International Journal of Scientific Engineering and Science
Volume 8, Issue 8, pp. 52-57, 2024. ISSN (Online): 2456-7361

Development of a Nigerian Vehicle License Plate Recognition System Using Deep Learning

Okebule Toyin[1*] Adesanya Iyanuoluwapo[2], Abiodun Oguntimilehin[3], Stephen E. Obamiyi[4], Abiola O. B[6], Kindele Oluwafemi Sanya[7], Attachin James[8], Oluwatoki T.G[9]
[1, 2, 3,4,5,6,7,8,9]Department of Computer Science, Afe Babalola University, Ado-Ekiti, Nigeria.
*Email of corresponding author: okebulet@abuad.edu.ng

Abstract— *License Plate Recognition (LPR) is a technology that combines object detection and optical character recognition (OCR) to automatically identify vehicles by their license plates. This study explores the development and evaluation of an LPR system using deep learning techniques. The system was trained and tested on a dataset of 1000 car images, with annotations provided using Label Studio. Various object detection models, including InceptionResNetV2, MobileNetV2, InceptionV3, and YOLOv8, were evaluated for their accuracy and efficiency. YOLOv8 emerged as the most suitable model due to its superior performance, achieving high precision, recall, and mAP (mean Average Precision) metrics. The study also investigated the challenges of character recognition in low-resolution images and explored the integration of a Super-resolution Generative Adversarial Network (SRGAN) with Tesseract-OCR to enhance character recognition accuracy. The findings of this research contribute to the advancement of LPR technology and its potential applications in traffic management, security, and law enforcement.*

Keywords— *License Plate Recognition (LPR), Deep Learning, Object Detection, Optical Character Recognition (OCR), Convolutional Neural Networks (CNNs), Intelligent Transportation Systems (ITS).*

I. INTRODUCTION

Automatic License Plate Recognition (ALPR) systems have developed as critical instruments in modern surveillance and tracking applications, allowing for the automatic identification and monitoring of cars in both private and public sectors. With the exponential rise of global vehicle traffic, together with growing concerns about security, traffic management, and law enforcement, the demand for efficient and accurate ALPR systems has become critical (Egwuonwu *et al*, 2021). In Nigeria, where security concerns are growing, there is an urgent need for sophisticated technologies that can efficiently monitor vehicle movements (Egwuonwu *et al*, 2021). The capacity to track cars via their license plates has become critical to security and law enforcement activities (Adedayo et al, 2021). License plates are the principal identifiers for automobiles across the country, allowing authorities to monitor traffic, enforce regulations, and investigate crimes (Egwuonwu *et al,* 2021). Traditionally, vehicle identification was based mainly on manual procedures, with law enforcement officers methodically documenting license plate numbers. However, technological advances, notably those in automatic vehicle identification systems, have transformed this strategy (Chandra *et al,* 2021). Automatic License Plate Recognition (ALPR) systems use image processing techniques to detect, retrieve, and recognize license plate numbers from pictures or video streams, providing several advantages including greater productivity, accuracy, and scalability (Chandra *et al,* 2021).

The progress of deep learning and computer vision has greatly simplified the creation of ALPR systems (Voulodimos *et al,* 2018). Deep learning models such as YOLOV8, InceptionResNetV2, InceptionV2, and MobileNet have played critical roles in changing license plate recognition by allowing automatic feature learning from raw image data. These models may learn complex patterns and representations, allowing for more robust and accurate license plate identification in a variety of scenarios (Voulodimos *et al*, 2018). The incorporation of deep learning-based ALPR systems into Nigeria's security architecture has the potential to significantly improve public safety and security. By automating the vehicle identification process, authorities can speed up law enforcement operations, improve traffic management, and better respond to security concerns (Adedayo et al, 2021). Additionally, ALPR devices can help detect stolen automobiles, desired individuals, and vehicles implicated in criminal activity (Adedayo et al, 2021). Despite the benefits, the use of ALPR systems raises significant concerns about privacy, data security, and ethical ramifications (Adedayo et al, 2021). Proper precautions and restrictions must be implemented to ensure responsible and ethical use of this technology. Furthermore, ongoing research and development efforts are necessary to improve ALPR algorithms, optimize performance, and address emerging challenges. Along with developments in ALPR technology, license plate standards and regulations play an important part in vehicle identification. Every jurisdiction requires that road vehicles have registration plates, which serve as unique identifiers for the cars or their owners. In Nigeria, the unique license plate set consists of three letters indicating the local government registration area, three numbers and two letters (Chandra et al., 2021).

