University of Ibadan
Journal of Science and Logics in ICT Research

A Statistical Learning Model for Number Plate Recognition for Vehicular Security

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Abstract
Conventional security protocols at organizational gates that depend on human monitoring of vehicle traffic frequently fall short because of data inconsistencies and errors. This research makes use of computer vision techniques to suggest a statistical image processing system for tracking vehicle movements within businesses. It focuses specifically on the University of Ibadan in Nigeria's innovative Vehicle License Plate Recognition (VLPR) system for tracking automobiles. The Tesseract OCR engine and YOLOv5 were utilized by the system to attain 89% detection accuracy and 93% recognition accuracy. This resulted in a reliable solution that can improve security, traffic monitoring, and decision-making. The present study addresses a significant void in the Nigerian setting by providing a beneficial framework for the effective surveillance and management of vehicles.

Keywords: *Computer Vision, Statistical image, License Plate Recognition, YOLOv5, Tesseract OCR Engine*

1. Introduction

In the past, vehicular movements in most organizations have been within the jurisdiction of security officials stationed at the gates to handle [3]. This mode of operation has been largely inadequate due to the manual method involved. Thus, it has been flawed due to data that is mismanaged, inaccurate, and in some cases, not in existence.

A specific shortcoming of the current operation includes non-registration of vehicles entering and exiting the facility, which constitutes serious security challenges. This is because the organization may not be able to obtain necessary information about such vehicles that comes in and out of the facility at any given time. Also, there is no provision for database in the system regarding vehicles entering and exiting the organization for strictly record and security purposes. It, therefore, becomes imperative to develop a statistical image processing system that monitor vehicular movements in and out of organizations [3]. This can help in dealing with situations that have to do with theft, inventory control, adequate monitoring of people and vehicles, as well as providing information that are reliable for making proper decision.

Currently, computer vision application has paved way for automatic vehicle identification at traffic scenes. This is possible because it makes allowance for individual vehicle identification, as well as parameter extraction relating to specific vehicle, like location, registration number, color, type, and so on [77]. Other parameters capable of being extracted from the monitoring system include rate of traffic flow, length of queue, count of vehicle and vehicular speed, all useful in traffic control systems. By and large, extracted information from the system could effectively be employed in traffic control, including security.

Udomboso C. G., Irmiya E. S., Akinyemi J. D., LADOJA K. T., Akinseye I. E. and Omoyajowo A. C. (2024). A Statistical Learning Model for Number Plate Recognition for Vehicular Security. *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 12 No. 1, pp. 74 - 88

A significant video-based monitoring systems applications is traffic surveillance [20]. For quite a while now, researches, with applications, have been focused on vision-based Intelligent Transportation System (ITS), traffic engineering and transportation planning. These had been used for extracting precise and useful traffic information for flow control and image analysis. Examples of these are not limited to vehicle tracking, flow count, trajectory, velocity, classification, as well as traffic density, lane changes, and license plate recognition [11, 75, 32 and 31]

Before now in the automation levy system, detection, segmentation and tracking systems have been employed in determining toll charges for vehicles [37]. Overtime, vehicle recognition system has been employed in vehicle detection including traffic lanes [80, 76, 56, 26, 40], or classify classes of vehicles like cars, buses, vans, motorbikes, heavy goods vehicles, and so on [37, 76, 14, 29, 44, 33, 34]. The traditional vehicle systems have been found inadequate in recognizing well due to occlusions or obstacles by vehicles or background like road signals, trees, conditions of weather, and so on.

An Interesting field of computer vision is detecting the change region of objects on motion within the same image sequence at various intervals. Diverse disciplines has employed various large applications for change detections. Some of these applications involve video surveillance, underwater sensing, remote sensing as well as medical diagnosis and treatment [21]. In the case of video surveillance, one of the areas it is applied is in the analysis of traffic image, such as motion vehicle detection and segmentation. Three methods have been used in detecting and segmenting vehicles. These are the background subtraction, frame differencing, as well as feature and motion based methods. Despite that studies have extensively been done for background subtraction and frame differencing [19, 48, 49, 65, 73, 30], there remains the task of detecting and segmenting vehicles in dynamic scenes.

The method of background subtraction involves the extracting from stored background image or static image, motion foreground objects or input image. This is a popular approach in detecting vehicle regions. The major disadvantage of this method is the inability to adapt to change in lighting and weather conditions [72]. To reduce the limitations imposed by some of these drawbacks, statistical and parametric techniques have been introduced for background subtraction, through the application of the normal probability distribution on each image pixel [78, 10, 15, 22, 68]. The updating by the normal distribution results into the new image series. Each image pixel (x, y) is categorized into the foreground or background, as the case may be, and is represented by the following equation

$$I(x,y) - mean(x,y) < [C.std(x,y)] \quad (1)$$

where $I(x,y) =$ intensity of pixel, $mean(x,y) =$ mean of pixel, $std(x,y) =$ standard deviation of pixel, and $C =$ constant
The background subtraction algorithm performs under various conditions that includes view-angles, illumination and overcrowding [42].

