

DEVELOPMENT OF REAL-TIME VEHICLE'S PLATE NUMBER RECOGNITION SYSTEM USING DEEP LEARNING APPROACH FOR SURVEILLANCE SYSTEM IN MALAYSIA

¹ Husna Osman, ² Munaisyah Abdullah, ³ Jawahir Che Mustapha, ⁴ Salah Mohammed Yahya Al-Nawah and ⁵ Jasrina Jaffar

¹⁻⁴ Malaysian Institute of Information Technology, Universiti Kuala Lumpur, Malaysia

⁵ Malaysian France Institute, Universiti Kuala Lumpur, Malaysia
*husna@unikl.edu.my

ABSTRACT

License Plate Recognition (LPR) is an image processing technology that uses license plate number to identify vehicles. Many current LPR research fully rely on still photos, whereby minimal attention is given to an automated real-time LPR. Several automated real-time based LPR methods are less practical in crucial circumstances, such as the use of non-fixed cameras, recognition of moving vehicles in complex scenes, and the occurrence of extreme illumination variations. Thus, the aim of this project is to develop an automated real-time car plate number detection and recognition system that utilize a mobile application. In this proposed system, the images captured from the mobile cameras can either be transmitted to a server or perform offline for automated detection and recognition using a suitable mobile resource. This can be achieved by enhancing the algorithm for LPR using deep learning. This paper presents a new proposed algorithm that efficiently identify license plate number accurately and without any human intervention. Hence, Intelligent Transportation Systems (ITS) will benefit considerably from the proposed automated real-time LPR system. The integration of advanced intelligent system in vehicle surveillance will allow an effective adoption of smart technologies in cities and transportation industry.

Keywords: License Plate Recognition, deep learning, Intelligent Transportation System, image processing.

1.0 INTRODUCTION

Crime rate in Malaysia is increasing day by day. One way to reduce the crime rates is by providing a means for law enforcement agencies to acquire detailed information about any suspicious vehicles/person quickly regardless of time or location. License Plate Recognition (LPR) is an application based on image processing technology used to identify vehicles from their license plate number. It plays a significant role in the Intelligent Transport Systems (ITSs). This technology is gaining popularity in security and traffic installations for maintaining law enforcement on public roads, toll collection, management of parking lots and stolen cars (Ibrahim et al., 2013).

Object recognition is not new, but extracting and matching the information for vehicle plate numbers for the local vehicles are tricky. Enhanced image processing and pattern recognition algorithms are necessary to get such information but with an acceptable delay. The code executed needs to be fast enough and not too bulky for a quick response in the time of emergencies of crime scenes or other relevant situations.

Various LPR algorithms have been proposed for Malaysian plate numbers to deal with either still or moving images. However, these algorithms have difficulties to recognize moving vehicles in complex situations due to different plate's sizes or font types, plate location, capturing noise, and the illumination (Al Faqheri and Mashohor, 2009; Diop and Ong, 2014). Therefore, this research aims to formulate a new algorithm using deep learning approach for Malaysian license plate numbers recognition that can perform detection and recognition successfully to such situations.

2.0 LITERATURE REVIEW

Since its first implementation in 1976 (Sharma, 2013), LPR systems have addressed many obstacles and challenges in recognizing licence plates (Weihong and Jiaoyang, 2020), such as low image quality (Abdullah, 2019; Seibel et al., 2017), distance from the camera, tilt angle, lousy weather, or illumination (Abdullah and Bakhtan, 2015; Khoshki and Ganesan, 2015; Mahamad, 2014). In countries like Malaysia, the unique features of their licence plates such as the use of non-standard (Chai et al., 2014) or special plates, have introduce additional challenges in recognizing the licence plates.

