise for subsequent processing.

Following successful vehicle plate localization, an Otsu thresholding method was applied to the binary image based on intensity levels. Additional morphological operations and image dimension filtrations were iteratively conducted until the total number of characters on the image aligned with the expected eight alphanumerical characters found in a standard vehicle license plate. The final stage involved implementing an Optical Character Recognition (OCR) algorithm, which compared the processed image with a pre-defined template. This comparison utilized normalized cross-correlation to assess similarities, with each character position undergoing thorough testing to store the highest probability match.

Lourdes conducted comprehensive testing on a Bulgarian vehicle license plate, evaluating 200 images. The results indicated an overall error rate of 17%, with specific attention to localization, segmentation, and recognition stages exhibiting an error below 8%. These findings underscored the efficacy of the proposed methodology in achieving accurate and reliable AVNPR, demonstrating its potential applicability in real-world scenarios.

Another notable contribution to the field of Automatic Vehicle Number Plate Recognition (AVNPR) using MATLAB comes from [21]. Their research focused on leveraging colour segmentation for license plate detection and extraction within an AVNPR framework. The developed AVNPR system was designed to detect vehicles passing through an access point, employing an Infrared (IR) sensor to initiate the image capture process once a vehicle is detected. The captured image, acquired using a USB camera, undergoes a transformation from RGB format to grayscale.

To identify the Region of Interest (ROI), colour segmentation is applied, specifically targeting the official Sindh plate number, characterized by a yellow background with black alphanumerical characters. The algorithm converts yellow pixels to binary (1) while setting other colours to (0), resulting in a black and white image that effectively represents the ROI of the vehicle license plate. Subsequent filtration stages involve the removal of background noises in the ROI image. The first filtration stage eliminates white patches on the image borders by setting them to 0 (black). The second stage utilizes the pixel count method to filter out white pixels without predefined threshold values, converting them to low (0). This process ensures that the resulting ROI image solely contains the vehicle number plate without any extraneous noise.

To crop the ROI, an innovative smearing algorithm is applied, identifying the coordinates of the first and last white pixels from the top-left corner to the last character. The final stages involve image colour inversion and Optical Character Recognition (OCR). Upon successful recognition, the results are stored and compared with a database for vehicle authorization.

The researchers concluded that the colour segmentation method for AVNPR demonstrated success in detecting vehicles, performing localization and segmentation, and achieving OCR of Sindh license plates under various lighting conditions, with a commendable detection and recognition rate. The study highlighted that distance impacts image size and, consequently, accuracy. Additionally, the OCR method utilized a correlation approach for character recognition, with the recognition probability being a calculable factor, though not explicitly presented in the research paper. The developed AVNPR system is recognized for its computational efficiency and potential for real-time implementation in vehicle identification systems.

In another research MATLAB was employed to develop a vehicle license plate recognition system, integrating edge detection and neural networks into their research framework [13]. Utilizing a digital camera, the researchers captured images of stationary vehicles, which were initially in RGB format and subsequently converted to grayscale using the NTSC standard method. Addressing image noise, a median filter was applied to the grayscale image, replacing each pixel with a value derived from the median value of the pixels.

To isolate the Plate Region of Interest (ROI), both horizontal and vertical localizations were implemented, filtering out extraneous details and retaining only the plate number. Horizontal localization focused on identifying horizontal segments within the plate, while vertical localization pinpointed the vertical segments. The Sobel operator,

