An Efficient and Robust Multi Directional Deep Learning Based Licence Plate Recognition

Niresh Sharma[1], Dr.Varsha Namdeo[2]

[1]*Department of Computer Science and Engineering,Sarvepalli Radhakrishnan University, Bhopal, India.* *nireshsharma@gmail.com*

[2]*Department of Computer Science and Engineering,Sarvepalli Radhakrishnan University, Bhopal, India.* *varsha_namdeo@yahoo.com*

Abstract: Smart cities must have all the important characteristics to achieve their intended goals. Proper traffic management and controlling, increased surveillance and safety, and enhanced management and avoidance of incidents must be the priorities of smart cities. Meanwhile, license plate recognition (LPR) has become the most debatable topic in the research community due to various real-time applications, such as "law enforcement, toll-free processing, access control, and traffic surveillance." Automated LPR is a technique based on computer vision to recognize vehicles with their number plates.

This study discusses various "Deep Learning based LPR" techniques to detect and identify "alphanumeric characters" in number plate. The projected model works on "license based detection" and "character recognition." This technique uses "Optical Character Recognition (OCR)" technology to detect and extract the alphanumerical numbers from the license plate. This study is based on secondary data collected from various studies conducted on Licence Plate Recognition using various Deep Learning models published in databases like Google Scholar, Science Direct, NCBI, etc.

Deep learning has been used widely in applications related to computer vision in recent years with great perfection. It is a great solution for modern and traditional image processing, object detection, and feature extraction issues. It has been widely used in different stages of LPR like character segmentation, license plate recognition, and OCR.

Keywords: Deep learning, OCR, LPR, Licence Plate Recognition, Optical Character Recognition, traffic management, traffic surveillance, smart cities.

1. INTRODUCTION

Number of vehicles is constantly growing with modernization and constant economic growth in India. Road safety is important for citizens with "automated license plate recognition (ALPR)" process in smart cities. There are various real-time benefits of adopting "license plate recognition (LPR)" technique, such as access control for "car parking [1], toll-free collection [2], and road traffic control [3]. ALPR is the most common research area which has got a lot of attention over the years. A lot of applications are there to deploy surveillance and smart transportation systems, while enhancing computation complexity and digital camera.

These "systems are designed to detect vehicles with number plates. These systems enable automatic recognition and identification of license plates of vehicles in real-time. After capturing the front view of the vehicle through camera, the image is transferred into the system as input to test, detect, and filter the plate with vision-based algorithms. The character is segmented through identification process in detected area after its recognition. Recognizing and identifying license plates are two different things. There are several deep learning models for different styles of number plates like font type, font size, colour of backdrop, and shape, or for conditions like camera angle, motion, occlusion, lighting, etc.

A. Background

Traditionally, machine learning models are used for LPR to highlight key features in the image of licence plate. These models collect some morphological items and might have complex backdrop and noise in image. Deep learning models have computerised feature selection from pictures by learning to identify data with different filters. One of the most effective and cutting-edge deep learning models is “Convolutional Neural Network (CNN)” which has been widely used in computer vision fields like recognizing handwriting, visual objects, texts, etc. in recent years [4][5].

Since it is not easy to identify the position of license plate, various location-based CNN algorithms can be used for detecting objects precisely and rapidly. The available models based on deep learning are categorized into “segmentation-free” and “segmentation-based” models. The “segmentation-based” model conducts the task of segmentation to separate characters and identify specific characters. On the other side, “segmentation-free” model detects characters rather than separating with “Recurrent Neural Network (RNN)” and other architectural algorithms. Localizing the bounding boxes of licence plate of the vehicle from actual input picture is one of the detection processes. Its outcome affects precision of detection process. Various LPR models are implemented and proposed in this study. The traditional machine learning models with manual features rely on specific descriptors like colour, edges, and textures [7]. LPR can detect homogenous location of the text by detecting characters directly from the picture [5].

2. LITERATURE REVIEWS

License plate recognition (LPR) and “vehicle identification” have been the hot topics in recent years as they have the core competencies of smart transportation. Several studies have been done on using deep learning techniques for this application area.

Wang et al [8] reviewed various deep learning techniques for “vehicle reidentification”. These techniques are organized and categorized into “local features, metric learning, representation learning, attention mechanism, and unsupervised learning.” These techniques were compared and researchers discovered potential research directions and challenges in this field. Boukerche and Ma[9] reviewed deep learning models for “vision-based automated vehicle recognition (VAVR)”. They proposed several datasets for vehicle recognition in VAVR as well as research trends and challenges, and features of VAVR approaches.

A VAVR approach has been proposed by “Llorca et al. [10] on the basis of geometric modelling and look of car emblems from “rear view pictures”. They used “linear SVM classifier” and “HOG features” and achieved 93.75% accuracy on a dataset which consists of 1.342 images of 52 car generations and models. Lee et al. [11] used “SqueezeNet architecture” with “bypass connections” for recognition of car models and makes with front views. They achieved 96.3% accuracy with 108.8 ms of inference time. Similarly, Manzoor et al. [12] used “SVM classifiers and classical random forest” to achieve 35.7 pictures per second of inference speed and 97.89% of maximum accuracy. These models have shown remarkable performance but none of them took the most of temporal redundancies in terms of video streaming as proposed in this study.

Shashirangana et al. [13] used ALPR approaches and recent techniques. They identified existing research and development challenges and categorized deep learning approaches in “multi-stage object detection deep learning methods” and “single-stage deep learning methods.” A lot of studies were done in vehicle identification and LPR. A deep learning approach is proposed by Liu et al [14] to “progressive vehicle reidentification (PROVID)”. They accepted two methods for progressive search, i.e., a “course-to-fine search” process to extract attributes like appearance with a CNN algorithm and a “near-to-distant search” approach for “Siamese neural network-based verification of license plate.” They also used surveillance videos to develop “VeRi-776” dataset.