The feature based method is motivated on the premise of sub-features such as vehicle edges and corners. The motion objects are segmented from the image background through feature collection and analyses of movements between subsequent frames. More so, this method could handle the occlusions occurring between overlapping vehicles. The computational difficulty is better in comparison with the background subtraction method [12]. [52] suggested an approach that discriminates objects from background through the use of its features, based on learning that uses a training data set for extraction. The feature extraction algorithm used is the Haar wavelets, while the classification process is with the use of the SVM.

Frame differencing method subtracts two frames that are subsequent in an image series, and segments the object at the foreground from that of the background. This is achieved through isolating objects in motion by analyzing and assigning sets of pixels into various object classes, based on their orientation and speed of their motion from the background [21, 72, 36, 79].

1.1 License Plate Recognition

Literature has shown that the principal vehicle identifier is the License Plate Recognition (LPR). The LPR detects and segments the characters of vehicle license plate, and process the recognition of its characters. Despite that license plates can be altered easily through fraud, light deflection and counterfeiting, this system of vehicle recognition is widely used.

LPR is a technology based on computer vision, which connects vehicles using their licensed number plates, and is devoid of human involvement [60, 16, 2]. The roads continue to see vehicle intensity on a daily basis, and stories abound of theft from parking lots, or use of vehicle for criminal purposes. It therefore becomes important to install license plate detection and recognition systems on CCTVs at strategic places [63, 47]. With this, it would be easy to track such vehicles by the law enforcement agencies, especially in charge of traffic offences [5, 61].

License plates vary with countries. However, certain rules and regulations govern vehicle license plates. Specifically, license plates follow the pattern below in most countries:

1. The 2 letters, either before or at the end, referring to the county, region, state or province where registration was done for the vehicle.
2. The 2 to 4 digits at the centre or the end, refer to when the license plate was issued, or the count of the vehicle.
3. The 3 letters chosen at random, or depicting the local government where the registration was issued.

The general concept of the characters, dimensions and styles of license plates are presented in the following example from the United Kingdom as at 01 September 2001 (see Figure 1). Variations exist on license plates across countries. For instance, the American license plates differ from their European counterparts; they have more features such as name of state, text colour, and pictures, whereas that of Europe is mainly for identification. The Nigerian license plate is similar to that of the American.

Automatic vehicle identification researches have been done in most advanced countries, and countries nowadays are spending huge economy on traffic automation and vehicle theft controlling [38], due to enormous increase in the vehicles on roads. However, studies of this nature are limited in Nigeria, except for a few [39, 4, 51, 50]. More importantly, there are no such studies ever conducted in any university in Nigeria, especially the premier institution, the University of Ibadan. The study is especially important for the premier university due to dramatic increase vehicular movements in recent years. This has brought about serious traffic congestion within and outside the immediate university environment, and further compounded security issues in the university. The objective of this study focusses on building a statistical NPR for detecting and tracking vehicles entering and exiting the University of Ibadan, Nigeria, to be used in place of the manual security method.

Recent works showed [66] developing a high-accuracy License Plate Recognition (LPR) system with practical applications in traffic management. An ANPR system using CNN and OCR Tesseract for diverse conditions was created by Khan *et. al.* [35]. While Pujar and Kulkarni [55] introduced a vehicle recognition system combining IR sensors, R-CNN, and OCR for secure gate access. On the other hand, Soni *et. al* [64] designed a security system with vehicle detection and database matching, and Ahire *et. al.* [1] improved identification using the Grab Cut algorithm and noise reduction filters. An enhanced recognition with data augmentation and transfer learning was studied by Mhatre *et. al.* [46], with Rao *et. al* [57] developing a real-time Python-based system, and Boby and Brown [7] utilized YOLO and GANs for clarity. In another scenario, Jain *et. al.* [28] employed YOLOv5 for accurate plate detection in intelligent transportation systems.

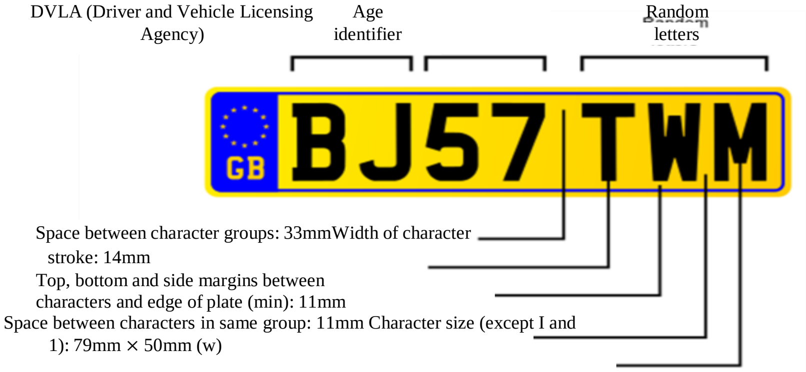


Figure 1: Typical fonts and spacing style for NP [Regtransfers.co.uk] (Adapted from Parvin *et. al.* [53])

1.2 Nigerian Vehicle License Plate System [23]

In 1992, the current vehicle registration plates used in Nigeria was introduced, with a revision mode in 2011. In Africa, it is only Nigeria and Liberia that use the standard size of the number plate similar to the North American system: 6 x 12 inches (152 x 300 mm). Egyptian number plate closes in size at 170 x 350 mm. Figure 2 are samples of vehicle plate numbers used in Nigeria. Generally, the number plates are white background with blue imprint, for private vehicle owners. The number plates for commercial vehicles and school buses has red imprint, and that of government and government institutions have green imprint.