In Nigeria, the deployment of license plate recognition systems is hampered by difficulties that prevent their successful implementation and exploitation, limiting their potential to improve tracking and monitoring capacities (Amusan *et al,* 2015). These problems include both technical and usability factors, emphasizing the necessity for bespoke solutions to meet Nigeria's specific objectives and operating circumstances. Acquiring large-scale license plate datasets in Nigeria can be costly, especially for law enforcement agencies or municipalities with limited resources (Xu *et al,* 2018). The high cost of data collecting impedes the development and deployment of license plate recognition solutions, restricting their potential to increase vehicle tracking and monitoring across the nation. The design of user interfaces for license plate recognition systems in Nigeria must take into account the different user demographics and degrees of technology literacy. Poorly designed interfaces with complex navigation or language obstacles can impede user adoption and system usability, reducing the effectiveness of vehicle tracking and monitoring operations.

Effective use of license plate recognition systems in Nigeria necessitates extensive training and support procedures that are adapted to the local environment (Xu *et al*, 2020). Insufficient training materials and minimal support resources can make it difficult for law enforcement professionals and system operators to successfully use the technology, limiting its potential to improve tracking and monitoring capabilities.

II. Theoretical Analysis

This section reviews the literature on gesture recognition and image processing, highlighting various methods authors have used to develop related systems.

Chen *et al.* (2021) proposed the HT-SSA-CNN architecture as a multi-stage paradigm for vehicle license plate recognition (VLPR). This architecture combines pre-processing approaches, Hough Transform-based character segmentation, and a Squirrel Search Algorithm-optimized Convolutional Neural Network (CNN) for character recognition. The model showed considerable gains in accuracy, precision, recall, F1-score, and mean Average Precision (mAP) across multiple datasets, demonstrating its durability and effectiveness.

Similarly, Gnanaprakash *et al.* (2021) developed a robust automatic number plate recognition (ANPR) system using deep learning and the Image AI framework. This system excels in vehicle detection, number plate detection, and character recognition using a four-stage method that includes vehicle detection, license plate localization, character segmentation, and character identification.

(Chen *et al.* (2021) presented a new approach to VLPR issues based on deep learning and clustering techniques. They presented a three-step methodology: detection and localization using linked component analysis and an improved binary algorithm, segmentation with K-means clustering, and character recognition with CNN models. This strategy claims to be more accurate and adaptable in a variety of settings than current solutions.

Habeeb *et al,* (2021) a deep learning-based technique specifically for Iraqi and Malaysian license plates was created attaining high recognition rates of 85.56% and 88.86%, respectively. This strategy outperformed classic SVM and NN approaches, resulting in advances in license plate recognition (LPR) technology. The authors also focused on finding and recognizing license plates in non-standard circumstances using a 53-layer deep CNN based on the YOLOv3 algorithm. When tested on a dataset of license plates from eight distinct Pakistani provinces, the approach achieved a high plate detection accuracy of 97.82% and a character identification accuracy of 96%, demonstrating its usefulness in difficult real-world scenarios.

Alghyaline *et al.* (2022) presented a real-time Jordanian license plate identification system based on deep learning algorithms. On the JALPR dataset, their system achieved a recognition accuracy of 87%, demonstrating its potential for real-time applications.

Marzuki *et al.* (2019) optimized a CNN architecture for license plate recognition. Their research obtained 74.7% accuracy in the pre-processing stage and an amazing 94.6% accuracy in the CNN recognition step, demonstrating CNNs' potential for accurate license plate recognition.