Selmi et al. [15] developed a “LP detection and recognition system” on the basis of deep learning approach with “character recognition, segmentation, and detection”. They applied various morphological operations like “fine contours, adaptive thresholding, and geometric filtering” before application of three steps. It is based on CNN and objects detected are categorized into “plate/no plate categories”. Then, they recognized upper-case characters (A-Z) and digits from 0 to 9 with 37 classes of CNN model. Kessentini et al.[16] also detected and recognized license plates in multiple languages.

Chen[17] used YOLO algorithm to detect license plates. They made changes in the previous YOLO algorithm to come up with 36 models in a “single-class detector”. There was a sliding window for all categories to avoid issues related to “small object detection” they applied their model in licence plates of a Taiwan’s car. They tested their proposed system in various conditions like darkness, rain, saturation, and various colours.

A. Research Gap

Deep learning models are widely used these days to localize the license plates of vehicles. CNN models are especially used for detection of text areas in input image. Later on, another “4-layer plate/non-plate CNN model” is used for differentiation of license plates from usual characters. Montazzolli& Jung [18] used “FAST-YOLO” classification model to detect frontal view of vehicles from the image. They extracted the details of licence plate from the front view. Rakhraet al [19] used a “pipeline architecture” with a range of deep CNNs for detection of licence plate” in various situations. They also used several designs of licence plates in the architecture. But it is originally designed to detect Arabian text. Hence, this study adds to the existing knowledge by presenting effective deep learning methods for LPR and identifying alphanumeric characters.

B. Research Question

- What are the effective and robust “deep learning systems used for licence plate recognition?”

C. Research Objective

- To propose effective “deep learning models used for license plate recognition”

3. RESEARCH METHODOLOGY

In order to provide a deep insight to various DL based methods and techniques used in ALPR, this study is based on secondary data collected from various studies published in peer-reviewed journals and databases. Literature search was conducted to identify relevant articles using keyword search method, which consists of keywords like “deep learning,” “automatic license plate recognition”, “LPR”, “licence plate recognition”, “CNN”, etc.

4. ANALYSIS OF STUDY

Researchers have paid a lot of attention on deep learning in the field of license plate recognition [20]. A lot of models have been used for character recognition, such as “Hybrid Discriminative Restricted Boltzmann Machine, Hidden Markov model, Support Vector Machine (SVM) (which has been used in license plates in China, Iran and Thailand) [21]-[23]. Template matching is used to recognize characters with fixed-size, not rotated, and single-font properties [24]-[28]. In addition, “Artificial Neural Network (ANN)” has got a lot of attention as it is capable to classify license plates [29]. A lot of approaches have been developed to recognize numbers and letters on license plates after passing the detection process. The character recognition approaches have been classified into two categories by Anagnostopoulos et al. [24] – pattern matching and classifiers (Table 1).

Table I. Deep Learning Approaches for Licence Plate Recognition [30]

Categories	Approaches	Description
Classifiers	“Computational Intelligence”	“Adaptive resonance theory neural networks”
		“Probabilistic neural networks”
		“Multi-layered feed-forward neural networks”
		“Self-organized neural networks”
		“Learning vector quantization neural network”
	“Statistical Classifiers”	Hidden Markov models
		“Likelihood models in tree structure”
		SVM
Pattern Matching	“Template Matching”	“Hausdorff distance”
		“Normalized cross correlation”
		“Root mean squared error (RMSE) for all the template changes”
		“Image partition: zoning, projections, contour distance, segment count”

A lot of algorithms have been used in license plate recognition as mentioned in Table 1. The relevant models and methods have shown their great performance. For instance, the "Hidden Markov model" is among the best classifiers used to recognize license plates like SVMs [22] [23]. In addition, the "artificial neural network (ANN)" has achieved a lot of attention as it can classify license plates [29]. It has been used widely for template matching [26]-[28] [33]. This method creates templates of A-Z letters or letters printed in other languages and number from the dataset.

Then, these templates can match the feature of each number and letter on the licence plate. Even though this approach has been highly efficient in license plate recognition, it is still not capable to manage characters with several positions [22] [24] [25]. Along with these models, a lot of attention is given to "Convolutional Neural Network (CNN)," a novel deep learning model because of its significant prediction and classification performance. It has been used recently in license plate recognition [34].

A. "MobileNets and Inception-v3"

These are some of the deep learning methods. The "Inception-v3" is an upgraded version of GoogLeNet aka Inception-v1 [31] [35] [36]. GoogLeNet was the novel concept of CNN with inception module which is designed to find the ideal construction in every layer. Each layer of inception was designed with various convolution nodes like "1x1, 3x3, and 5x5) and 3x3 max pooling node" (Fig. 1).

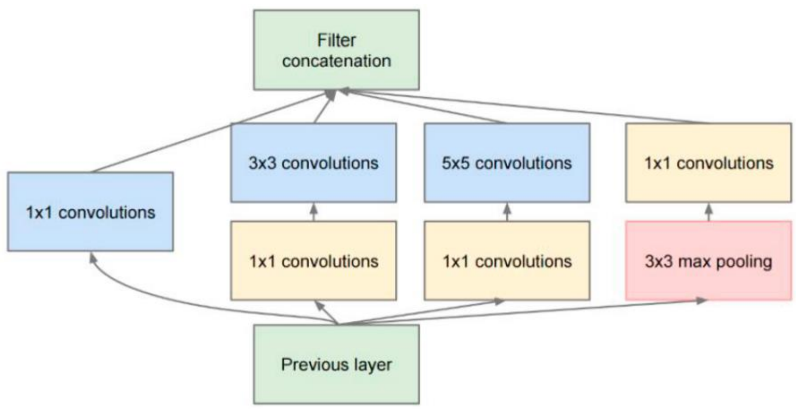

Fig. 1 A flowchart of GoogLeNet Inception Module

Source – Szegedy et al. (2015)

A new concept was implemented by Inception-v3 into inception node. The convolution node was factored and became smaller. For instance, one "nxn kernel is factorized into nx1 and 1xn kernels" (Figure 2). Better performance is achieved with Inception-v3 as compared to original one for both time saving and accuracy in image recognition (Szegedy et al, 2016).

