



AUTOMATIC MALAYSIA LICENSE PLATE RECOGNITION USING DEEP LEARNING



MASTER OF SCIENCE IN ELECTRONIC ENGINEERING

2021



Faculty of Electronics and Computer Engineering

AUTOMATIC MALAYSIA LICENSE PLATE RECOGNITION USING DEEP LEARNING



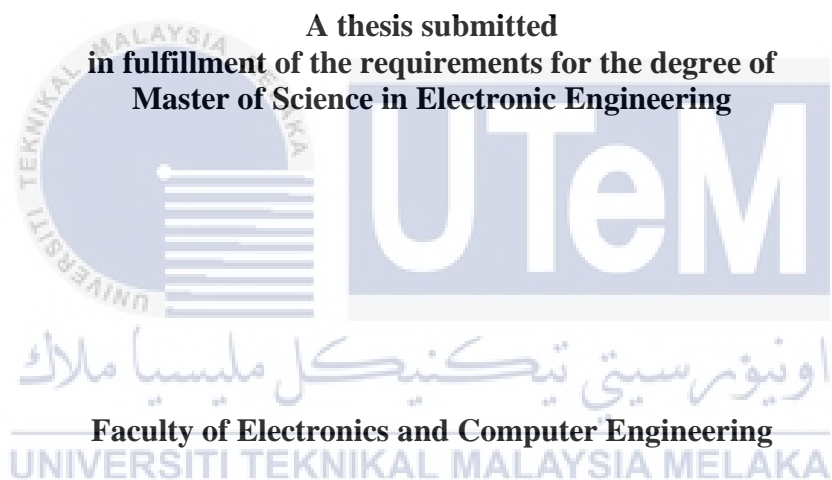
Tay Choon Kiat

Master of Science in Electronic Engineering

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**AUTOMATIC MALAYSIA LICENSE PLATE RECOGNITION USING DEEP
LEARNING**

TAY CHOON KIAT



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2021

DECLARATION

I declare that this thesis entitled “Automatic License Plate Recognition for Malaysia Using Deep Learning” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science in Electronic Engineering.

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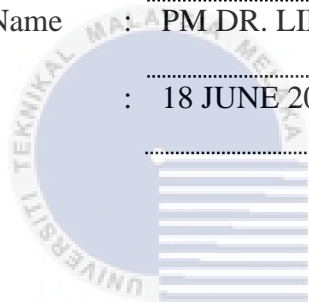
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DEDICATION

To my beloved father and mother



ABSTRACT

Since 2008, Malaysia government has initiated the multi-lane free flow (MLFF) highway plans to improve traffic quality. To support the initiative, a robust license plate recognition system is required to track the highway vehicle passing the toll as MLFF do not have barrier gate to control the vehicle if the driver payment card has insufficient credit. Conventional license plate recognition system uses template matching, a simple image processing technique with manually defined image template to identify target character in the captured license plate images. Template matching based license plate recognition system proven to be useful in many countries where the license plate is issued by relevant authority but not in Malaysia. Correctly recognizing all the characters with various readable font types and spacing on the captured Malaysia license plate image will required deep learning type of technique to reduce the handcrafting of the matching templates/features. The first problem faced in this study was the collected 80,000 Malaysia license plate images suffering from character imbalance (skewed class). To form a good dataset for both training and testing, 297,840 synthetic images were generated, together with 73,000 original images to form the training and validation dataset of 370,840 images (remaining 7,000 images were used for the testing). A deep learning-based end to end segmentation-free character recognition model, Convolutional Recurrent Neural Network (CRNN), was used to train on the 370,840 training images and achieved only 55% of preliminary recognition accuracy. With the proposed image pre-processing of input license plate image, hyper parameters tuning (regularization, LSTM time step optimization) and better decoder, the recognition accuracy of the CRNN model increased to 95%.

اویور سیتی تکنیکل ملیسیا ملاک
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

PENGECAMAN AUTOMATIK PLAT LESEN MALAYSIA MENGGUNAKAN PEMBELAJARAN MENDALAM

ABSTRAK

Sejak tahun 2008, Malaysia sudah berusaha dalam teknologi multi-lan free flow (MLFF) untuk memajukan perkhidmatan lebuh raya. Oleh itu, sistem pengenalan plat kenderaan yang mantap tetap diimplementasikan sebab kenderaan yang tiada cukup kredit tidak akan dikawal dengan pintu gerbang dalam highway MLFF. Pengenal plat kenderaan biasanya dicipta dengan teknik template matching dalam negara-negara yang mengeluarkan plat kenderaan dari pihak kerajaan. Sisyem pengenalan plat kenderaan dengan teknik template matching adalah diiktirafkan berguna dalam pengenalan plat kenderaan negara-negara yang play kenderaannya dibuat oleh pihak penguatkuasa. Untuk mendapat pengenalan yang tepat terhadap pelbagai jenis fon dalam plat yang senang boleh dibaca, teknologi deep learning harus diimplementasikan bagi mengurangkan kerja menghasilkan berbagai-bagai template. Masalah pertama dalam penyelidikan ini adalah 80,000 gambar plat yang ditutip dari kamera lebuh raya adalah tidak seimbang dalam segi jumlah nombor dan huruf (skewed class). Sejumlah 297,840 plat kenderaan sintetik telah dicipta dan ditambah dengan 73,000 plat kenderaan dari kutipan untuk menjadi training dataset dan validation dataset berjumlah 370,840 gambar plat. Ini adalah untuk mencapai kumpulan data yang seimbang. Selain itu, 7,000 plat kenderaan dari kutipan dijadikan testing dataset. Convolutional Recurrent Neural Network (CRNN) merupakan algoritma pembelajaran dalam yang digunakan dalam pengenalan huruf dan nombor dengan teknik tanpa pembahagian. Keputusan awal dengan CRNN asli hanya mencapai 55% ketepatan pengenalan. Namun, dengan cadangan prapemprosesan gambar plat, penyelarasan parameters hiper (regularization, LSTM time step optimization) dan menggunakan penyahkod yang lebih teguh, ketepatan pengenalan telah dimajukan kepada 95%.