III. Materials And Methods/Methodology/Experimental Procedure

The proposed methodology for the Automatic License Plate Recognition (ALPR) system, as illustrated in Figure 3.3, leverages deep learning techniques and image processing to accurately detect and recognize license plates in real-time. The system architecture comprises several key components, each playing a crucial role in the overall functionality.

A. Data Preparation and Gathering

The initial step involves collecting a diverse dataset of license plate images. These images can be obtained through various methods, such as web scraping, utilizing publicly available datasets, or manual capture using cameras. In this project, images were manually captured and annotated using Label Studio, a versatile annotation tool as it shown in Figure 1 as a sample of car dataset.

Figure 1. Car Dataset.

B. Labelling the Data

Labeling involves manually drawing bounding boxes around the license plates in the images. Label Studio, an open-source tool, was employed for this task due to its support for various data types, customization options, and export capabilities in multiple formats. Figure 2 is an illustration of car with labelled studio.

C. Splitting Data

The labeled dataset is then split into training, validation, and testing sets. This division is crucial for assessing the model's performance during training and evaluating its ability to generalize to unseen data. The scikit-learn library was utilized to split the dataset, with approximately 70% allocated for training, 10% for validation, and 20% for testing.

International Journal of Scientific Engineering and Science
Volume 8, Issue 8, pp. 52-57, 2024. ISSN (Online): 2456-7361

Figure 2. Labelled Car Dataset

D. Detection of Number Plates

The core of the ALPR system lies in the detection of number plates. Various object detection models, including InceptionResNetV2, MobileNetV2, InceptionV3, and YOLOv8, were explored. These models employ deep learning techniques to accurately locate and identify license plates within images.

1) Training Phase

During the training phase, the selected model (YOLOv8) learns to detect license plates by adjusting its parameters based on the training dataset. The model is fed batches of annotated images, and through backpropagation and gradient descent, the model's weights are optimized to minimize the difference between predicted and ground-truth annotations. GPU acceleration, using CUDA and cuDNN, is employed to expedite this computationally intensive process.

2) Validation Phase

After training, the model is validated against a separate validation dataset to assess its generalization ability and fine-tune hyper parameters if necessary. This step ensures that the model performs well on unseen data and avoids overfitting or under fitting.

3) Testing Phase

The final evaluation of the model's performance occurs in the testing phase, where it is tested on a distinct test dataset. Metrics such as accuracy, F1 score, precision, and recall are used to gauge the model's effectiveness in accurately detecting license plates under real-world conditions.

E. Character Recognition

Optical Character Recognition (OCR) is employed to extract the alphanumeric characters from the detected license plates. The EasyOCR library, a high-performance OCR library, is utilized for this purpose. EasyOCR can recognize text in multiple languages and provides results efficiently.

F. Creating Web Application

To enhance user interaction and accessibility, a web application is developed using Flask, a Python web framework. The web application allows users to upload images or videos containing license plates, and the ALPR system processes them in real time, displaying the results within the web interface. The recognized license plate numbers and associated metadata can be downloaded as a report. By integrating these components, the proposed ALPR system offers a comprehensive solution for automatic license plate detection and recognition. In Figure 1, the system's architecture ensures robustness, accuracy, and real-time performance, making it suitable for various applications in traffic management, law enforcement, and security.