employed for edge detection of the number plate, facilitated the localization process.
Character recognition was executed through the deployment of two Artificial Neural Networks (ANN). One ANN was dedicated to alphabet identification, and the other to numerical identification. This dual-network approach, featuring identical architectures, significantly reduced the likelihood of misidentifying a number as an alphabet and vice versa. The feed-forward back-propagation algorithm was utilized for ANN training, with training performance gauged using a mean square error (MSE) function.
The developed algorithm underwent rigorous testing using Nigerian plate numbers under various lighting conditions. The research reported notable accuracy percentages: 97% for vehicle license plate extraction, 96% for character segmentation, and an impressive 98% for character recognition across 200 tested plate numbers. These findings underscore the promising capabilities of the proposed system, showcasing its robust performance in key aspects of license plate recognition under diverse conditions.
Exploration of Automatic Vehicle Number Plate Recognition (AVNPR) highlighted the efficacy of Hough transforms and Otsu segmentation as a robust method for license plate recognition systems [22]. The AVNPR system incorporates an image recognition algorithm to capture images of moving vehicles along with their license plates, offering a comprehensive approach to image enhancement.
The algorithm commences with image smoothing and sharpening, employing a median filter for the latter. Differential operations, utilizing the Sobel method in both vertical and horizontal directions, enhance the image quality. The subsequent conversion to a binary image, with an optimal threshold value determined through discriminating analysis based on pixel variance and density, ensures clarity for subsequent processing steps. A swelling and shrinking algorithm is iteratively applied to refine any rough outlines present in the image.
The process of pixel labelling involves categorizing pixels into groups based on density, assigning distinct numbers to each group. Otsu's threshold method is employed for edge detection, delineating the rectangular shape of the license plate for effective localization. The image then undergoes separate erosion and dilation processes, enhancing the visibility of plate characters in preparation for identification.
Character identification is accomplished using the Hough transform technique. The developed algorithm undergoes rigorous testing on fifty license plates, encompassing varied cameras, heights, and weather conditions, exhibiting a commendable success rate. However, the researchers note that while the Hough transform and Otsu's segmentation system demonstrated good success rates, the Hough transform method posed challenges with different-sized characters and tilted registration plates. Consequently, the researchers advocate for the adoption of neural networks for character recognition as a more versatile alternative to the Hough method proposed. This recommendation underscores the researchers' forward-looking perspective on enhancing the adaptability and robustness of license plate recognition systems.

III. RESEARCH METHODOLOGY

In the implementation of the Automatic Vehicle Number Plate Recognition (AVNPR) system in this study, a Python script, executed in Jupyter Notebook, was employed to harness the capabilities of the TensorFlow object detection API. Leveraging the TensorFlow object detection API facilitated the automatic detection of vehicles through a USB camera, capturing images and extracting their respective license plate numbers. This algorithm enabled real-time extraction from live camera feeds as well as from locally stored images on a computer (laptop).
The process of image capture is initiated upon vehicle recognition through the AVNPR USB camera. For the TensorFlow API to autonomously detect vehicles and localize their number plates, a diverse set of vehicle images was curated from various sources and incorporated into the API for the purpose of transfer learning. This transfer learning approach allowed the pre-existing knowledge within the API to adapt and make inferences on new objects, specifically targeting vehicle license plates.
The dataset used for vehicle object detection and plate number localization was sourced from two distinct repositories: the online vehicle sales site www.jiji.com.ng and the Kaggle database. Kaggle provided an extensive dataset containing various vehicle images, complete with annotations detailing the coordinates of the vehicle plate numbers in pixels. Images obtained from jiji.com.ng were annotated separately. A total of 203 datasets were collected and subsequently trained using the TensorFlow object detection API. The training process involved dividing the dataset into test and training files in a 4:1 ratio, resulting in a training dataset of 160 vehicle images with corresponding annotations and a test dataset comprising 40 images with corresponding annotations.
The creation of a label map was executed through a Python script utilizing the dataset's annotation names. As the TensorFlow model necessitates the use of a record file format for training, the train and test datasets were converted to this format using another Python script. Before training the model, the configuration was copied to the training folder, a step automated by a script. The dataset was then trained for 10,000 steps, requiring a total of 12 hours. At the conclusion of training, a checkpoint data file was generated and utilized as the model for AVNPR object detection and plate localization.
Subsequently, a Python script was crafted to process individual test images, feeding them into the model. The results, along with confidence levels, are depicted in Figure 2. This method, involving the adaptation of a pre-trained model for custom object detection, is commonly referred to as transfer learning.
Following the successful detection of the Region of Interest (ROI), the image was subjected to an Optical Character Recognition (OCR) algorithm for text extraction. The Easyocr

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Python library was employed for this purpose, reading the alphanumeric characters within the ROI and converting them into text. Given the varying sizes of characters on Nigerian number plates, an algorithm was developed to filter out the character with the largest pixel size, designating it as the plate character of interest and converting it to text. The extracted text was then used to query an SQLite database, containing driver records. The SQLite database was constructed by importing the driver records into the SQLite browser and implemented through the developed Python script.