Diplomatic vehicles, on their part have either purple, blue or red backgrounds with white imprints. The country of the vehicle owner is represented by the first two or three digits, which is followed by two letters and numbers, respectively. For security organs, such as Nigerian Armed Forces, Police Force, Custom and Immigration Service, Federal Road Safety Corps, Corps of Nigerian Commissionaire (Nigerian Legion), and the Nigerian Security & Civil Defence Corps (NSCDC), their number plate system is white background with black imprint.
The national flag or coat of arms is at the upper left corner of the number plate, while the "Federal Republic of Nigeria is indicated at the bottom centre, and the name and slogan of the state is located at the top centre. The map of the country is at the centre-background, while the green vegetation is drawn at the base of the number plate, both as watermarks. Especially for government, government institutions and diplomatic vehicles, the top centre indicates the name of the government ministry or parastatals, or the name of the diplomatic corp.

In the case of private and commercial vehicles, the number plate has a unique ABC-123DE format. The ABC indicates the local government area of registration. The three digits and last two letters are simply for listing. This means, two typical vehicles might have the formats AAA-111AA and AAA112AA, or AAA-999AA and AAA-111AB, respectively. When the plate number system was first introduced in 1992, the representation as it is now was in the reverse order. That is, the three letters representing the local government is at the end. Each category of plate numbers described earlier has their unique representations.

The LPR technique has triggered other challenges ranging from number plate shape, colour, consistency, as well as vehicle type, with major problem focusing on divers features categories, relating to the level of illumination, visualization geometry, as well as the background [6, 18]. The procedure for LPR is in three parts, which includes (1) area identification, (2) character segmentation, and (3) character recognition [45, 70, 9, 69, 59]. These procedures have been used in automated toll collection, automatic parking, terrorism tracking, speed control, monitoring of stolen vehicles, and management and optimization of traffic, as well as vehicle access control [5, 61, 9, 25, 17]. Table 1 identifies vehicle number plate recognition inhibitors, including various plate and environmental variants.

In Number Plate Detection (NPD), certain features of the image are used to understand number plates in order to assess location data [9, 27]. A region in the NP having similar structures is identified by NPD in order to determine the location frames [62]. In identifying vehicle plate number registration, a number of factors are considered.

Figure 2: Sample of Nigerian Vehicle Plate Numbers

Table 1: Certain Inhibitors of Vehicle Number Plate Recognition

NP Variants	Environmental Variants
Size of plate	Brightness
Background of plate	Background similarity
Location of plate	
Quantity	
Font	
Angle	
Screw	

Adapted from Boliwala and Pawar [9] & Pujar, A. M., and Kulkarni [54].

Various researches have proposed methods for the identification of LPR such as edge detection, segmentation, feature-based and colour code-based techniques, as well as machine learning techniques.

This study is motivated by the need to tackle vehicular security challenges and enhance automatic vehicle identification, which is essential for effective law enforcement and traffic management at the University of Ibadan, Nigeria. Furthermore, it aims to boost operational efficiency, minimize the reliance on manual checks, and drive innovation. This approach not only addresses current security issues but also positions the university at the forefront of advanced security solutions.
Hence, the focus of this research is on developing a statistical learning model to enhance number plate recognition accuracy and reliability for improved vehicular security.

2. Methodology

Images are random due to the fact that, sometimes the colours of a particular objects may not be homogeneous. Hence, statistical approach to image analysis cannot be ruled out. In mathematical term, a digital image is represented with a matrix. Images are of two kinds, which are grayscale (monochrome) and colour. In a grayscale image, the matrix whose intensity is represented as integer values, it ranges from 0 to 255 and constitute 256 levels (0 represents black, while 1 represent white). This is due to the fact that 256 is conveniently equal to a byte. There are 8 bits in 1 byte, so that 2^8 = 256. Hence, the single binary image is a special case of the grayscale image, having intensity values of 0 and 255, which is simply pure black and white. Each elements of the matrix, $M(PxQ)$, represents an image pixel, whose value is rescaled into $\frac{255(M-M_{min})}{(M_{max}-M_{min})}$, and rounded. In an image, P and Q may be running into hundreds or thousands. This tends to make the digital image large.

Figure 3 displays the study's architecture, starting with data acquisition (see Figure 4; cross-section of the sample datasets collected), where an 8-megapixel digital camera and a 13-megapixel mobile phone camera are used to capture the front and rear view of the vehicle, including the license plates. 2500 images were collected and annotated for training the detection model and Optical character recognition.

2.1 The YOLOv5 Algorithm

The architecture on which the YOLOv5 algorithm is based include the backbone[(a)] as well as the neck and head[(b)] architectures. The former is based on the Cross Stage Partial Network (CSPNet), which enhances computational efficiency and feature learning by partitioning feature maps into two parts and then merging them through a cross-stage hierarchy [74]. On the other hand, the latter is responsible for feature pyramid generation and final predictions.