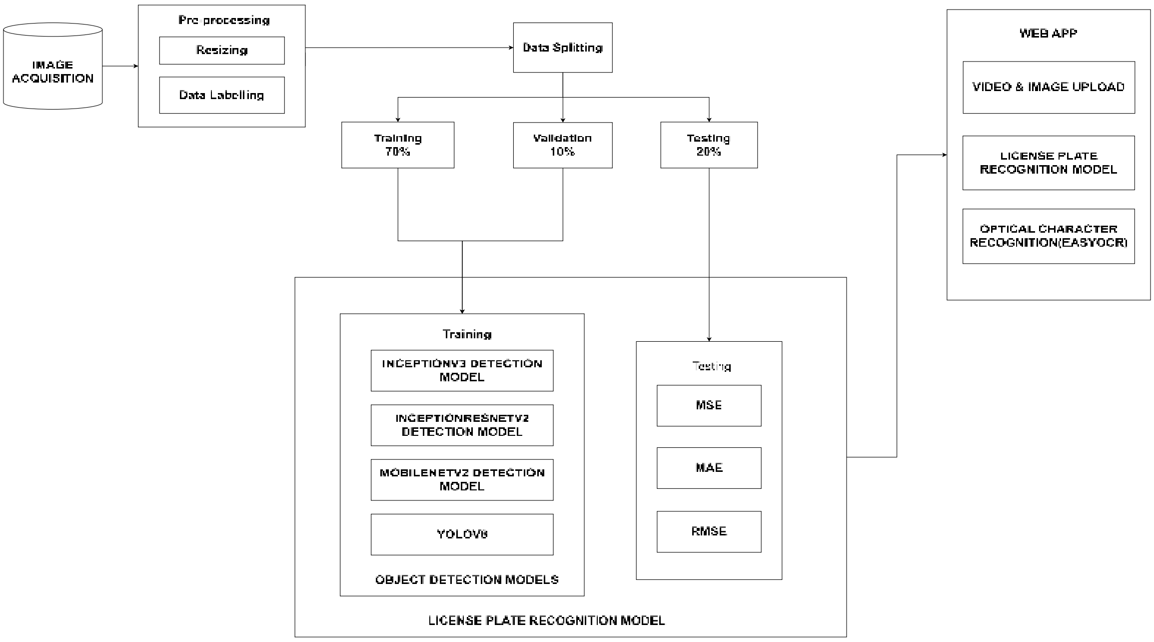

Figure 1. System Architecture

International Journal of Scientific Engineering and Science
Volume 8, Issue 8, pp. 52-57, 2024. ISSN (Online): 2456-7361

IV. Results And Discussion

The evaluation of the ALPR system involved rigorous testing and analysis of various deep learning models, including InceptionResNetV2, MobileNetV2, InceptionV3, and YOLOv8 as shown in Figure 2 and Figure 3. The performance of these models was assessed using key metrics such as accuracy, mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE). Among the TensorFlow models (InceptionResNetV2, MobileNetV2, and InceptionV3), InceptionResNetV2 emerged as the top performer, achieving a test accuracy of 85.14% and exhibiting the lowest error metrics (MSE: 0.0059, RMSE: 0.0768, MAE: 0.0547) in Figure 4. This indicates that InceptionResNetV2 effectively learned to detect and recognize license plates with high accuracy and minimal errors.

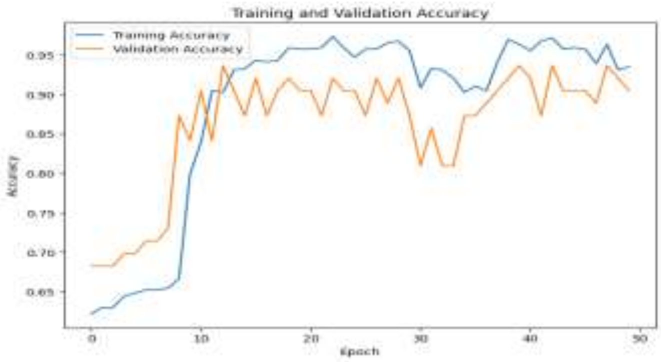

Figure 2. InceptionResnetV2 Training and Validation Accuracy.

However, the YOLOv8 model surpassed all other models in terms of overall performance as shown in Figure 5. Its training and validation metrics demonstrated consistent improvement and strong generalization capabilities. The model achieved high precision, recall, and mAP values, indicating its robustness and accuracy in detecting and classifying objects, including license plates.

