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RESEARCH ARTICLE

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DESIGN OF AN AUTOMATIC LICENSE PLATE READER

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ABSTRACT

The increase in the number of vehicles and the alarming rate of theft and defaulters daily prompts the need for sophisticated matching technology to curb car theft, reduce traffic offenders, and any other anomalies/irregularities affecting vehicles' smooth operation. This study deals with the design of an automatic license plate reader which automatically captures an image of the vehicle's license plate, transforms that image into alphanumeric characters using optical character recognition or similar high-tech software, and compares the plate number acquired to one or more databases of vehicles of interest to law enforcement and other agencies against those of stolen cars or people suspected of being involved in criminal activities. The automated capture, analysis, and comparison of vehicle license plates typically occur within seconds enabling the officer in charge to take appropriate actions.



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I. INTRODUCTION

The increase in the number of vehicles daily prompts the need for matching technology to curb car theft, reduce traffic offenders, and any other anomalies/irregularities affecting vehicles' smooth operation. However, identifying a vehicle by its license plate (LP) is an imperative task that can be hindered by factors such as uneven lighting conditions, distortions of the license plate, varying sizes of the license plate, multi-plate detection, etc. in a varying environment when a proper detection technique is not put in place [1-2].

Consequently, license plate recognition is a form of automatic vehicle identification system with image processing technology used to identify vehicles by their number plates. However, government personnel mandate most vehicle owners to attach registration plates at the front and rear of a vehicle, while vehicles such as motorboats require only a single plate attached to the rear of the vehicle. They can use existing cameras, or ones specifically designed for the task. They are used by various

security personnel as a means of automating toll collection, monitoring of traffic, and detection of vehicles crossing the speed, it is also useful for the identification of black-listed cars for speedy interception [3].

Due to the high crime rate in the nation most especially kidnapping, car theft, and also to reduce the number of citizens breaking traffic rules. Law enforcement agencies are increasingly adopting automatic license plate recognition/reader (ALPR). The two major types of Automatic License Plate Reader (ALPR) are: Stationary and mobile [4], the Stationary method has infrared (IR) cameras that are used at high fixed positions, while the Mobile uses vehicle-mounted IR cameras. Problems with the ALPR can be from Character Recognition (CR), Vehicle Capture Image (CI), License Plate Detection (LPD), and License Plate Segmentation [5-7]. An automated license plate readers (ALPR) is a high-tech device that captures computer-readable images of license plates and compares the information with what is available in the database [8].

Automatic license plate detection (ALPD) is a technique used in extracting a vehicle's license plate (LP) area from an image

without human intervention [9]. Traditionally, automatic license plate recognition systems use machine learning techniques capable of capturing certain morphological attributes such as color, text, etc. and they are keen to complex background and image noise [10]. An Automatic Number Plate Recognition (ANPR) is an image processing innovation that adopts the use of optical character recognition on images to capture vehicle registration plates and translate them into machine-readable formats, which can then be processed and indexed into appropriate database [11–13], and it has three major sections: vehicle number plate extraction, character segmentation and Optical Character Recognition (OCR). License plate extraction is the stage where a vehicle license plate is detected.

Many advancements in Digital Image Processing have been used in a variety of sectors, as have advances in Optical Character Recognition Technology. In recent years, various ways of utilizing digital image processing have been created. OCR was made available as a service online in the 2000s (WebOCR) [14]. Early LPR systems had a poor recognition rate, which was lower than what actual systems required. External factors (sun and headlights, poor plates, a large number of plate kinds) combined with the low level of recognition software and vision hardware resulted in low-quality systems. Image enhancement is a critical approach that relies on filters to reduce noise and undesired light effects to obtain clear and readable images.

Over the last decade, many efforts have been made to solve the problem of detecting potential LP areas from an image or a video. Consequently, [15] proposed the installation of HD video cameras at an intersection to detect and capture vehicle images at every point in time. Hence, digital video recorders (DVR) are now integrated with Closed Circuit Television (CCTV) systems to store a large amount of data [16]. Sensors and other hardware peripherals are utilized to increase image acquisition and remove extraneous features, and for surveillance and forensic purposes, Manufacturing has improved the accuracy of LPR systems.

Sasi et. al proposed the usage of plate localization for edge detection in the study titled Automatic Car Number Plate Recognition which uses the Modified Ant Colony Optimization Algorithm. The Kohonen neural network is used to classify the location and dimensions of each character [3].