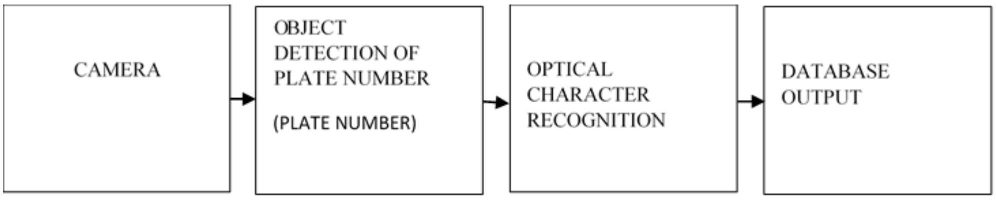

Fig. 1. Flow Diagram of AVNPR System

IV. RESULTS

Figure 2 vividly demonstrates the real-time efficacy of the script in detecting various vehicle number plates and their corresponding images. The displayed confidence levels further illustrate the reliability of the captured images. Notably, the minimum confidence level from the trained class was 84%, while the maximum reached an impressive 87%. It is worth mentioning that this accuracy holds the potential for refinement through additional training steps.

Fig. 2. Samples of Vehicle Number plate object detection and localization of in real-time

Figure 3 and Table 1 provide a comprehensive overview of the plate number conversion from image to text using Easyocr. The script, thoughtfully designed to prioritize the extraction of larger characters, achieves accurate and reliable text conversion.

In Figure 3, the red bounding box visually highlights the automatically captured characters that are subsequently converted to text, while the black text characters represent the successfully extracted information from the image. This illustrative representation underscores the script's precision in character recognition and text conversion.

Fig. 3. Localization of ROI as input to Easyocr.

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In Figure 4, the implementation of the database using the SQLite browser is evident. User records were meticulously input into the various fields, establishing a robust foundation for efficient query processing. Consequently, when a license plate match is identified, the script promptly retrieves and prints the corresponding user details, showcasing the seamless integration of the Automatic Vehicle Number Plate Recognition (AVNPR) system with the database functionality.