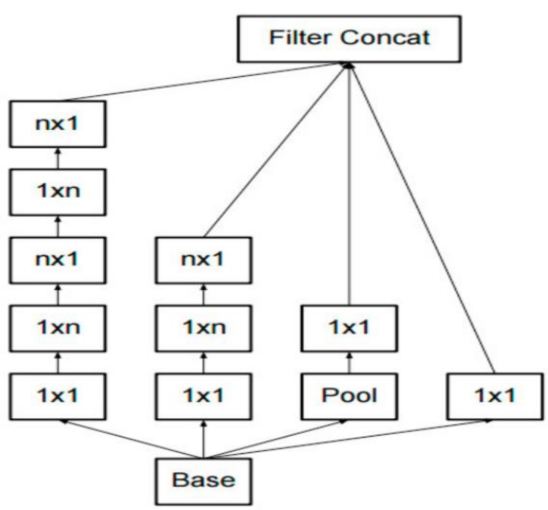

Fig. 2 Factorization in Inception-v3 [35]

However, the size of training model was the main issue behind GoogLeNet. MobileNets is another model that outperforms GoogLeNet in scalability [31]. Developed by Howard et al. [31], MobileNets reduces the size of the model for mobile version with the "Depthwise Separable Convolution" technique (Fig. 3). It can be closely accurate to "Inception-v3" but its size is quite small.

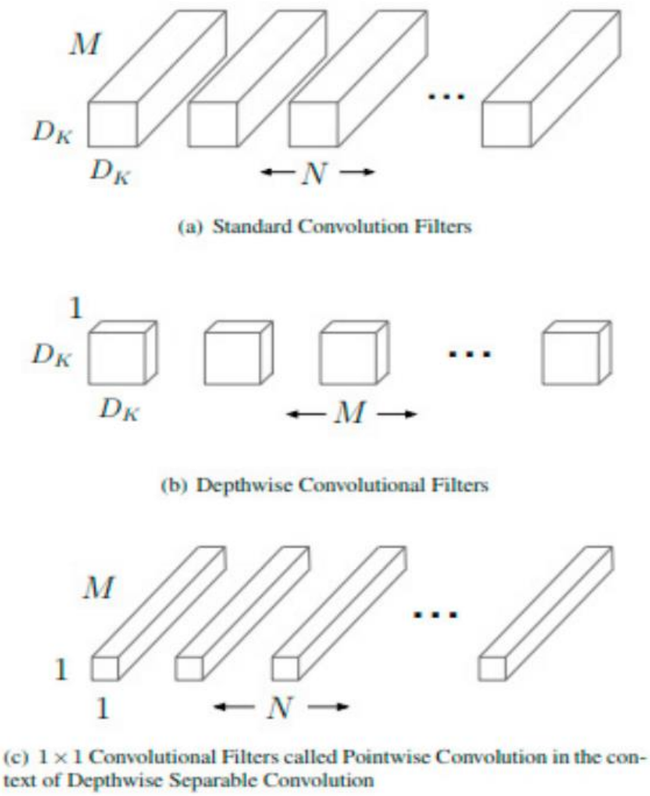

Fig. 3 "Depthwise Separable Convolution used by MobileNets [31]

B. "Single Shot Multibox Detector (SSD)"

MobileNets and Inception-v3 are the deep learning approaches for licence plate recognition. Image segmentation is also required for complete image recognition process. These two models are not sufficient to perform both processes simultaneously. The "Single Shot Multibox Detector (SSD)" is another technique to solve this issue [37]. SSD can create an area or "bounding boxof each segment with high odds to be similar object in the picture. It can work with other LP recognition techniques to detect various "object bounding boxes" and their categories (Fig. 4).

Fig. 4 An illustration of MobileNets and SSD [31]

C. DL-VLPNR Model

Vetriselvi et al. [38]proposed the "Deep Learning based Vehicle Licence Plate Number Recognition (DL-VLPNR)" model (Fig. 5). There are two key stages of DL-VLPNR model. First of all, Inception V2 and "Faster Regions with Convolutional Neural Networks (RCNN)" models are used for detecting number plates. Then, the Tesseract OCR model is used to detect characters in the number plate. The "Tesseract OCR" model can observe the alphanumeric characters in the licence plate. This Tesseract model is trained for accuracy, which consists of developing characters in the image which should be predicted with the given fonts."