Similarly, [6] worked on Image Extraction from Number Plates that is based on an area extraction technique combined with morphological image processing using deep learning where a pre-trained Convolution Neural Network is used as a feature extractor (CNN) The "Alex-Net" algorithm is employed, and SVM is used as a classifier. The algorithm is implemented in the C++ computer language for morphological image processing.

Jamtsho et. al opined on the need for the safety of the motorcyclists at all times using a single convolutional neural network deployed to automatically detect the License Plate (LP) of a non-helmeted motorcyclist from the usage of a video stream [17].

Satsangi et. al proposed "License Plate Recognition: A Comparative Study on Thresholding, OCR, and Machine Learning Approaches", which examined license plate recognition using the Viola Jones algorithm. The primary focus of the study was on the classification and recognition of characters on license plates [18]. The photos were obtained with the help of a magnetic loop detector sensor. The identification of the license plate is accomplished in three steps: picture detection, number plate extraction, and image segmentation, the proposed algorithm's output is compared to the output of threshold and OCR technologies. The accuracy of all

three implementations shows that the viola jones provides the best performance of 80 percent [18].

Omar et. al analysed several image process techniques using a cascaded deep learning approach and the results showed that the Automatic License Plate employs several preprocessing techniques with filtering and contrast enhancement capabilities suited for image processing [19].

Gao et. al use a quantitative approach to determine the privacy disclosure risk in an LPR data set based on the concept of k-anonymity, the study shows that there is a high possibility of anonymous individuals being re-identified, and the study concluded that five spatiotemporal records are enough to uniquely identify about 90% of individuals even the temporal granularity is set to be half of one day [20].

Selmi et. al proposed a Deep Learning System for Automatic License Plate Detection and Recognition. The author uses the pre-processing procedures to identify license plates and non-license plates in the work, which employs the first CNN model for LP detection, and the second CNN model is used for classification and recognition. The canny edge detection approach is used for character segmentation. Further character recognition is built on a tensor flow framework that employs a second CNN model with 37 classes. The datasets used in this study were obtained from the Caltech dataset and the AOLP dataset [21].

Shivakumara et. al proposed keyword spotting in the video, natural scene, and license plate images, which helps us to retrieve accurate and efficient information from large and diversified databases [22].

Wang et. al worked on a detection and tracking strategy for license plate detection in video, the study integrates the cascade detectors and TLD algorithm for detecting license plates in video sequences. The cascade detectors are applied to detect newly appearing license plates from the video sequences for TLD's tracking and to detect the license plates with a higher degree of confidence for improving the shortcoming of an existing draft in TLD's long-term tracking [23].

II. MATERIALS AND METHODS

In this study, our focus is on reducing the crime rate and increasing adherence to traffic regulations, this prompted the need for the development of an application that will provide access control through automated car plate recognition with the following objectives:

- Obtaining Nigerian plate number images through a solar camera
- Segmentation of plate numbers to extract the text on the number plate
- Build a database that will serve as a repository for car plate numbers already registered.

Automated License Plate Recognition (ALPR) can assist security personnel to identify a vehicle of interest associated with criminal activity, with the ability to read up to 1,000 plates an hour, this technology can improve results. Not only does the system read plates fast, but data are accepted only on vehicles displaying license plates that match the desired criteria and appear in the database. The ALPR detects crimes committed along the traffic highway and with an embedded system of data on a website. The offender can be sent a text message automatically by the officer in charge and be charged for particular misconduct.

This section shows an overview of how the system works and how the algorithms are created. The mathematical foundations as well as particular issues are discussed.

The application is intended to recognize number plates automatically based on the following characteristics:

- Nigerian Plate numbers
- Rectangle plates
- Single plate (One line of characters)
- Arrangement of letters and numbers

The resolution of a photograph entered into the software varies depending on the hardware. The size of the image is reduced to lower the required computational time. The lessened image is used in the processing until a certain ROI (Region of Interest) is established.

The initial processing step sequence is designed to locate and chop off a Region of Interest, which is thought to include the license plate. In this step, intensity detection will be used to obtain feature data from the image so that it can be modified.

II.1 ANPR

This is the main function where the output is a list that contains all numbers plate recognised by a set of previous functions. In this paper, the directory name 'image', contains a total of 50 pictures for the execution. All of them are realized within the community in Ogun State.