Many studies have been done in LPR systems using various algorithms. These studies can be classified into two categories, namely traditional

computer vision techniques and deep learning approach. Generally, the pipeline of developing an LPR system in these studies are similar, which consist of three main phases (Abdullah et al., 2017; Ibrahim et al., 2013; Khoshki and Ganesan, 2015; Ng et al., 2015; O'Mahony et al., 2019; Weihong and Jiaoyang, 2020):

1. Plate Localization – to locate the plate position on an image is the initial stage in plate number recognition.
2. Character Segmentation - a process of separating a plate into regions containing letters and numbers.
3. Character Recognition – to convert segments of the plate into digital form (character or number).

The traditional computer vision techniques use image processing techniques to extract the feature or region of interest (ROI) and pre-define them to localize or recognize license plate. The techniques include Morphological Processes, Edge detection, Smearing, Histogram of Oriented Gradients (HOG) feature and Support Vector Machine (SVM). Most of these techniques proposed a pre-processing phase immediately after picture acquisition to downsize and enhance the input image so that it is more suitable for computer processing (Khoshki and Ganesan, 2015; Kumari and Prakash, 2017; Ng et al., 2015).

Deep learning is a subfield of machine learning concerned with algorithms inspired by the brain's structure and function called Artificial Neural Networks (ANN) (Kumari and Prakash, 2017). Deep learning LPR technique could provide a comprehensive solution as in (Agarwal et al., 2018; Gao et al., 2018; Keong and Iranmanesh, 2016; Tejas et al., 2017). For each stage, either a single neural network or a combination of ANNs are employed. There are two types of LPR solutions based on deep learning (Tejas et al., 2017):

- With Segmentation: using the standard three phases pipeline of traditional computer vision techniques.
- Segmentation-free approach: the pipeline consists of plate localization and character recognition without segmentation process.

Recently, there has been a growing interest in utilizing deep learning techniques for LPR, which include Single Shot MultiBox Detector (SSD), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). These techniques can detect objects with high accuracy (Laroca et al., 2018).

2.1 Traditional Vs Deep Learning Techniques

The main difference between the two techniques is that the deep learning technique does not require the features engineering and classification phases in its pipeline. However, most traditional computer vision techniques add a pre-processing phase directly after acquiring the image and before localization (Ng et al., 2015; Gou et al., 2015; Jiang et al., 2018). Furthermore, character segmentation might be skipped in deep learning-based techniques (Weihong and Jiaoyang, 2020) which provide segment-free solution like what is in (Han et al., 2015).

Nevertheless, traditional computer techniques perform well in solving some specific issues faced by the LPR system. However, providing an end-to-end solution requires the use of multiple techniques in each phase together, which affect the overall performance of the system in terms of processing speed and tackling different challenges or scenarios. On the other hand, it has been proven that deep learning techniques are capable of handling different scenarios better than traditional techniques as a unified end-to-end solution.

2.2 You-Only-Look-Once (YOLO)

The object detection algorithm based on deep learning can be divided into two-stage detection algorithm and one-stage detection algorithm. In two-stage algorithm, it first generates a region of proposal, and then target the boundary box and category prediction of the region proposal. The one-stage detection algorithm does not need to select region proposals but use the regression to directly calculate the positioning box and object category, which further reduces the running time. YOLOv4 uses one stage detection algorithm in the detection model. YOLO is an object detection algorithm to detect specific objects from either video or images in real-time.

2.3 Related Studies

Studies on LPR have been done in various countries, where mostly were conducted in China, India and Malaysia (Agarwal et al., 2018a; Agarwal et al., 2018b; Chai et al., 2014; Diop and Ong, 2014; Gao et al., 2018; Ha and Shakeri, 2016; Huang et al., 2021; Ibrahim et al., 2013; Jiang et al., 2018; Joshi and Kulkarni, 2017; Kassentini et al., 2019). Khoshki and Ganesan, 2015; Keong and Iranmanesh, 2016; Laroca et al., 2018; Mahamad et al., 2014; Ng et al., 2015; Omran and Jarallah, 2017; Qadri et al., 2009; Shivakumara et al., 2018; Tejas et al., 2017). The most common issues that were addressed in these

studies include the use of double row license plate numbers, bad weather and lighting effects on the plate numbers, as well as skewed or tilted plate numbers. The issue of the use of non-standard plate numbers was only encountered in some countries like Brazil, China, Malaysia, Tunisia, USA and Europe (Ha and Shakeri, 2016; Huang et al., 2021; Laroca et al., 2018; Masood et al., 2017; Ng et al., 2015; Omran and Jarallah, 2017; Qadri et al., 2009).