(a) Feature Map Splitting and Processing

Let X be the input feature map, which is split into two parts, x_1 and x_2, where $X = [x_1, x_2]$, and be given as

$$x_1, x_2 = split(X) \quad (2)$$

Each part is separately processed with a function f, except one, typically a series of convolutional layers. In this case, $Y_1 = f(X_1)$ is processed, while $Y_2 = X_2$ is not. Then, Y_1 is concatenated with Y_2, and further processed with a function g as

$$Y = g(concat(Y_1, Y_2)) \quad (3)$$

(b) Feature Pyramid Network (FPN)

Let F be the set of feature maps from the backbone. The FPN generates feature maps at different scales (Lin et al., 2017), and written as

$$\{P_1, P_2, P_3, P_4\} = FPN(F) \quad (4)$$

where each P_i is a feature map at a different scale, used to detect objects of various sizes. For each feature map P_i, the prediction head outputs bounding box coordinates, objectness score, and class probabilities, is given as

$$\{(b_x, b_y, b_w, b_h, confidence, P(class|object))_i\} = Head(P_i) \quad (5)$$

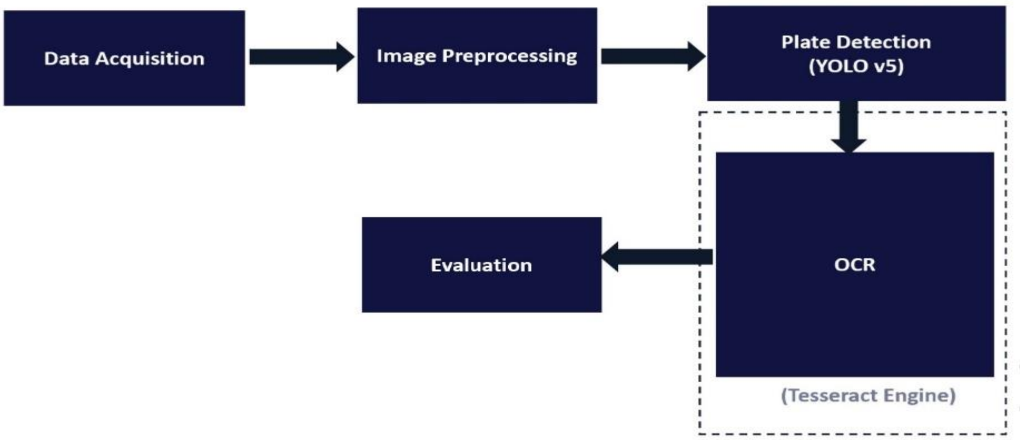


Figure 3: Generic architecture of the proposed model, showing the pipeline of the VLPR process

2.1.1 *Anchor Boxes and Bounding Box Prediction*

Definition 1: Let $\{A_i\}$ be the set of predefined anchor boxes. Each anchor box A_i has a width a_w and height a_h. For each grid cell and anchor box, the model predicts offsets to the anchor box.

Let (t_x, t_y, t_w, t_h) be the predicted offsets. The final bounding box coordinates (b_x, b_y, b_w, b_h) are computed as

$$b_x = \sigma(t_x) + c_x \quad (6a)$$

$$b_y = \sigma(t_y) + c_y \quad (6b)$$

$$b_w = a_w e^{t_w} \quad (7a)$$

$$b_h = a_h e^{t_h} \quad (7b)$$

where σ is the sigmoid function, and (c_x, c_y) is the top-left corner of the grid cells [8].

Definition 2: For a predicted probability $\hat{p}$ and true label $y \in \{0,1\}$, the loss function L, (commonly referred to as the focal loss), is defined as

$$L = -\alpha(1-\hat{p})^{\gamma} y \log(\hat{p}) - \alpha\hat{p}^{\gamma}(1-y)\log(1-\hat{p}) \quad (8)$$

where α is a balancing factor, and γ is the focusing parameter.

2.2 *Statistical Learning Paradigm of the YOLOv5 Algorithm*

In the context of YOLOv5, the hypothesis space $\mathcal{H}$ is denoted by the architecture of the neural network, including the backbone (CSPNet), the neck (FPN), and the head layers that output predictions. Each hypothesis $h \in \mathcal{H}$ corresponds to a specific set of weights and biases in the neural network.

The goal during training is to minimize the empirical risk $R_{emp}(f)$, which is the average loss over the training data $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i are the input images, and y_i are the corresponding ground truth labels (boundary boxes and class labels). Hence, the empirical risk is given as

$$R_{emp}(f) = \frac{1}{N}\sum_{i=1}^{N} L(f(x_i), y_i) \quad (9)$$

where L is the loss function combining localization loss, confidence loss, and classification loss, each measuring the errors in predicted bounding box coordinates, objectness score predictions, and class label predictions, respectively [41]. Therefore we write L as,

$$L = \sum_{i-1}^{N_{anchors}} \left(L_{loc}(b_i, \hat{b}_i) + L_{conf}(c_i, \hat{c}_i) + L_{cls}(p_i, \hat{p}_i) \right) \quad (10)$$

where b_i are the ground truth bounding box coordinates, $\hat{b}_i$ are the predicted coordinates, c_i is the ground truth objectness score, $\hat{c}_i$ is the predicted objectness score, p_i is the ground truth class probability, and $\hat{p}_i$ is the predicted class probability.