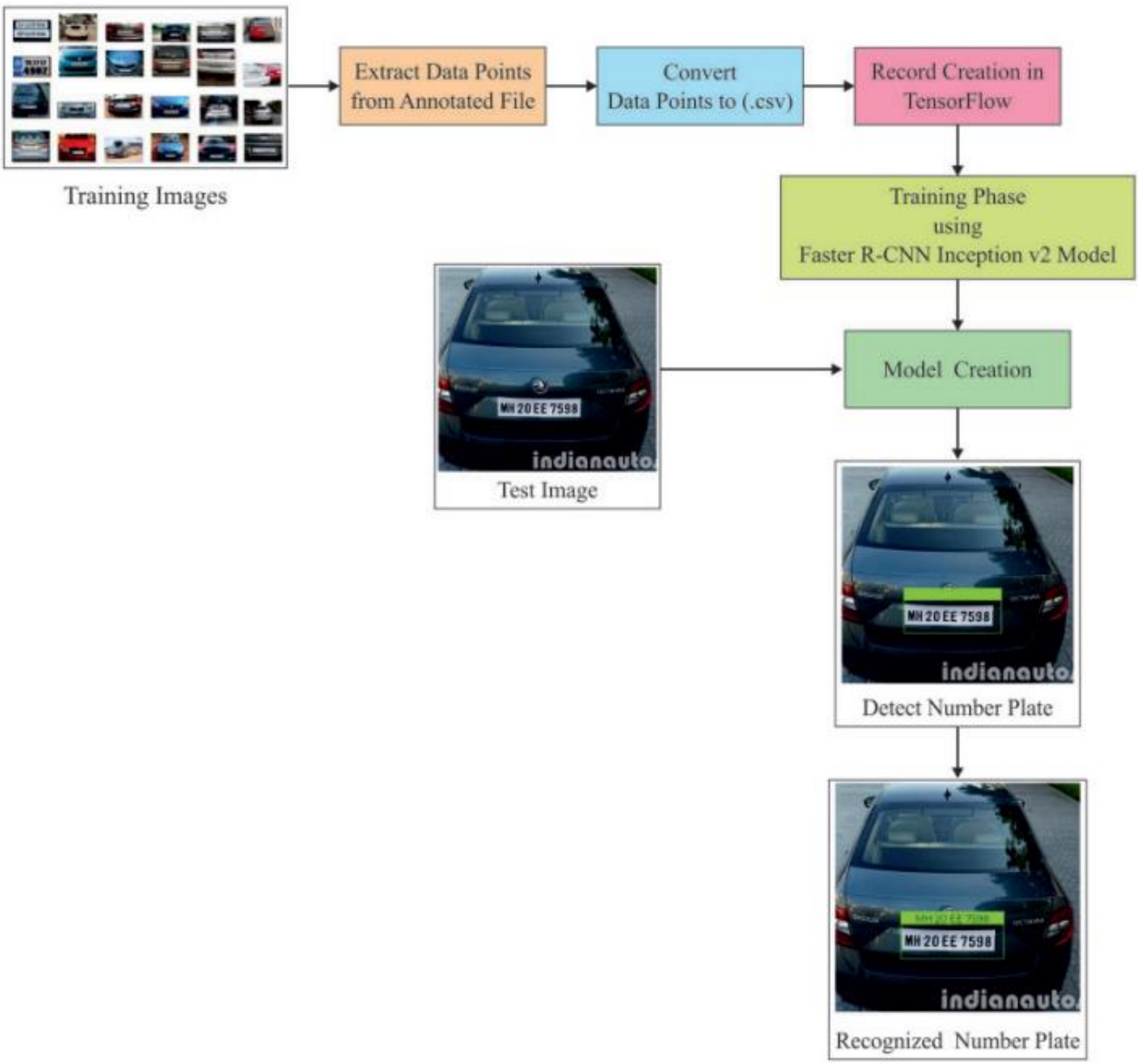

Fig. A The Roadmap of "DL-VLPNR Model" [38]

There are two key stages of "Faster RCNN" – "Fast RCNN and "Region Based Proposals (RPN)" techniques. When trusted feature rules restrict the RPN, the objects are being explored by "Fast R-CNN model." The outcome of identification is given to RPN for creating region proposals. The whole image is obtained by the "Faster RCNN" model and value of "object proposals" as input to foresee the unusual aspects in input image (Fig. 6) [39].

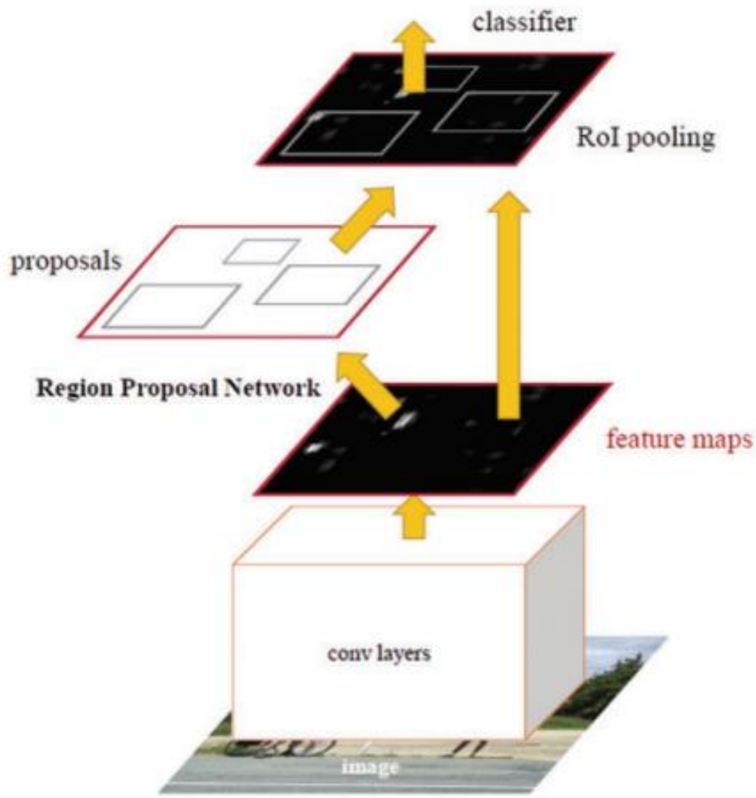

Fig 6 “Faster RCNN Model” [39]

D. Tesseract OCR Engine

Fig. 7 illustrates the overall pipeline of OCR engine named “Tesseract”. First of all, “Adaptive Thresholding” changed the picture into binary vision with “Otsu’s approach.”The next step here is “Page layout analysis” and is applicable to extract text blocks in the area. Then texts are split into words and baselines are detected in each line while applying fuzzy spaces and limited spaces.