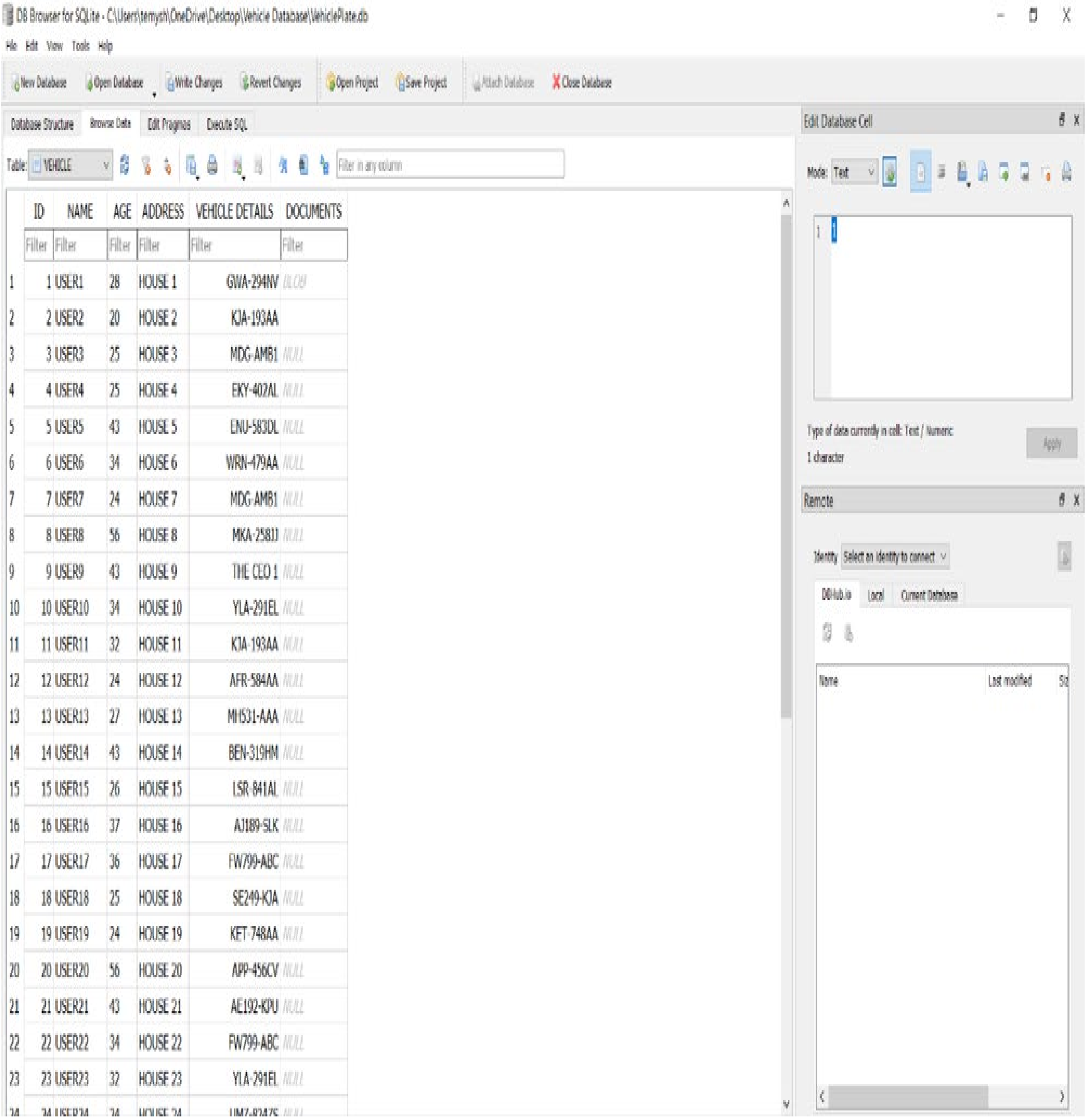

Figure 4: Picture of SQlite database

Table -1 Easyocr image to text extract from plate number

S/N	PLATE NUMBER	EASYOCR IMAGE TO TEXT CONVERSION	PERCENTAGE ACCURACY (%)
1	GWA-294NV	GHA-294NV	88.90
2	KJA-193AA	KJA-19344	77.78
3	MDG-AMB1	NDG-AHB1	77.78
4	EKY-402AL	EKY-A0ZAL	77.78
5	ENU-583DL	ENU-583DL	100.00
6	WRN-479AA	WRN-479AA	100.00
7	MDG-AMB1	HDG-AHB1	77.78
8	MKA-258JJ	HK4-258AJ	77.78
9	THE CEO 1	THE CEO 1	100.00
10	YLA-291EL	YLA-291EL	100.00
11	KJA-193AA	KJA-193AA	100.00
12	AFR-584AA	AFR-5844A	88.90
13	MH531-AAA	MH53-AAA	100.00
14	BEN-319HM	BEN-319HH	88.90
15	LSR-841AL	LSR-A41AL	88.90
16	AJ189-SLK	AJIBF-SLH	44.44
17	FW799-ABC	FW799-ABC	100.00
18	SE249-KJA	SE249-KJA	100.00
19	KET-748AA	KET-74B1	77.78
20	APP-456CV	APP-A56CV	88.90
21	AE192-KPU	AE192-KPU	100.00
22	FW799-ABC	FW799-ABC	100.00
23	YLA-291EL	YLA-Z91EL	100.00
24	UMZ-824ZS	UMZ-824ZS	100.00
25	AP214-YEN	AP214-YEN	100.00
26	TKP-973AR	TKP-973AR	100.00
27	AJ189-SLK	AJ189-SLK	100.00
28	BEN-319HM	BEN-319HM	100.00
29	KWL-406BF	HWL-406BF	88.78
30	LSD-302AM	LSD-302AM	100.00
31	FST-828GA	FST-828GA	100.00
32	KSF-362GE	KSF-362GE	100.00
33	FST-284FV	FST-284FV	100.00
34	AKD-228GV	AKD-228GV	100.00
35	KJA-682GD	KJA-682GD	100.00
36	GGE-574GR	GGE-57AGR	88.78
37	MUS-568CF	MUS-568CF	100.00
38	NDN-63PG	NDN-63PG	100.00
39	KJA-626CJ	KJA-626CJ	100.00
40	KTU-117DV	KTU-117DV	100.00
AVERAGE PERCENTAGE ACCURACY			**93.33%**