However, only Malaysia uses special license plate numbers (Huang et al., 2021) which poses another challenging task for the researchers to come up with an algorithm to recognize such plate numbers. The distance between the camera and car plate number is another biggest challenge in most studies as the captured image may not be clear if the distance is too far. In addition, only a number of studies were carried out to capture real-time images for moving vehicles. In Malaysia, although there have been several studies conducted to address most of the issues mentioned above, there is still little effort aimed at providing real-time license plate number detection involving moving vehicles.

There are numerous deep learning techniques that can be used to detect and recognize license plate numbers, which include CNN, template matching, OCT, HOG features, SVM, Pearson correlation and edge detection (Agarwal et al., 2018a; Agarwal et al., 2018b; Chai et al., 2014; Diop and Ong, 2014; Gao et al., 2018; Ha and Shakeri, 2016; Huang et al., 2021; Ibrahim et al., 2013; Jiang et al., 2018; Joshi and Kulkarni, 2017; Kassentini et al., 2019; Keong and Iranmanesh, 2016; Khoshki and Ganesan, 2015; Laroca et al., 2018; Mahamad et al., 2014; Masood et al., 2017; Ng et al., 2015; Omran and Jarallah, 2017; Qadri et al., 2009; Tejas et al., 2017).

Most of these techniques are capable of providing more than 90% accuracy in image localization. While some of them provide more than 90% accuracy in image recognition. Only a few techniques are capable of image segmentation and almost all of them provide an accuracy of more than 90%. Pearson correlation and edge detection are the two techniques that have the ability to perform image localization, segmentation and recognition, as well as having an accuracy of more than 90% for all processes. Overall, almost all techniques have shown a high success rate in detecting and recognizing license plate numbers.

3.0 RESEARCH METHODOLOGY

The primary activities of this study involved the following stages:

3.1 Stage 1: Data Collection

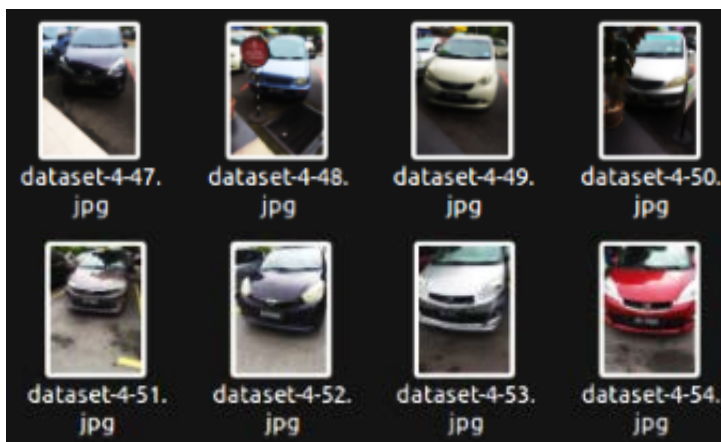
In this stage, a total of 3188 images were collected from various sources, which include the following:

- i. Static images by a camera (High Quality)
- ii. Static images by a mobile phone (Standard Quality)
- iii. Images converted from a video (High and Low Quality).

Figure 1 shows the sample images collected from various locations and conditions.