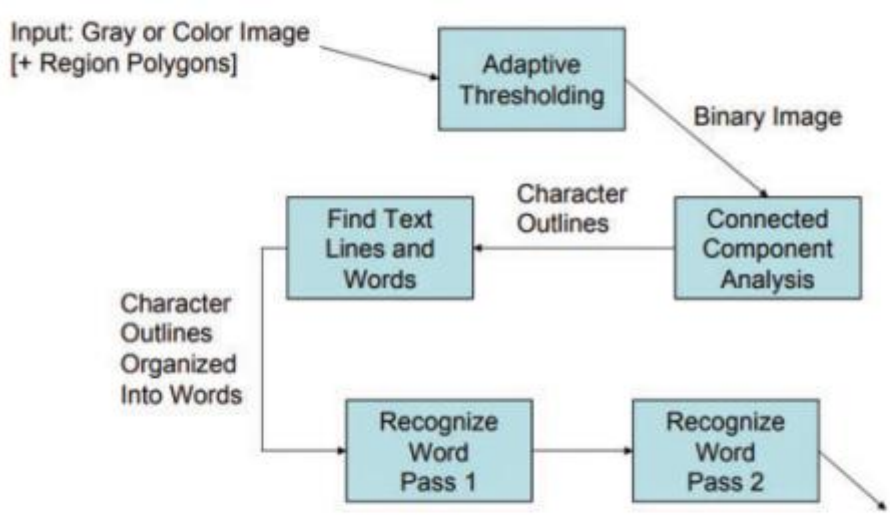

Fig. 7 Tesseract-based Recognition Process [38]

The outlines of the characters are gathered from the words. Text is recognized as “2-pass method”. Word recognition is done in the first pass while applying static classification. Every word is passed to “adaptive classifier” as training data. Second pass is run with a “novel adaptive classification” approach where words are not tested to retest the unit [38].

E. YOLOv4

YOLOv4 is the module designed to detect number plate from the frame of video clip or image. It can use any single shot or region-based detector. YOLOv4 is well known for its accuracy and good speed to detect small objects. Sanyam [40] implemented YOLOv4 with darknet framework. Darknet is a neural network-based open-source model which is written in CUDA and C programming languages. The “CSPDarknet53 CNN” is the backbone of YOLOv4 to detect objects and use Darknet53 with 53 “convolutional layers”. Darknet needs a few lines of code and is very simple to use and install. Data is important for an AI application and the most important and first steps. The vehicle dataset of “Google Open Images” is used to train the YOLOv4 detector. This open-source dataset contains thousands of pictures of objects with annotations for segmentation and object detection. There are 300 validation and 1500 training images in the dataset in YOLO format (Fig. 8).

```
import math
# Creating a list of image files of the dataset.
data_path = './data/obj/train/'
files = os.listdir(data_path)
img_arr = []

# Displaying 4 images only.
num = 4

# Appending the array of images to a list.
for fimg in files:
    if fimg.endswith('.jpg'):
      demo = img.imread(data_path+fimg)
      img_arr.append(demo)
      if len(img_arr) == num:
        break

# Plotting the images using matplotlib.
_, axs = plt.subplots(math.floor(num/2), math.ceil(num/2), figsize=(50, 28))

axs = axs.flatten()

for cent, ax in zip(img_arr, axs):
    ax.imshow(cent)
plt.show()
```

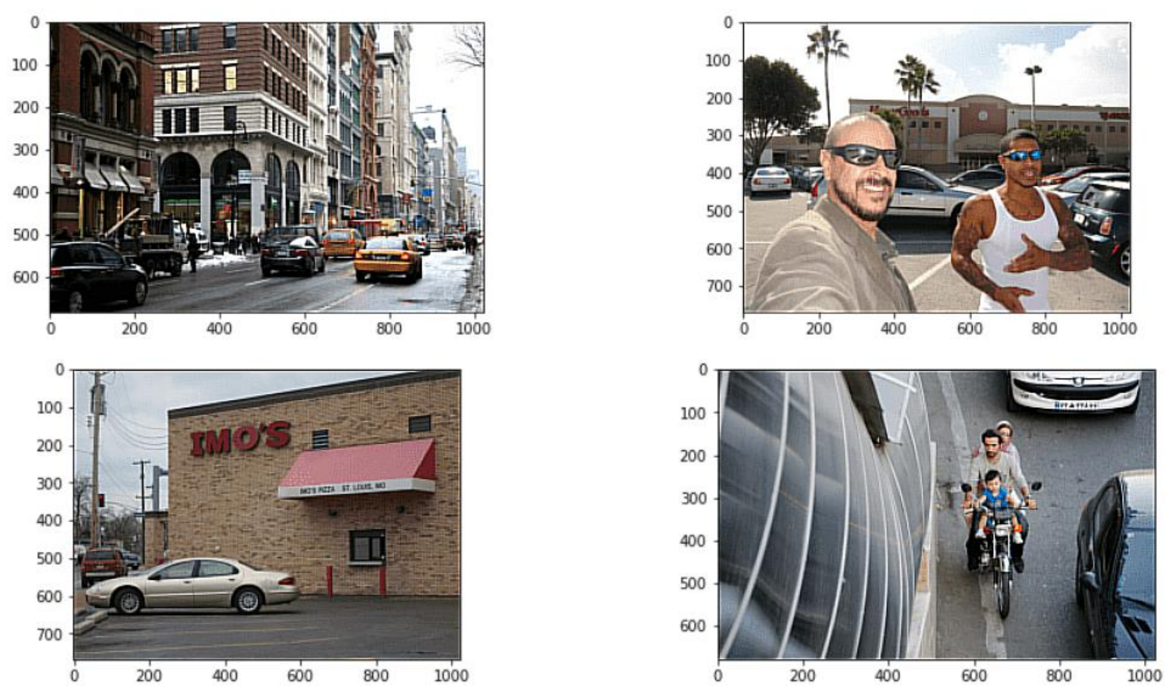

Fig. 8 An illustration of Open Images Dataset [40]

The model needs to be trained, but before training, it is important to modify the "config file (.cfg)." Subdivision, batch size, and classes are the parameters that should be modified. It is vital to judge the performance of the trained model on unseen data. It is ideal to know whether there is overfitting or best performing model. The "Mean Average Precision (mAP)" is a metric for object detection. The comparison is made between the "predicted bounding box" and "detected bounding box" on high-level explanation and "mAP" score is returned. This code saves the chart for training process to achieve 90% mAP in 5.3 seconds after performing 3000 epochs (Fig. 9).