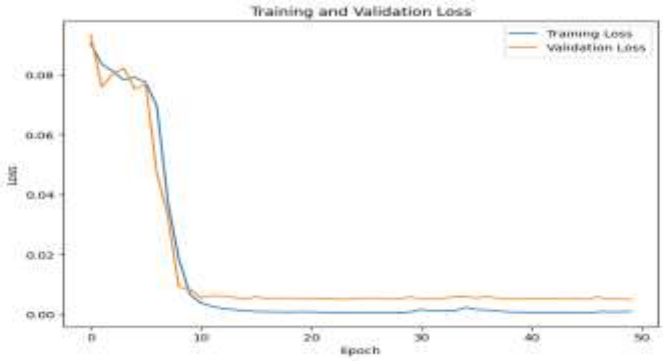

Figure 3. InceptionResnetV2 Training and Validation loss.

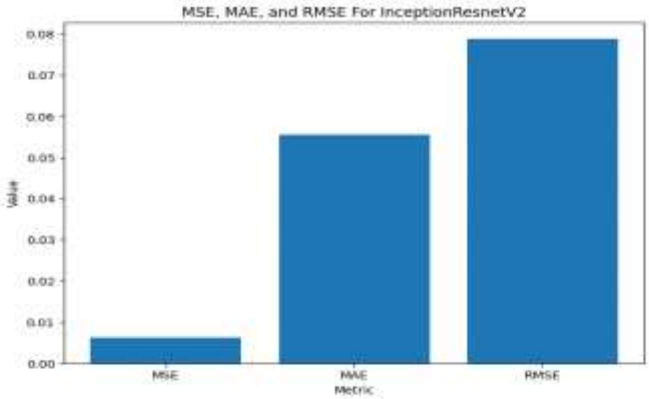

Figure 4. MSE, MAE & RMSE Metrics for InceptionResnetV2.

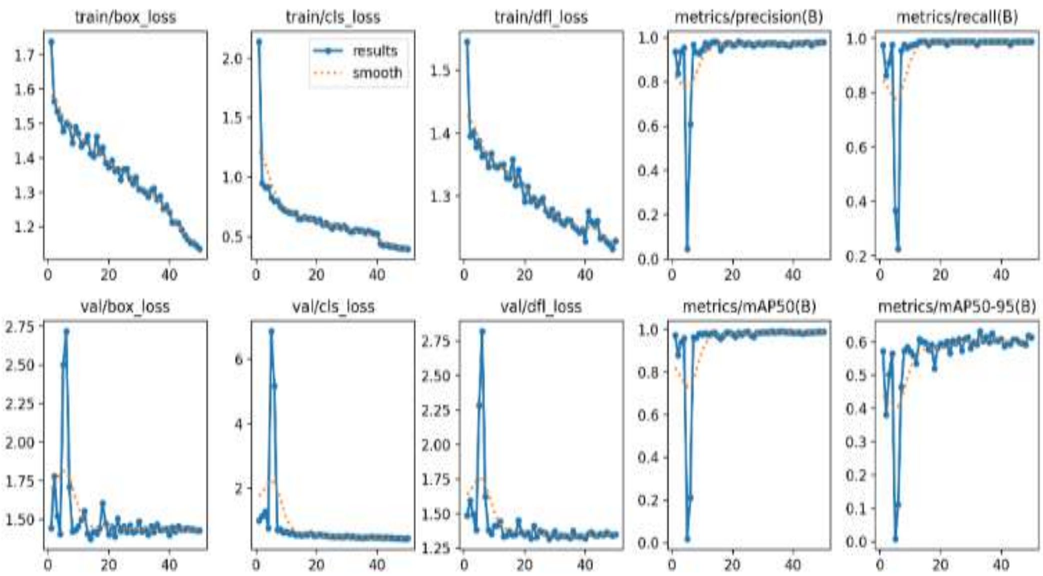

Figure 5: Performance metrics for YOLOV8.

6.1 Development of the License Plate Recognition System

The implementation of the ALPR system involved developing a user-friendly web application using the Flask framework as it shown in Figure 6.

Volume 8, Issue 8, pp. 52-57, 2024. *ISSN (Online): 2456-7361*

Figure 6. Home page.

Figure 7. App Age Upload Page.

This web application allows users to upload images or videos of vehicles for license plate recognition. The supported file extensions for images include JPEG (.jpg, .jpeg), PNG (.png), and WEBP (.webp), while videos can be uploaded in MP4 (.mp4) format as shown in Figure 7 and 8.