II.2 WEBSITE

A website that acts as the database for the registered license plate is built to assist traffic wardens in the tracking of vehicles via their plate numbers.

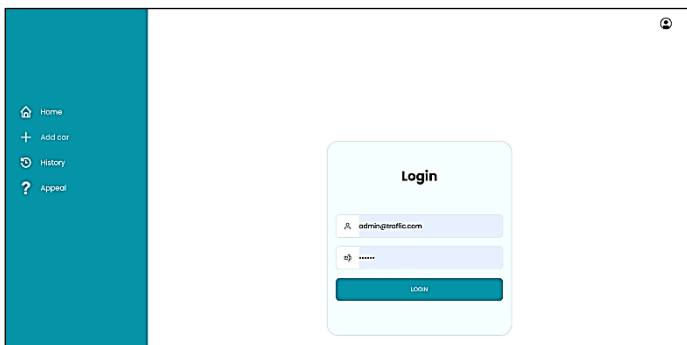


Figure 1: Login Page for Traffic Warden.

Source: Authors, (2022).

Figure 1 above shows a pictorial representation of the login page for different traffic wardens' details and locations each connected to different automatic license plate devices.

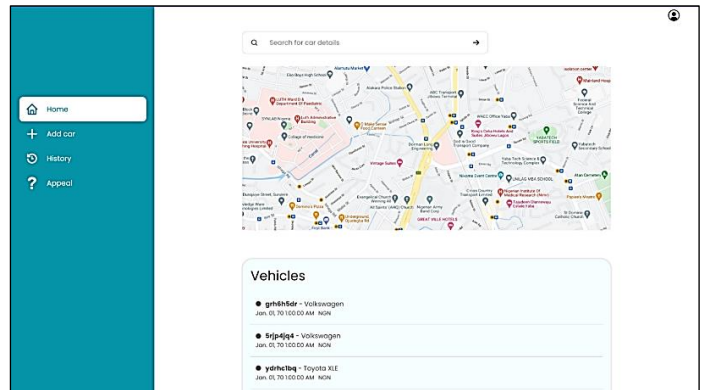


Figure 2: Home Page.

Source: Authors, (2022).

Figure 2 shows a pictorial representation of the homepage which contain different car details and location in different regions

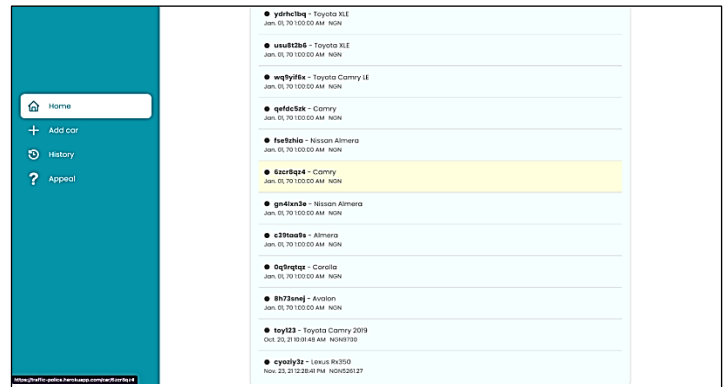


Figure 3: List of Registered Cars.

Source: Authors, (2022).

Figure 3 shows a pictorial representation of the list of registered cars on the website.