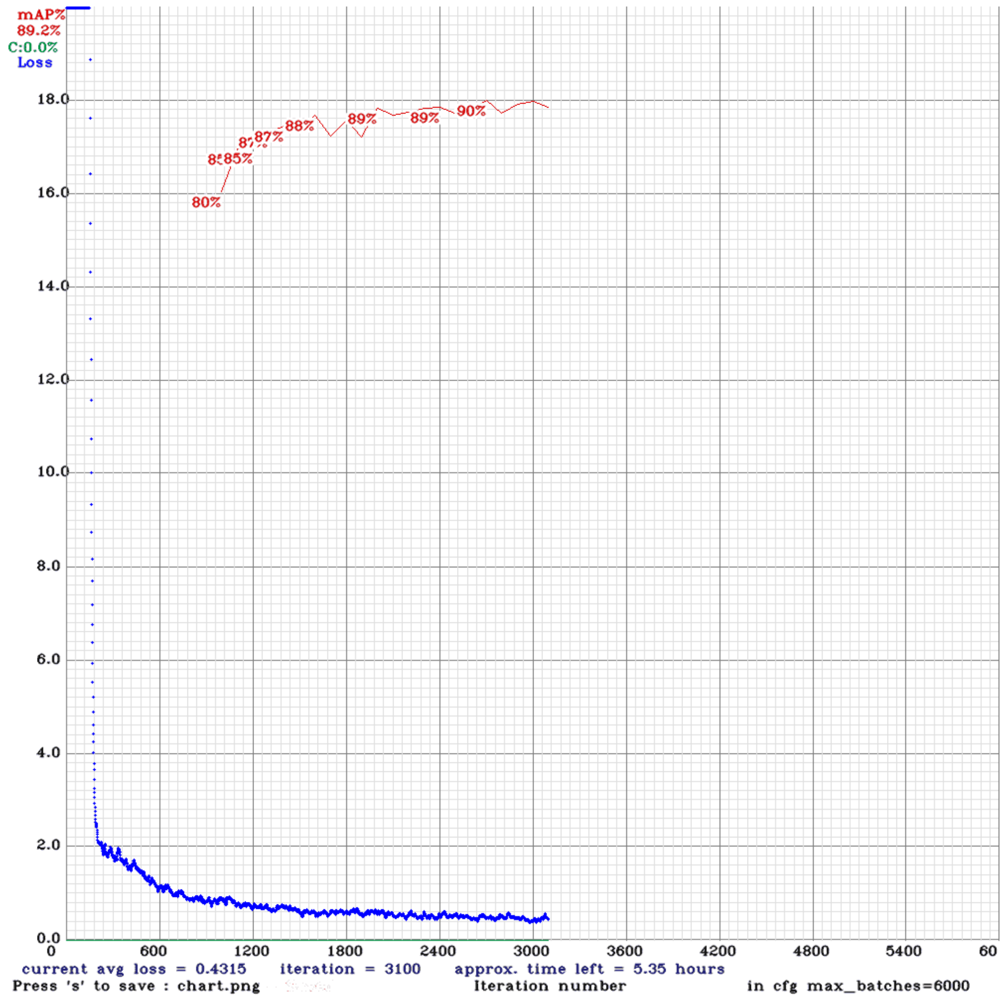

Fig. 9 Training Process Chart for mAP score [40]

F. Template Matching

It is the simplest deep learning approach for LPR. This cross-correlation approach compares or calculates the similarity of character which is extracted using the set of template characters. It selects the character which comes up with the highest match among the images. The grey level may be affected by the change in lighting which intensifies in the image. Hence, this approach is ideal for binary images. Slimani et al. [42] used template matching to detect the characters which are segmented with four different sets of licence plates in Moroccan format with success rates of "98.1%, 96.37%, 93.07%, and 92.52%" in a row. Several researchers have proposed the use of template matching in their studies[33][43]-[48] . The characters are scanned in every column to match with the templates. The top match is found with highest correlation value. However, characters should not be tilted, broken, resized, and be in different fonts for proper use of Template Matching [41].

5. RESULTS

Some of the licence plate recognition systems can use simple techniques of image processing under controlled environments for typical types of licence plates. However, some cutting-edge license plate recognition systems use specific object detectors like CNN, HOG, YOLO, SVM, etc. Further smart and state-of-the-art ANPR systems use dedicated software powered by “Neural Network techniques” which have AI capabilities. Machine learning and computer vision are used in ANPR like in other areas. ANPR becomes challenging due to high diversity of licence plates across countries, states, and territories. The “Number Plate identification” is further complicated by any model which should work at the same time. Hence, ANPR can also be empowered by CV, AI, and machine learning techniques.

Chou & Liu [49] provided a collection of good references for novel researchers in the field of licence plate recognition. However, the performance of those techniques is not compared for accuracy. Bakhtan et al. [50] explored the performance of several models used from 1999 to 2015 for ANPR system. They didn’t find stable efficiency of ANPR system and there was also change in performance because of factors like environmental condition, noise, and choice for models training and algorithm. Vetriselvi et al. [38] also proposed “DL-VLPNR” model to analyse and identify vehicle’s licence plates. It is based on “Inception V2 and Faster RCNN” models for detection of alphanumeric characters. Then, it uses Tesseract OCR algorithm to extract the numbers and characters.

For better speed, YOLO-tiny is recommended to use for license plate recognition. But for better speed and accuracy, YOLOv4 is highly recommended by the researchers. To get the best results of OCR, it is also suggested to use a tracker for ALPR. Computer vision has a lot of amazing applications with recent improvements in deep learning, such as autonomous driving to precise recognition of objects to reading images automatically in several applications. YOLO can be evaluated and trained for real-time object detection.

6. CONCLUSION

This study collected an in-depth insight to various deep learning methods proposed by various researchers for licence plate recognition. These algorithms are based on complex computing, digitizing, and optical features which may be slow for recognition. The commercially available ANPR systems may not provide a standard set of features because each company should provide an optimized system for various countries. The system which is developed should be designed as per the region where it is being deployed, considering the factors which might affect its efficiency. Usually, OCR engines are optimized for particular countries to ensure that the engine or library required is installed on the camera. All in all, there are strengths and weaknesses of each ANPR system.