The generalization error $R(f)$, which is the expected loss over the true data distribution P, is given as the minimization of the expected loss,

$$R(f) = E_{(x,y)\sim P}[L(f(x), y)] \quad (11)$$

Using the Vapnik-Chervonenkis (VC) theorem, we define $R(f)$, bounded by the empirical risk, and a complexity term that depends on the hypothesis space $\mathcal{H}$,

$$R(f) \le R_{emp}(f) + \sqrt{\frac{h(\log(2N/h)+1) - \log(\delta/4)}{N}} \quad (12)$$

where h is the VC-dimension of $\mathcal{H}$, N is the number of training samples, and δ is the confidence level [71].

In optimizing the model in this study, the best parameter θ that minimizes the empirical risk is obtained using the Stochastic Gradient Descent (SGD) with momentum. The update rule for the SGD is given as

$$v_{t+1} = \beta_{v_t} + (1-\beta)\nabla_{\theta} R_{emp}(\theta_t) \quad (13a)$$

$$\theta_{t+1} = \theta_t - \alpha v_{t+1} \quad (13b)$$

where β is the momentum term, α is the learning rate, and $\nabla_{\theta} R_{emp}(\theta_t)$ is the gradient of the empirical risk with respect to the parameters θ.

The proposed system described above is implemented using the Python programming language on Google Colab.

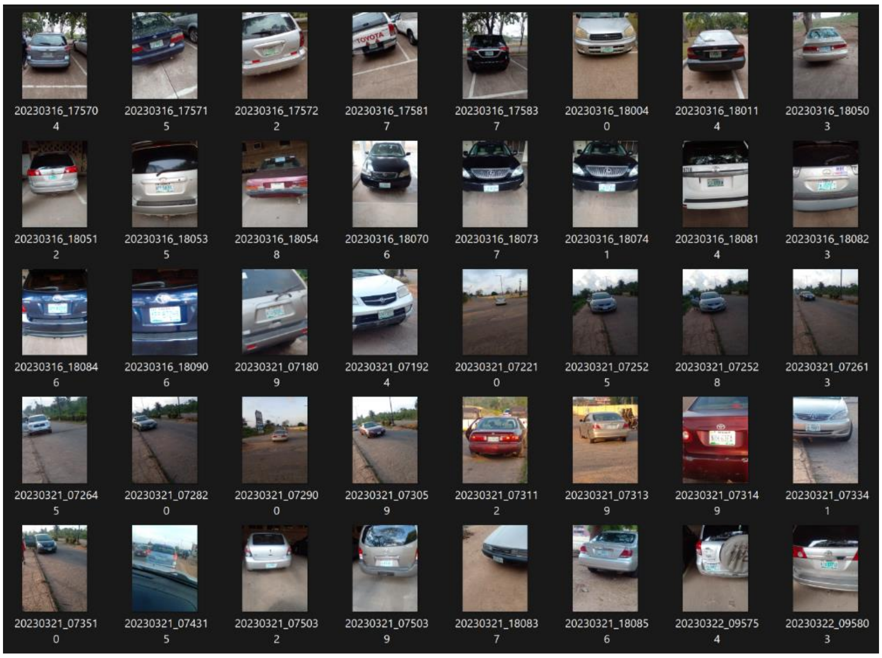


Figure 4: A cross-section of the sample datasets collected.

2.3 License Plate Detection

Plate detection is the first step in VLPR. In this phase, a 3D image is fed into the YOLOv5tiny pre-trained object detection model, which returns bounding box coordinates for license plates. The ROI is retrieved and passed to the next stage. The input images are first resized to a standard size of 800 x 1067 pixels. The accuracy of the plate detection is shown in the results and discussion section.

2.3.1 Plate Segmentation and Recognition

After the detection phase, the ROI was extracted, and adaptive thresholding was carried out to enhance recognition quality using the Tesseract engine. It recognizes and clusters neighbouring pixels to isolate characters and improve OCR accuracy.

3. Results and Discussion

The license plate detection model was trained on 2,000 images and tested on 500. The results from the model's license plate detection were quite impressive. For example, Figure 5 shows the model's performance after training.