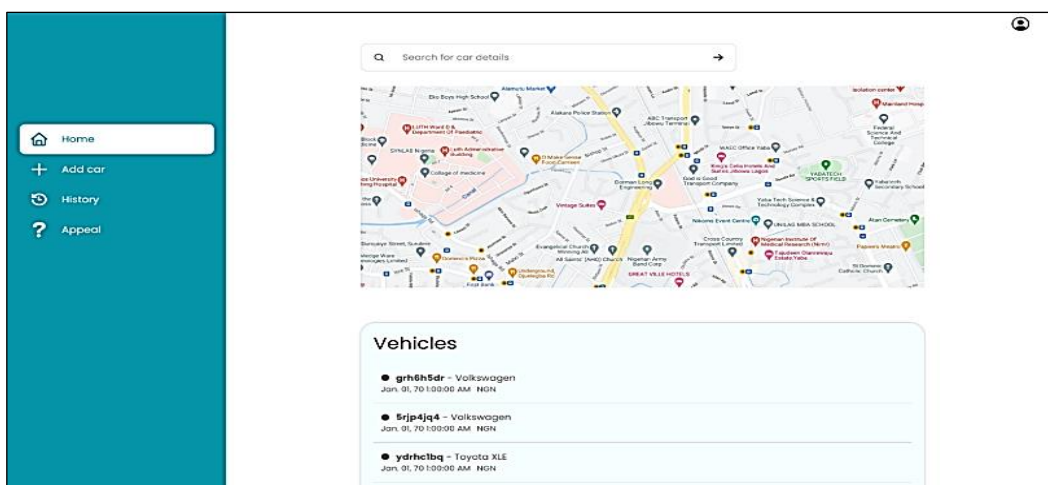


Figure 4: Details of Registered Cars.

Source: Authors, (2022).

Figure 4 contains the name, plate number, and model of the registered cars.

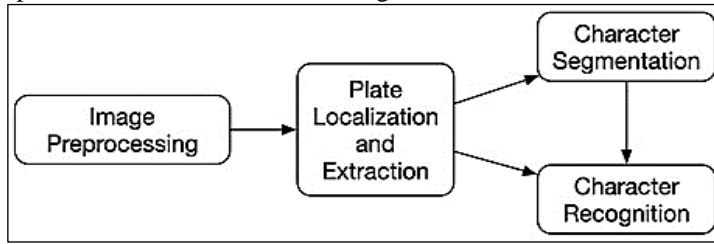


Figure 5: Flowchart for successful execution.

Source: Authors, (2022).

III. RESULTS AND DISCUSSION

This section shows the results of the study with the interpretation of the data obtained.

Table 1: Displaying Results of Success and Failures of our algorithm.

Plate number	Discovered	Authenticity	Plate Number	Discovered	Authenticity
ISDYE	ISD1E	FALSE	06H-100G	06H-100G	TRUE
REP324FL	REP324FL	TRUE	AGE323674	AGE 323674	TRUE
FKJ259FC	FKJ259FC	TRUE	KSF-716HD	KSF-716HD	TRUE
ADK997JB	ADK997JB	TRUE	06H-100G	06H-100G	TRUE
SHM394AA	SHM394AA	TRUE	IJB-566FV	Nil	FALSE
APP456CV	APP456CV	TRUE	IKJ-234GA	32B-234GA	TRUE
THE CEO 1	THE CEO 1	TRUE	IKD-859MN	45G-859MN	TRUE
FKJ-160GP	FKJ-160GP	TRUE	ADK-543GH	ADK-543GH	TRUE
JJJ-267GV	JJJ-267GV	TRUE	BOSS 1Q	Nil	FALSE
LND-129EA	LND-129EA	TRUE	LND-345 BF	Nil	FALSE

Source: Authors, (2022).



Figure 6: Edge Detection.

Source: Authors, (2022).

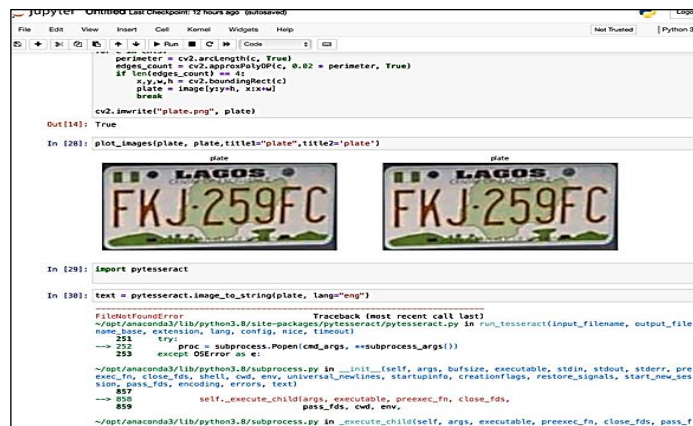


Figure 7: License Plate detected.

Source: Authors, (2022).