V. DISCUSSION

A comprehensive training dataset comprising 203 images with vehicle plate numbers was utilized to train the TensorFlow API model, specifically the efficientDet-lite0 architecture. Subsequently, 40 images underwent testing, encompassing both real-time captures and saved images. The outcomes from the TensorFlow object detection model were highly promising, achieving a remarkable 100% success rate for vehicle plate localization across all 40 tested images. It is noteworthy that varying confidence levels, each exceeding 83%, accompanied these successful localizations.

On the other hand, the Optical Character Recognition (OCR) library, Easyocr, played a crucial role in converting the identified plate number Regions of Interest (ROIs) into text, as detailed in Table 1. Out of the 40 plate numbers subjected to testing with the Easyocr library, 38 were accurately read. This underscores the developed system's commendable OCR accuracy, averaging at an impressive 93.33% for the 40 tested plates.

It is imperative to acknowledge that the accuracy of each OCR read is intrinsically linked to the choice of the OCR package integrated into the developed Automatic Vehicle Number Plate Recognition (AVNPR) system. Given Easyocr's general accuracy of 97%, the observed success rate, while not surpassing this benchmark, remains notably high. The extracted text, representing the plate numbers, was subsequently employed to query the SQLite database, yielding matching records corresponding to user information. This seamless integration between object detection, text conversion, and database interaction further emphasizes the robustness and efficiency of the developed AVNPR system.

VI. CONCLUSION

The devised system for vehicle plate number extraction has demonstrated remarkable effectiveness and efficiency, boasting a flawless 100% accuracy in vehicle plate number detection. Additionally, the average OCR read accuracy, as facilitated by the Easyocr library, stood at an impressive 93.33% across a comprehensive test set of 40 plates. These results remained consistent whether obtained from real-time captures or saved images on the PC. It's crucial to note that the OCR read accuracy can be influenced by varying illuminating conditions on the license plate.

While the SQLite database employed in this study served the purpose of retrieving text records effectively, it's worth highlighting that its suitability for graphical contents remains limited.

In future iterations of the Automatic Vehicle Number Plate Recognition (AVNPR) system, enhancements will be pursued to enable the use of generated plate numbers for querying cloud-based databases. Databases such as MySQL or MongoDB, offering expansive storage for driver particulars, including graphical images and vehicle data, could open avenues for web-based Internet of Things (IoT) applications. This adaptation could potentially make the system universally accessible. Additionally, the developed script holds the potential to run on a standalone microprocessor interfaced with a microcontroller, facilitating the automation of final control elements such as gates, barricades, signal lights, and more. These envisioned improvements underscore the versatility and scalability of the AVNPR system for broader applications and enhanced functionality.

VII. DATA AVAILABILITY

The data that espouse the findings in this work are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST OR COMPETING INTEREST

There is no conflict of interest or competing interest among the authors.

VIII. REFERENCE

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