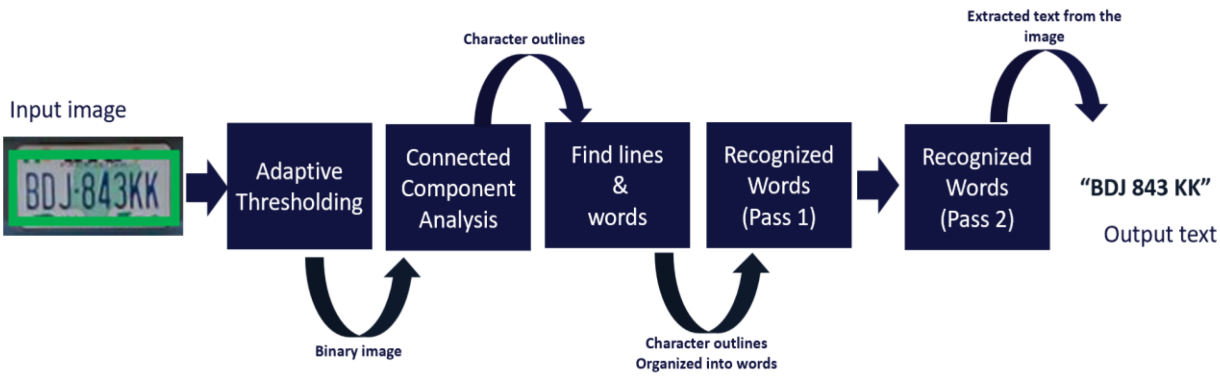


Figure 5: Model performance after training

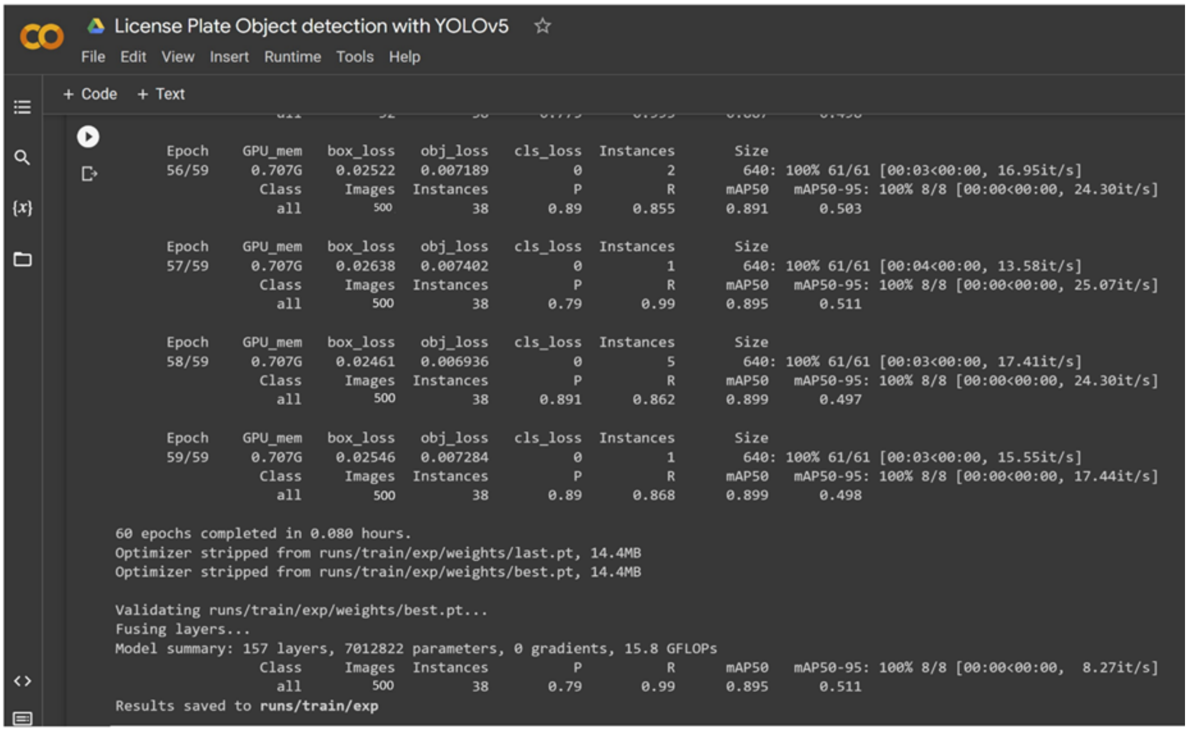


Figure 6: The performance of the model for license plate detection

In Figure 6, the pretrained YOLOv5s model achieves its best performance during training at the 60th epoch with an object loss value of 0.007824 for a batch of 32 instances. This value indicates an accuracy of 89%.

From Table 2, it was observed that model's best performance during license plate detection was at a batch size of 32 on the 60th epoch, garnering an improved accuracy of 89%.

Table 2 Detection accuracies at different batch sizes and Epochs

Batch size	*Epoch*	*Accuracy*
2	8	67%
16	50	78%
32	60	89%

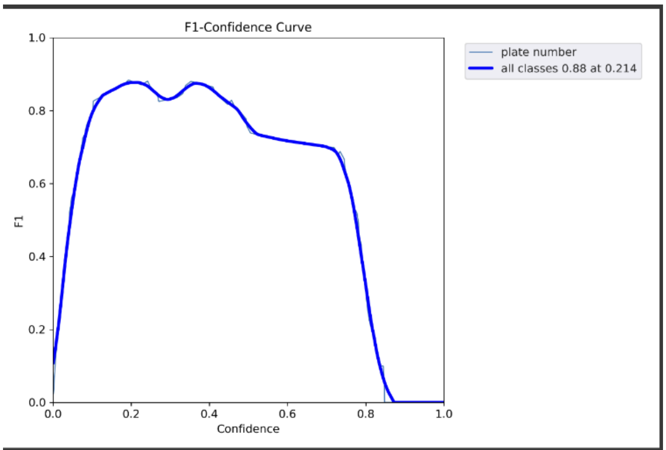


Figure 8: F1-confidence curve for detection accuracy

Figure 8 shows the F1-Confidence curve which indicates the model's performance at different confidence thresholds. The F1 score measures or combines precision and recall providing a balanced evaluation of the model's accuracy. The curve shows here that all classes (for license plate in this case) the model achieves an F1 score of 88% at 0.214 confidence threshold.

Figure 9 shows the Precision-Recall curve indicating the model's detection performance in terms of Precision/Recall trade-offs. The curve shows an average precision of 0.895 across all classes (number plates) at an intercession over union (IOU) of 0.5. The curve helps provide insights into the performance of the model.