Figure 1

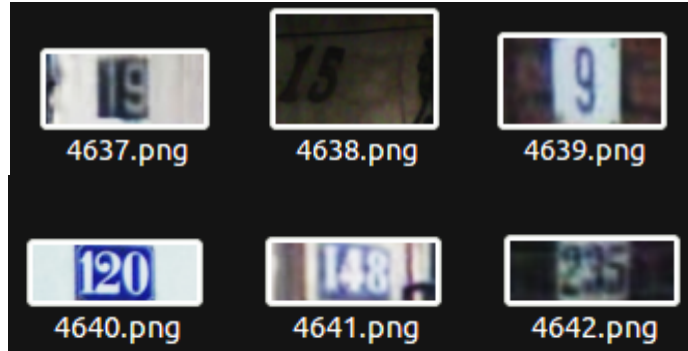
Sample of collected images



The collected data is used to train the neural network to detect and localize the vehicle plate on an image/video frame. Then, another dataset using Text Recognition Data Generation that mimics the content of Malaysian plate numbers is generated for character recognition. Figure 2 shows the dataset that contains 25993 images that covers different parts of plate number such as 1 to 3 characters, 1 to 4 numbers and personalised plates.

Figure 2

Sample of the open-source dataset



Besides, to enhance the characters' recognition, a Generative Adversarial Network (GAN) will generate a plate-like images with unique words and other characters due to the lack of special plate collected images. Special words are the non-standard/special plate characters such as patriot, proton, Malaysia, Putrajaya, etc. GAN network is an algorithmic architecture that uses neural networks to generate new, synthetic data instance with the same characteristic as the actual collected data. They are used widely in an image generation, video generation, and voice generation. GAN will generate more special plates based on the collected set of plates in this context.

3.2 Stage 2: Data Cleaning and Labeling

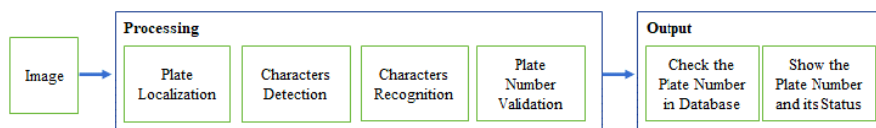
In this stage, the images were filtered to remove unsuitable images such as duplicated or distorted images. A Labelbox cloud service is used to label and classify the images into 4 main categories: namely single-row plate, double-row plate, private-vehicle plate and special word. Although Labelbox provides an excellent tool for data labelling and classification, it does not support exporting labelled data with the Yolo algorithm. Thus, a script to re-arrange the exported data from Labelbox to Yolo data format was developed.

3.3 Stage 3: Detection and Recognition Algorithm.

YoloV5 was used for plate detection and recognition. Multiple iterations of training the algorithm were conducted on the datasets. After each modification of the algorithm parameters such as Epoch, image size and batch size and more data added, the algorithm was retrained and then its performance was tested. Figure 3 shows the steps involved in the plate detection and recognition process. It started with getting real-time data/streams from cameras that are either directly connected to the server or mobile. The data/streams will then go through several processes which include plate localization, characters detection and recognition, and plate number validation. The detected plate number will then be determined to whether it existed in the reported or the blacklisted plate number database. Then, it's status will be displayed on the output screen.

Figure 3

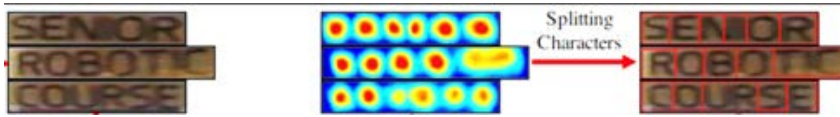
Platform flow



In this study, the Yolo neural network was used for plate localization only. To perform character recognition, another neural network customized for Optical Character Recognition (OCR) was used. This is due to the limitations of Yolo neural network in detecting small objects. In addition to that, Character Region Awareness for Text Detection (CRAFT) was used to detect and segment the characters in the plate, shown in Figure 4. Then, a custom algorithm was created to use a Convolutional Recurrent Neural Network (CRNN) developed by Baoguang Shi, Xiang Bai, Cong Yao for plate recognition. The generated dataset of characters and numbers was used to train the model.