7. REFERENCES

[1] E. J. Sen *et al.*, “Advanced License Plate Recognition System for car parking,” *2014 International Conference on Embedded Systems (ICES)*, 2014. doi:10.1109/embeddedsys.2014.6953109

[2] Suryatali and V. B. Dharmadhikari, “Computer Vision Based Vehicle Detection for Toll Collection System Using Embedded Linux,” *2015 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2015]*, 2015. doi:10.1109/iccpct.2015.7159412

[3] Naimi, Y. Kessentini, and M. Hammami, “Multi-nation and multi-norm license plates detection in real traffic surveillance environment using Deep Learning,” *Neural Information Processing*, pp. 462–469, 2016. doi:10.1007/978-3-319-46672-9_52

[4] Y. LeCun *et al.*, “Backpropagation applied to handwritten zip code recognition,” *Neural Computation*, vol. 1, no. 4, pp. 541–551, 1989. doi:10.1162/neco.1989.1.4.541

[5] C. D. Nguyen, M. Ardabilian, and L. Chen, “Robust car license plate localization using a novel texture descriptor,” *2009 Sixth IEEE International Conference on Advanced Video and Signal Based Surveillance*, 2009. doi:10.1109/avss.2009.22

[6] H. Wang *et al.,* “MFDL: A multicarrier Fresnel penetration model-based device-free localization system leveraging commodity Wi-Fi cards,” 2012. *arXiv preprint arXiv:1707.07514.*

[7] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, “Automatic License Plate Recognition (ALPR): A state-of-the-art review,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 23, no. 2, pp. 311–325, 2013. doi:10.1109/tcsvt.2012.2203741

[8] H. Wang, J. Hou, and N. Chen, “A survey of vehicle re-identification based on Deep Learning,” *IEEE Access*, vol. 7, pp. 172443–172469, 2019. doi:10.1109/access.2019.2956172

[9] Boukerche and X. Ma, “Vision-based Autonomous Vehicle Recognition,” *ACM Computing Surveys*, vol. 54, no. 4, pp. 1–37, 2021. doi:10.1145/3447866

[10] D. F. Llorca, D. Colas, I. G. Daza, I. Parra, and M. A. Sotelo, "Vehicle model recognition using geometry and appearance of car emblems from rear view images," *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2014. doi:10.1109/itsc.2014.6958187

[11] H. Lee, I. Ullah, W. Wan, Y. Gao, and Z. Fang, "Real-time vehicle make and model recognition with the residual SqueezeNet architecture," *Sensors*, vol. 19, no. 5, p. 982, 2019. doi:10.3390/s19050982

[12] M. A. Manzoor, Y. Morgan, and A. Bais, "Real-time vehicle make and Model Recognition System," *Machine Learning and Knowledge Extraction*, vol. 1, no. 2, pp. 611–629, 2019. doi:10.3390/make1020036

[13] J. Shashirangana, H. Padmasiri, D. Meedeniya, and C. Perera, "Automated License Plate Recognition: A survey on methods and Techniques," *IEEE Access*, vol. 9, pp. 11203–11225, 2021. doi:10.1109/access.2020.3047929

[14] X. Liu, W. Liu, T. Mei, and H. Ma, "A deep learning-based approach to progressive vehicle re-identification for Urban Surveillance," *Computer Vision – ECCV 2016*, pp. 869–884, 2016. doi:10.1007/978-3-319-46475-6_53

[15] Z. Selmi, M. Ben Halima, and A. M. Alimi, "Deep Learning System for Automatic License Plate Detection And Recognition," *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*, 2017. doi:10.1109/icdar.2017.187

[16] Y. Kessentini, M. D. Besbes, S. Ammar, and A. Chabbouh, "A two-stage deep neural network for multi-norm license plate detection and recognition," *Expert Systems with Applications*, vol. 136, pp. 159–170, 2019. doi:10.1016/j.eswa.2019.06.036

[17] R.-C. Chen, "Automatic license plate recognition via sliding-window darknet-yolo deep learning," *Image and Vision Computing*, vol. 87, pp. 47–56, 2019. doi:10.1016/j.imavis.2019.04.007

[18] S. Montazzolli and C. Jung, "Real-time Brazilian license plate detection and recognition using deep convolutional neural networks," *2017 30th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, 2017. doi:10.1109/sibgrapi.2017.14

[19] M. Rakhra, D. Singh, A. Singh, A. A. Ahdal, and D. Gupta, "Classification and prediction of license plates using deeply learned convolutional neural networks," *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, 2022. doi:10.1109/icrito56286.2022.9965111

[20] P. Sa-ngamuang, C. Thamnittasana, and T. Kondo, "Thai car license plate recognition using essential-elements-based method," *2007 Asia-Pacific Conference on Communications*, 2007. doi:10.1109/apcc.2007.4433496

[21] C. Gou, K. Wang, Y. Yao, and Z. Li, "Vehicle license plate recognition based on extremal regions and restricted boltzmann machines," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 4, pp. 1096–1107, 2016. doi:10.1109/tits.2015.2496545

[22] H. Ashtari, Md. J. Nordin, and M. Fathy, "An Iranian license plate recognition system based on color features," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 4, pp. 1690–1705, 2014. doi:10.1109/tits.2014.2304515

[23] Y. Wen *et al.*, "An algorithm for license plate recognition applied to Intelligent Transportation System," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 3, pp. 830–845, 2011. doi:10.1109/tits.2011.2114346

[24] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, V. Loumos, and E. Kayafas, "A license plate-recognition algorithm for Intelligent Transportation System Applications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 3, pp. 377–392, 2006. doi:10.1109/tits.2006.880641