The model's recognition performance was quite impressive as shown in Figures 10 and 11, as well as Table 3.

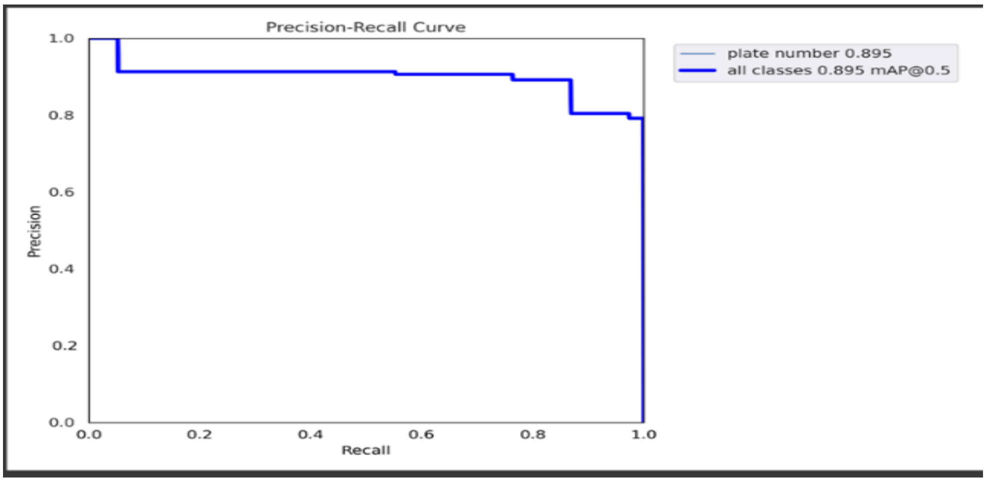
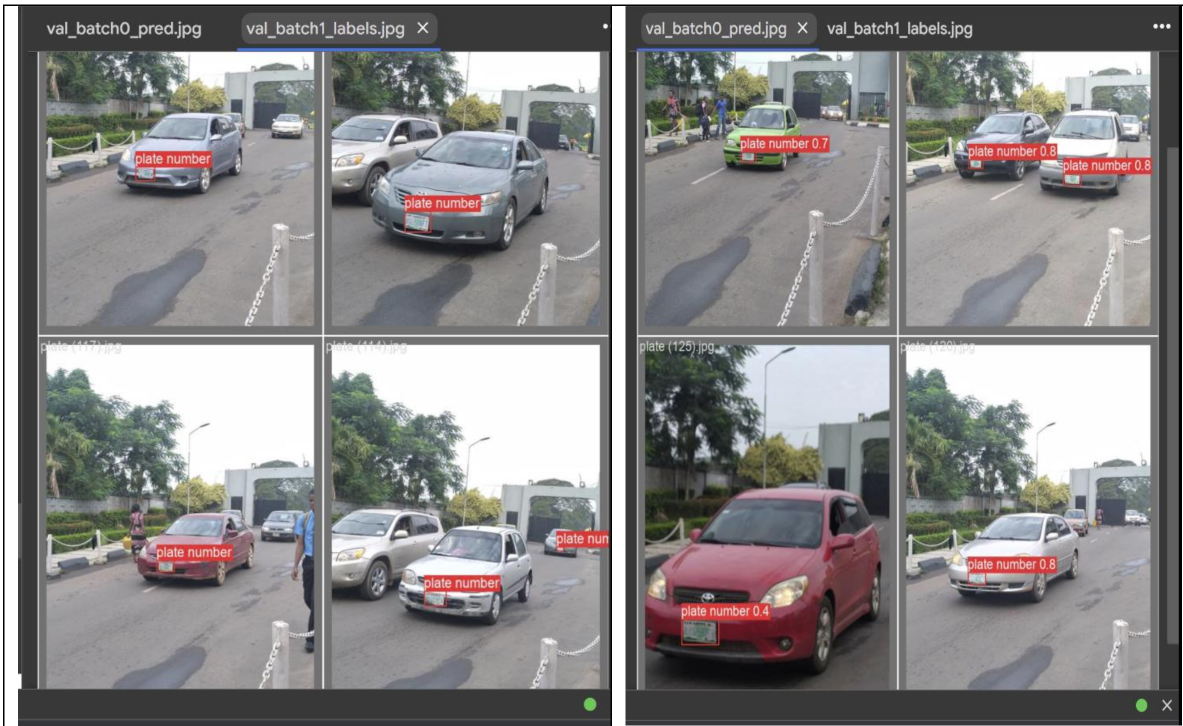