Figure 4

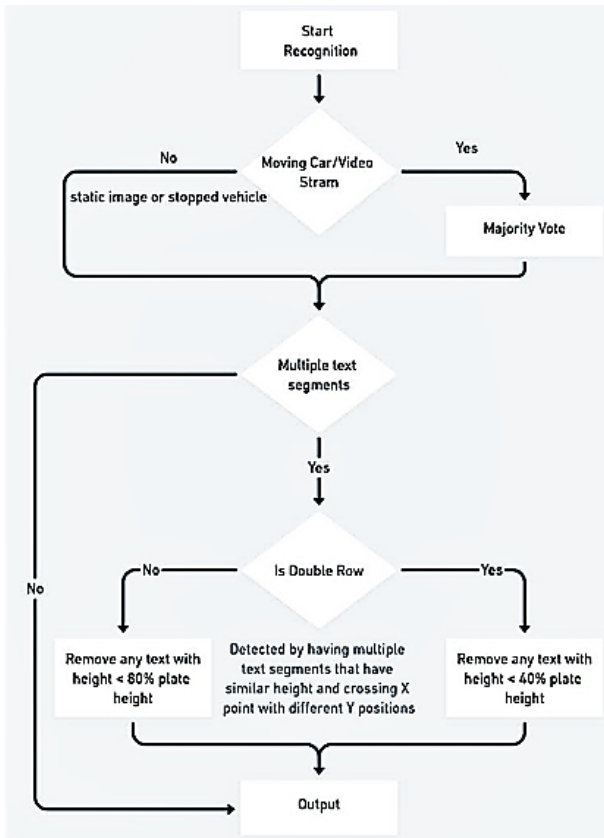
Segmentation using CRAFT



The final step is validating the recognized plate number and removing unwanted texts. To determine whether the plate number is correct or not, the following algorithm has been developed, as depicted in Figure 5.

Figure 5

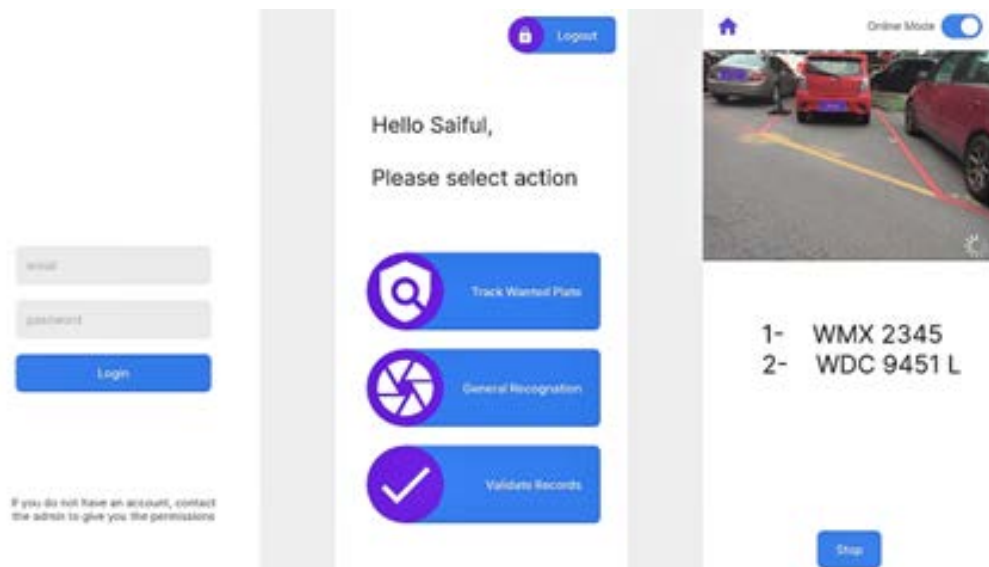
Text noise and plate validation filtration flow



3.4 Stage 4: Mobile App Development

In this stage, a mobile application has been developed using the Ionic framework with firebase to manage the authentication and recognition log, as illustrated in Figure 6. To enable the mobile application to use the proposed recognition algorithm, the server script had been developed in Python using the Bottle framework. The mobile application will send a request that consists of data stream captured by the camera to the endpoint in the processing server. The data stream which includes frames/images will be sent to the processing server as a sequence of HTTP requests. The server will then response with the location and characters of the license plate.