Figure 8. Working License Plate Recognition for Images Website.

Figure 9. Video Frame Extracted.

In figure 9, shows the image processing of the vehicle plate, the uploaded image is first pre-processed to enhance its quality and ensure compatibility with the deep learning model. The YOLOv8 model then performs license plate detection, accurately identifying and localizing the license plate region within the image as indicated in Figure 8. Subsequently, character recognition techniques are applied to extract the alphanumeric characters from the detected license plate, providing the final output to the user.

Figure 10. Working License Plate Recognition for Video Website Records.

In the case of video processing, the system employs video frame extraction techniques to break down the video into individual frames as shown in Figure 10. Each frame is then processed similarly to an image, with license plate detection and character recognition performed on each frame. The recognized license plate information from each frame is then compiled and presented to the user, enabling real-time tracking and monitoring of vehicles.

V. CONCLUSION

The research successfully developed an Automatic License Plate Recognition (ALPR) system tailored for Nigerian license plates, leveraging deep learning techniques and image processing algorithms. The YOLOv8 model emerged as the most effective model for license plate detection and recognition, outperforming other evaluated models. The implementation of a user-friendly web application using Flask further enhanced the system's usability and accessibility. The developed ALPR system holds significant potential for improving traffic management, law enforcement, and security measures in Nigeria. Future research directions include expanding the dataset, exploring model optimization techniques, and addressing challenges related to diverse environmental conditions and non-standard license plate formats.

ACKNOWLEDGMENT

The authors are grateful to the founder and the management of Afe Babalola University, Ado-Ekiti, Nigeria for providing the publication fees of this work.

Conflicts of Interest

The authors declare that there is no known competing financial or personal interests to declare

Volume 8, Issue 8, pp. 52-57, 2024. ISSN (Online): 2456-7361

References

[1]. Adedayo, K. D., and Agunloye, A. O. (2021). Real-time automated detection and recognition of Nigerian license plates via deep learning single shot detection and optical character recognition. Computer and Information Science, 14(4): 11-19. (https://doi.org/10.5539/cis.v14n4p11)

[2]. Adedokun, E. A., Mua'zu, M. B., Iloka, B. O., and Salefu, O. N. (2020). Development of a Nigeria Vehicle License Plate Detection System. International Journal for Computational Methods in Engineering Science and Mechanics, 10(38): 4806-4811. (https://www.researchgate.net/publication/346351931).

[3]. Alghyaline, S. (2022). Real-time Jordanian license plate recognition using deep learning. Journal of King Saud University – Computer and Information Sciences, 34(1): 2601-2609. (https://doi.org/10.1016/j.jksuci.2020.09.018)

[4]. Amusan, D.G., Arulogun, O.T., and Falohun, A.S. (2015). Nigerian Vehicle License Plate Recognition System using Artificial Neural Network". International Journal of Advanced Research in Computer and Communication Engineering, 4(11): 32- 41. (https://doi.org/10.17148/IJARCCE.2015.41101)

[5]. Chandra, B. M., Sonia, D., Devi, A. R., Saraswathi, C. Y., Rathan, K. M., and Bharghavi, K. (2021). Recognition of Vehicle Number Plate Using Matlab. Journal of the University of Shanghai for Science and Technology, 23(2): 363-370.(https://jusst.org/wp-content/uploads/2021/02/RECOGNITION-OF-VEHICLE-NUMBER-PLATE-USING-MATLAB.pdf)

[6]. Chen, J. I. Z. (2021). Automatic vehicle license plate detection using K-Means clustering algorithm and CNN. Journal of Electrical Engineering and Automation (EEA), 3(1):152311. (https://www.irojournals.com/iroeea)

[7]. Egwuonwu, A. C., Okemiri, H. A., and Anikwe, C. V. (2021). Vehicle Monitoring System Based On IOT, Using 4G/LTE. International Journal of Engineering and Management Research, 11(4). (https://doi.org/10.31033/ijemr.11.4.2)