Figure 9: Precision-Recall Curve



(A) Labels (B) Predicted

Figure 10: Labelled license plates against the model's detection prediction

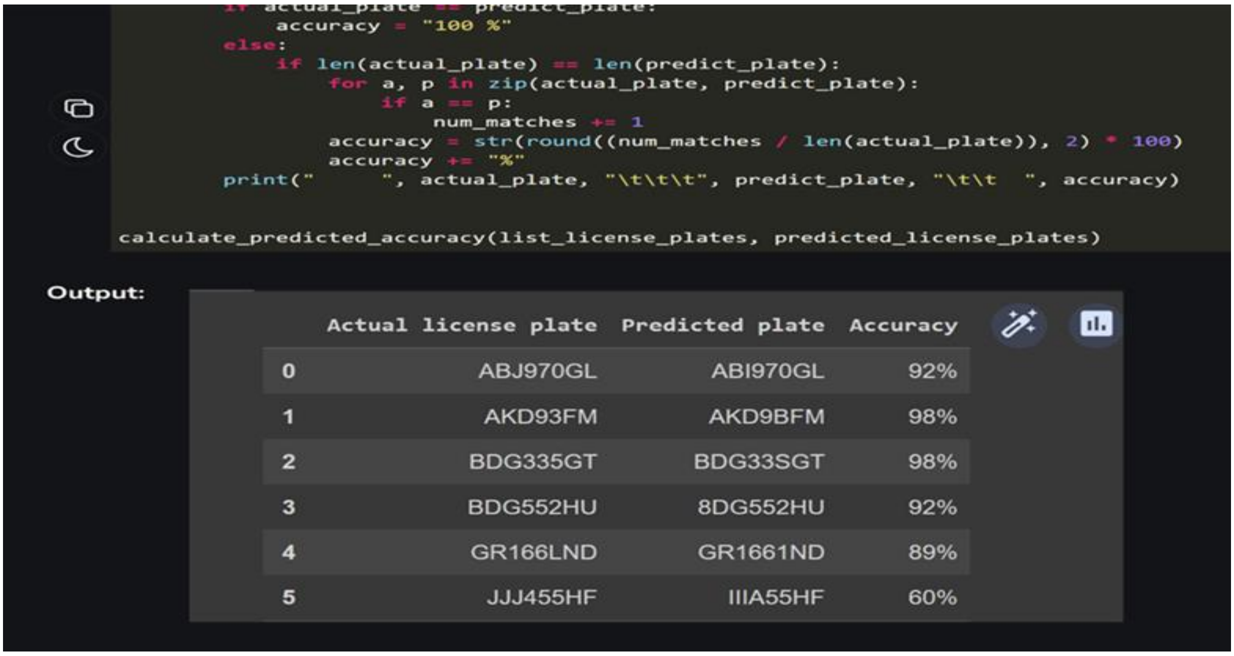
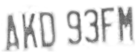
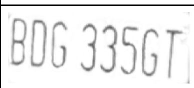
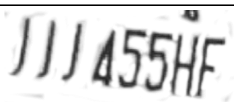


Figure 11: License Plate Prediction Accuracy

Table 3: Five distinct identified license plates and their corresponding plate segments and OCR results

S/No	Plate detected	Plate strip	Ground truth	OCR Result	Accuracy
1.			ABJ - 970GL	ABI 970GL	92%
2.			AKD 93FM	AKD9BFM	98%
3.			BDG 335GT	BDG33SGT	92%
4.			GR 166 LND	GR1661ND	89%
5.			JJJ-455HF	IIIA55HF	60%

Among the 450 plates that were precisely detected, the OCR engine successfully extracted the plate details, including the state code, with accuracy. Nonetheless, there were 22 license plates where the OCR engine mistakenly identified a single character, and in the case of 28 license plates, it inaccurately identified two or more characters.

4. Conclusion

This research proposes a potent technique for detecting and recognizing Nigerian vehicle license plates using deep learning. The method used involved YOLOv5 made up of several layers of convolutional neural networks for detecting the license plate numbers, the image was converted to grayscale and adaptive thresholding was used to convert the plate number into a binary image finally tesseract OCR engine was used for character recognition.
In developing our vehicle license plate model, a sample of 2500 datasets of Nigerian vehicle license plates were gathered from still and moving vehicles using a digital camera, and a mobile phone camera on Nigerian roads.

The dataset was split into training (2000 images) and validation (500 images) sets. The images were preprocessed and annotated in the standard

YOLO format. The techniques utilized involved grayscaling and adaptive thresholding, thereafter the tesseract OCR engine was used for character recognition.

Out of the 450 accurately detected plates, the OCR engine proficiently extracted plate information, including the state code, with precision. Nevertheless, there were instances where the OCR engine misidentified a single character in 22 license plates, and in 28 license plates, it erroneously recognized two or more characters.

In this research, detection accuracy of 89% and a recognition accuracy of 93% at an average of 600 milliseconds were obtained. This research demonstrates a promising technique for detecting and recognizing Nigerian vehicle license plates using deep learning. To enhance performance, it is recommended to expand the dataset with varied images, improve preprocessing methods, and fine-tune the Tesseract OCR engine. Additionally, implementing post-processing steps to correct OCR errors and conducting real-time testing on diverse Nigerian roads would validate the system's reliability. By addressing these recommendations, the license plate recognition system can achieve greater accuracy and robustness, making it a valuable tool for traffic monitoring and law enforcement in Nigeria.

In conclusion, this research was able to build a vehicle license plate recognition system using state-of-the art deep learning techniques. The results obtained are performed satisfactorily than some already existing models.

Acknowledgment

Authors acknowledge the following for their supports:

i) Associates Programmme, QLS Section, Abdus Salam International Centre for Theoretical Physics, Trieste, Italy.

ii) Campus Security and Transport Unit, University of Ibadan, Nigeria.

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