Figure 6
Mobile Application interface



4.0 ANALYSIS AND DISCUSSION

This section discusses the process to train Yolo v5 algorithm using the collected dataset for plate number localization. It also discusses several tests that had been carried out to recognize Malaysian plate numbers.

4.1 Training

In this project, Yolo v5 was employed for plate recognition and detection. In order to assess its performance, the algorithm was retrained using several parameters, including batch size, image size, and epochs. Figures 7 – 9 show the outcomes of the training phase with two main indicators; Precision and Recall;

- Precision: quantifies the number of positive class predictions that are belong to the positive class, or it is the number of instances that are relevant, out of the total instances the model retrieved.

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

For example, there are 100 plates in the testing dataset and if the neural network recognizes 90 of them and identifies 20 other objects as plates, then the network's precision will be 81%.

- Recall: quantifies the number of positive class predictions made of all positive examples in the dataset or to compare the number of instances which the model correctly identified as relevant out of the total relevant instances. For the last example, the recall will be 90% or 0.9.

Figure 7
Experiment 2

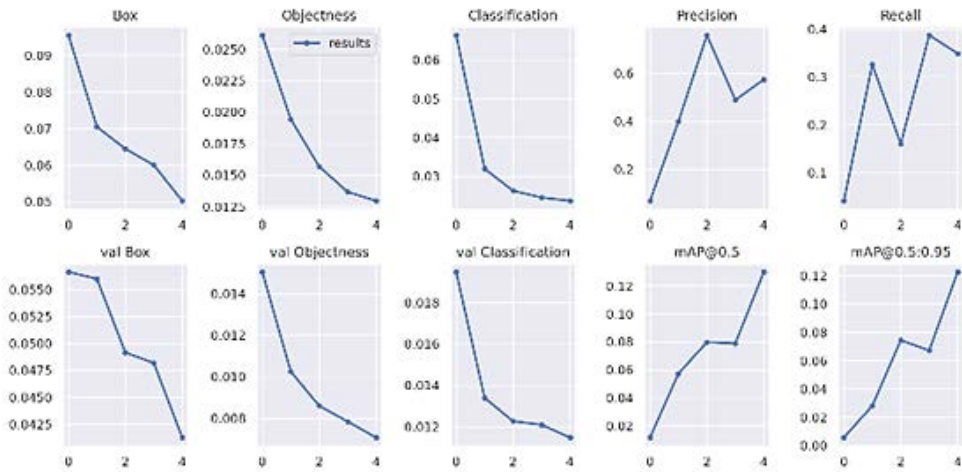


Figure 8:
Experiment 10

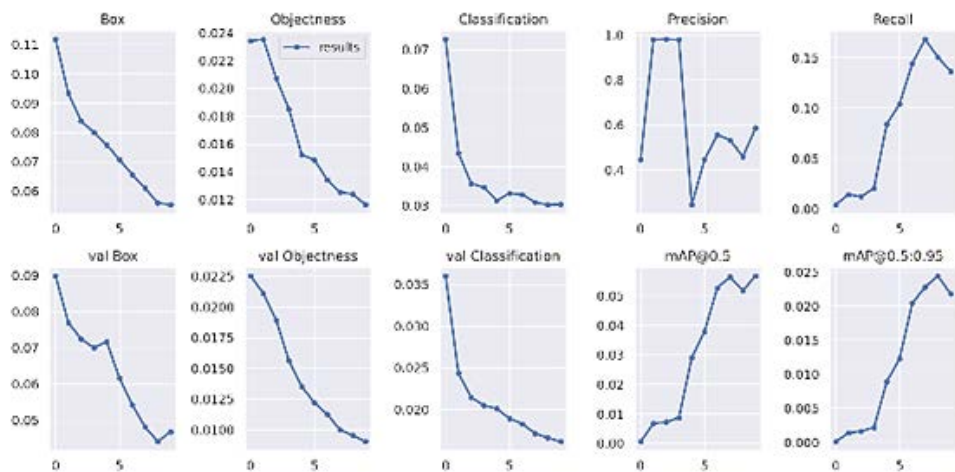
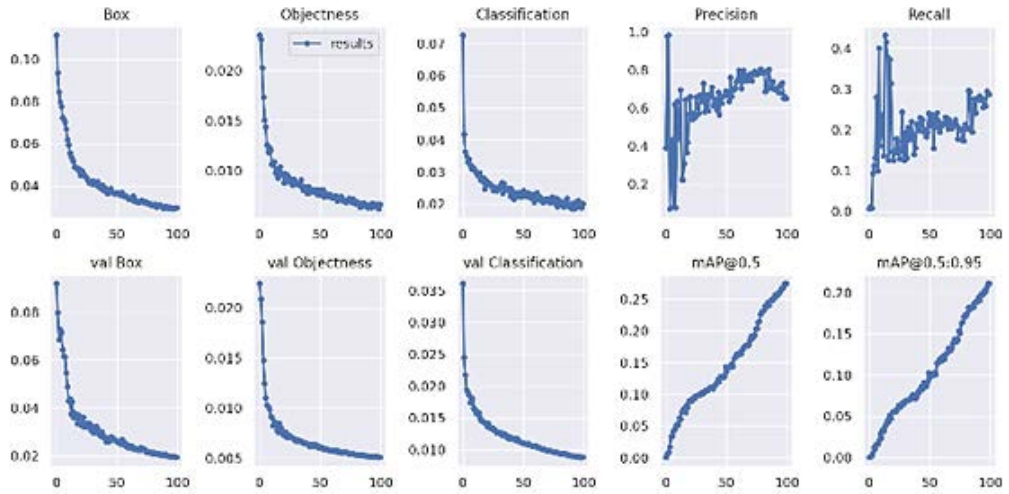


Figure 9
Experiment 35



Several training iterations for the localization neural network were carried out by updating the parameters in each iteration, which include the dataset size, number of epochs, and size of each epoch. Sample results of localization process are shown in Figure 10. The results had shown 0.87 and 0.92 for precision and recall respectively.

Figure 10
Samples of localization testing results



4.2 Plate Recognition

Several tests had been conducted based on processing time, localization confidence and recognition accuracy, as shown in the sample images in Figure 11. The results of the tests had shown an average of 90% overall accuracy in recognizing plate number for moving vehicles.