[25] C.-N. E. Anagnostopoulos, I. E. Anagnostopoulos, I. D. Psoroulas, V. Loumos, and E. Kayafas, "License plate recognition from still images and video sequences: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 3, pp. 377–391, 2008. doi:10.1109/tits.2008.922938

[26] C. A. Rahman, W. Badawy, and A. Radmanesh, "A real time vehicle's license plate recognition system," *Proceedings of the IEEE Conference on Advanced Video and Signal Based Surveillance, 2003.*, 2003. doi:10.1109/avss.2003.1217917

[27] P. Comelli, P. Ferragina, M. N. Granieri, and F. Stabile, "Optical recognition of motor vehicle license plates," *IEEE Transactions on Vehicular Technology*, vol. 44, no. 4, pp. 790–799, 1995. doi:10.1109/25.467963

[28] M. Yu and Y. D. Kim, "An approach to Korean license plate recognition based on vertical edge matching," *Smc 2000 conference proceedings. 2000 ieee international conference on systems, man and cybernetics. "cybernetics evolving to systems, humans, organizations, and their complex interactions" (cat. no.0*, vol. 4, pp. 2975–2980, 2000. doi:10.1109/icsmc.2000.884453

[29] J. Tarigan, R. Diedan, and Y. Suryana, "Plate recognition using backpropagation neural network and genetic algorithm," *Procedia Computer Science*, vol. 116, pp. 365–372, 2017. doi:10.1016/j.procs.2017.10.068

[30] W. Puarungroj and N. Boonsirisumpun, "Thai license plate recognition based on Deep Learning," *Procedia Computer Science*, vol. 135, pp. 214–221, 2018. doi:10.1016/j.procs.2018.08.168

[31] A.G. Howard, M. Zhu, B. Chen, *et al*., "Mobilenets: Efficient convolutional neural networks for mobile vision applications,"*arXiv preprint arXiv:1704.04861*.

[32] G. R. Goncalves, D. Menotti, and W. R. Schwartz, "License plate recognition based on temporal redundancy," *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, 2016. doi:10.1109/itsc.2016.7795970

[33] M. Sarfraz, M. J. Ahmed, and S. A. Ghazi, "Saudi Arabian License Plate Recognition System," *2003 International Conference on Geometric Modeling and Graphics, 2003. Proceedings*, 2003. doi:10.1109/gmag.2003.1219663

[34] V. Jain *et al.*, "Deep Automatic License Plate Recognition System," *Proceedings of the Tenth Indian Conference on Computer Vision, Graphics and Image Processing*, 2016. doi:10.1145/3009977.3010052

[35] C. Szegedy *et al.*, "Going deeper with convolutions," *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. doi:10.1109/cvpr.2015.7298594

[36] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. doi:10.1109/cvpr.2016.308

[37] W. Liu *et al.*, "SSD: Single shot multibox detector," *Computer Vision – ECCV 2016*, pp. 21–37, 2016. doi:10.1007/978-3-319-46448-0_2

[38] T. Vetriselvi *et al.*, "Deep Learning based license plate number recognition for Smart Cities," *Computers, Materials & Continua*, vol. 70, no. 1, pp. 2049–2064, 2022. doi:10.32604/cmc.2022.020110

[39] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017. doi:10.1109/tpami.2016.2577031

[40] Sanyam, "Automatic License Plate Recognition using Deep Learning," LearnOpenCV., https://learnopencv.com/automatic-license-plate-recognition-using-deep-learning/ (accessed Jul. 16, 2023).

[41] M.-S. Pan, J.-B. Yan, and Z.-H. Xiao, "Vehicle license plate character segmentation," *International Journal of Automation and Computing*, vol. 5, no. 4, pp. 425–432, 2008. doi:10.1007/s11633-008-0425-0

[42] Slimani, A. Zaarane, A. Hamdoun, and I. Atouf, "Vehicle license plate localization and recognition system for Intelligent Transportation Applications," *2019 6th International Conference on Control, Decision and Information Technologies (CoDIT)*, 2019. doi:10.1109/codit.2019.8820446

[43] S. Ahmad, B. Boufama, P. Habashi, W. Anderson, and T. Elamsy, "Automatic License Plate Recognition: A comparative study," *2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, 2015. doi:10.1109/isspit.2015.7394415

[44] O. Hommos *et al.*, "HD Qatari ANPR system," *2016 International Conference on Industrial Informatics and Computer Systems (CIICS)*, 2016. doi:10.1109/iccsii.2016.7462420

[45] K. Kanayama, Y. Fujikawa, K. Fujimoto, and M. Horino, "Development of vehicle-license number recognition system using real-time image processing and its application to travel-time measurement," *[1991 Proceedings] 41st IEEE Vehicular Technology Conference*, 1991. doi:10.1109/vetec.1991.140605

[46] K. Miyamoto et al. "Vehicle license-plate recognition by image analysis," *[1991 Proceedings] International Conference on Industrial Electronics, Control, and Instrumentation*, 1991, 1734-1738.

[47] Eun Ryung Lee, Pyeoung Kee Kim, and Hang Joon Kim, "Automatic recognition of a car license plate using color image processing," *Proceedings of 1st International Conference on Image Processing*, 1994. doi:10.1109/icip.1994.413580

[48] Y. Jia, T. Gonnot, and J. Saniie, “Design flow of vehicle license plate reader based on RGB color extractor,” *2016 IEEE International Conference on Electro Information Technology (EIT)*, 2016. doi:10.1109/eit.2016.7535290

[49] J.-S. Chou and C.-H. Liu, “Automated Sensing System for real-time recognition of trucks in river dredging areas using computer vision and Convolutional Deep Learning,” *Sensors*, vol. 21, no. 2, p. 555, 2021. doi:10.3390/s21020555

[50] M. A. Bakhtan, M. Abdullah, and A. A. Rahman, “A review on License Plate Recognition System algorithms,” *2016 International Conference on Information and Communication Technology (ICICTM)*, 2016. doi:10.1109/icictm.2016.7890782.

DOI: https://doi.org/10.15379/ijmst.v10i2.2783