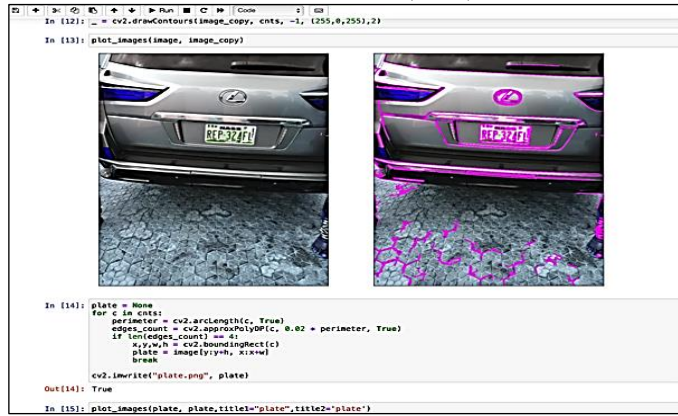


Figure 8: Car detection.
Source: Authors, (2022).



Figure 9: Image of a vehicle not successfully detected.
Source: Authors, (2022).

Table 2: Table of Results.

Total Images	Error	% Error	% Success
20	4	20	80

Source: Authors, (2022).

Location Plate mistakes

1. Locates the grids of the bonnet and not the plate of a similarity of shape, intensity, and color (two image failures).
2. Locates headlights of the car (one image failure).
3. Character attached to an impurity; the division does not remove invalid objects (one image failure).



Figure 10: Image of Vehicle.

Source: Authors, (2022).

```

edges_count = cv2.approxPolyDP(c, 0.02 * perimeter, True)
if len(edges_count) == 4:
    x,y,w,h = cv2.boundingRect(c)
    plate = img[y:y+h, x:x+w]
    break
cv2.imwrite("plate.png", plate)

Out[14]: True

In [15]: plot_images(plate, plate,title1="plate",title2="plate")

In [16]: import pytesseract

In [17]: text = pytesseract.image_to_string(plate, lang="eng")

TesseractError                                Traceback (most recent call last)
<ipython-input-17-3e1db69bb647> in <module>
----> 1 text = pytesseract.image_to_string(plate, lang="eng")

~/opt/anaconda3/lib/python3.8/site-packages/pytesseract/pytesseract.py in image_to_string(image, lang, config, nice,
, output_type, timeout)
    411     args = image, 'text', lang, config, nice, timeout!
    412
--> 413     return {
    414         Output.BYTES: lambda: run_and_get_output(*args + [True]),
    415         Output.DICT: lambda: {'text': run_and_get_output(*args)},
    416     }
~/opt/anaconda3/lib/python3.8/site-packages/pytesseract/pytesseract.py in <lambda>()
    414     Output.BYTES: lambda: run_and_get_output(*args + [True]),
    415     Output.DICT: lambda: {'text': run_and_get_output(*args)},
--> 416     Output.STRING: lambda: run_and_get_output(*args),
    417 }[output_type]()
    418

```

Figure 11: Poor detection.
Source: Authors, (2022).

IV. CONCLUSIONS

In this paper, a system that can obtain Nigerian plate number images through a solar camera was developed with the capability of extracting the text on the number plate, then send to a website (the database) to check for details of registered vehicles. The result from the data obtained shows that each 16 out of the 20 data were read correctly, this amount to an 80% success rate and 20% failure rate. The total elapsed time of recognition is 1561.36 seconds. The average time of recognition of each image is 5.80 seconds. The plate status, environmental conditions and the hardware used to capture the pictures are deterministic important factors for the proper functioning program. Good image preprocessing almost guarantees successful recognition. It is recommended that a proper adaptive mask of the picture should be employed to improve the choice of level to the threshold and not lose information about the shape of the characters found.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Matthew B. Olajide, Najeem O. Adalokun, David S. Kuponiyi, Zaid O. Jagun and Charity S. Odeyemi.

Methodology: Zaid O. Jagun and Charity S. Odeyemi.

Investigation: Matthew B. Olajide and Najeem O. Adalokun.

Discussion of results: David S. Kuponiyi, Zaid O. Jagun and Charity S. Odeyemi.

Writing – Original Draft: Matthew B. Olajide and Najeem O. Adalokun.

Writing – Review and Editing: Matthew B. Olajide and Najeem O. Adalokun.

Resources: Matthew B. Olajide and Najeem O. Adalokun.

Supervision: Matthew B. Olajide and David S. Kuponiyi.

Approval of the final text: Matthew B. Olajide, Najeem O. Adalokun, David S. Kuponiyi, Zaid O. Jagun and Charity S. Odeyemi

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