Figure 11

Sample of Plate Recognition Results



5.0 CONCLUSION

This project had successfully developed a mobile application prototype that can detect and recognize Malaysian license plate numbers in real-time. The proposed LPR aims to facilitate real-time license plate identification by incorporating deep learning algorithm with an emphasis on the recognition of Malaysian license plate number features for the purpose of vehicle surveillance systems.

The improved efficiency of real time LPR systems will provide a significant importance in ITS where it will incorporate advance intelligent system in vehicle surveillance enabling effective implementation of smart technologies in cities and transportation sector. This is aligned with the objective of Malaysian Ministry of Works towards realization of ITS as published in Malaysia ITS Blueprint (2019-2023). The proposed LPR also offers a promising, low-cost, and efficient solution where vehicles can be monitored automatically in real-time to ease surveillance and enforcement activities. Moreover, it can also be employed and further commercialized to many other applications such as entrance admission, road traffic control, speed control and etc.

Henceforth, this research can offer a promising and competitive opportunity to support the newly launched entrepreneurship and educational initiatives by

Majlis Amanah Rakyat (MARA) in Investment Sector Strategic Plan 2021-2025 due to the Covid-19 pandemic. The research knowledge gained and its potential for commercialization can be benefited by MARA to create business opportunities for Bumiputera SME entrepreneurs as well as educational institutes under the support of the programme. In conclusion, this research will bring a huge impact in national socio-economic expansion where transportation infrastructure will be strengthened by improving safety and efficiency of transport operations.

For future work, a web-based application with management dashboard feature will be developed to provide a platform for the LPR user to manage and monitor the system.

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