[8]. Gnanaprakash, V., Sivakumar, S., and Senthilkumar, S. (2021). Automatic number plate recognition using deep learning. IOP Conference Series: Materials Science and Engineering, 1084(1): 012027. (https://doi.org/10.1088/1757-899X/1084/1/0120)

[9]. Habeeb, D., Noman, F., Alkahtani, A. A., Alsariera, Y. A., Alkawsi, G., Fazea, Y., and Aljubari, A. M. (2021). "eep-learning-based approach for Iraqi and Malaysian vehicle license plate recognition. Computational Intelligence and Neuroscience, 2021, Article ID 3971834. (https://doi.org/10.1155/2021/3971834)

[10]. Laroca, R., Zanlorensi, L. A., Gonçalves, G. R., Todt, E., Schwartz, W. R., and Menotti, D. (2021). An efficient and layout-independent automatic license plate recognition system based on the YOLO detector. IET Intelligent Transport Systems, 15, 483-5031 (https://arxiv.org/pdf/1909.01754).

[11]. Marzuki, P., Syafeeza, A. R., Wong, Y. C., Hamid, N. A., Alisa, A. N., and Ibrahim, M. M. (2019). A design of license plate recognition system using convolutional neural network. International Journal of Electrical and Computer Engineering (IJECE), 9(3), 2196-2204. (https://doi.org/10.11591/ijece.v9i3.pp2196-2204)

[12]. Park, S.-H., Yu, S.-B., Kim, J.-A., and Yoon, H. (2022). An All-in-One Vehicle Type and License Plate Recognition System Using YOLOv4". Sensors, 22(3), 921. (https://doi.org/10.3390/s22030921)

[13]. Rai, R., Shitole, S., Sutar, P., Kaldhone, S., and Jadhav, J. D. (2022). Automatic license plate recognition using YOLOv4 and Tesseract OCR. International Journal of Innovative Research in Computer and Communication Engineering, 10(3), 1656-1661. (https://www.ijircce.com/upload/2022/march/89_Automatic.pdf)

[14]. Shafi, I., Hussain, I., Ahmad, J., Kim, P. W., Choi, G. S., Ashraf, I., and Din, S. (2022). License plate identification and recognition in a non-standard environment using neural pattern matching. Complex and Intelligent Systems, 8: 3627-36391. (https://doi.org/10.1007/s40747-021-00419-5)

[15]. Shashirangana, J., Padmasiri, H., Meedeniya, D., and Perera, C. (2021). Automated License Plate Recognition: A Survey on Methods and Techniques. IEEE Access, 9. (https://doi.org/10.1109/ACCESS.2020.3047929).

[16]. Vaiyapuri, T., Mohanty, S. N., Sivaram, M., Pustokhina, I. V., Pustokhin, D. A., and Shankar, K. (2021). Automatic vehicle license plate recognition using optimal deep learning model". Computers, Materials and Continua, 67(2): 1881-1897. (https://doi.org/10.32604/cmc.2021.0149)

[17]. Voulodimos, A., Doulamis, N., Doulamis, A., and Protopapadakis, E. (2018). Deep Learning for Computer Vision: A Brief Review. Computational Intelligence and Neuroscience, 2018. (https://doi.org/10.1155/2018/7068349).

[18]. Xu Z, Yang W, Meng A, Lu N, Huang H, Ying C, and Huang L. (2018). Towards End-to-End License Plate Detection and Recognition: A Large Dataset and Baseline. In: Ferrari V, et al., editors. ECCV 2018: Proceedings of the European Conference on Computer Vision. Springer Nature Switzerland AG.: 261-277.

Author Contributions

Okebule Toyin, Adesanya Iyanuoluwapo, and Abiodun Oguntimilehin: Conceptualization, Methodology. Stephen E. Obamiyi and Abiola O. B: Software. Akindele Oluwafemi Sanya: Supervision. Attachin James and Oluwatoki T.G: Review and editing

[1, 2, 3,4,5,6,7,8,9.] Department of Computer Science, Afe Babalola University, Ado-Ekiti, Nig