ACKNOWLEDGEMENTS

Academic research is a long-haul marathon, and I am not the only one feeling that way. I am glad it will soon be over upon my successful completion of this thesis.

I would like to thank all the people around me, especially my family and girlfriend when I almost gave in and walk away. They were always there for me, and I am lucky to be blessed by all their unconditional support and unfailing love throughout the two years of my research work. Deep in me, I did not have any doubt and fear that I could go all out to completion.

To Recogine Technology, the company I work for, I would like to express my gratitude for giving me the opportunity to showcase a discovery that the Malaysia made license plate recognition system can be at par and compete in world class competition. I have learnt a lot, both in academic research on license plate recognition and practical implementation of the whole recognition system while working with Recogine Technology. The learning that I had acquired truly enlightened me. Not forgetting to mention, my Recogine Technology colleague who been with me through good and hard time in delivering project expectations, never leaving the challenges alone to me. Thank you for all the advice and guidance in time of need.

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LIST OF SYMBOLS AND ABBREVIATIONS

OCR	-	Optical Character Recognition
CCTV	-	Closed-Circuit Television
LSTM	-	Long Short-Term Memory
MLFF	-	Multi-Lane Free Flow
RFID	-	Radio-Frequency Identification
JPJ	-	Jabatan Pengangkutan Jalan
KLIA	-	Kuala Lumpur International Airport
ALPR	-	Automatic License Plate Recognition
ETC	-	Electronic Toll Collection
SLFF	-	Single Lane Free Flow
MLFF	-	Multi Lane Free Flow
OBU	-	On Board Unit
LLM	-	Malaysian Association of Highway Concession Companies
CNN	-	Convolutional Neural Network
HOG	-	Histogram of Gradient
SVM	-	Support Vector Machine
NMS	-	Non-Maximum Suppression
RLSA	-	Run Length Smoothing Algorithm
CTC	-	Connectionist Temporal Classification
ANN	-	Artificial neural network
ReLU	-	Rectified Linear Unit
RNN	-	Recurrent Neural Network
LM	-	Language Model
RAM	-	Random Access Memory
CRNN	-	Convolutional Recurrent Neural Network
RGB	-	Red, Green, Blue
ROI	-	Region-of-Interest
CPU	-	Central Processing Unit
GPU	-	Graphics Processing Unit

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LIST OF PUBLICATIONS

Journal with Impact Factor

Tay, C.K. and Lim, K.C., 2020 A Deep Neural Network for Automatic License Plate Recognition with Hyperparameters Study and Regularization, *International Journal of Advanced Science and Technology*, 29(04), 11275-11284.



CHAPTER 1

INTRODUCTION

1.1 Introduction

The first Malaysia license plate issued was upon the introduction of motor vehicles in early 1940s, during the colonial British Malaya. The format of license plate had never gone through any significant changes since its introduction. However, the fonts and the material used have been changed according to the needs of every era. As time goes by, license plate variants came to the fore such as to commemorate certain events like the Commonwealth games in 1998 and also the introduction of special units like the Federal and military license plates. With the traffic volume in major cities increasing exponentially over the years, conventional toll collection system can hardly sustain a smooth traffic flow on the highways. In developed countries such as Australia, Singapore and Taiwan, they have implemented multi-lane free flow (MLFF) toll collection on their highways. Waiting time by highway users in toll collection has been greatly reduced as a result of implementing the MLFF.

Since 2008, the Malaysia government had worked closely with the highway concessionaires to work on the multi-lane free flow system, but had been delayed due to immature technologies in certain areas. Today, with the introduction of RFID, a good backbone infrastructure, the implementation of multi-lane free flow highway is to be soon realized. License plate recognition system is an essential module to complement multi-lane free flow toll collection. To avoid any monetary loss of highway operators from

irresponsible highway users, license plate recognition can act as a record for law enforcement to act on these drivers. However, current license plate recognition system is yet to be foolproof, therefore this research is aimed to improve the current license plate recognition system.

1.2 Multi-Lane Free Flow

1.2.1 Multi-Lane Free Flow in Other Countries

Far Eastern Electronic Toll Collection (2014) implemented Multi-Lane Free Flow in Taiwan expressway since 2014. The implementation consists of 5 main modules which are detection module, deduction module, audit module and enforcement module. The system requires expressway users to install an RFID tag that linked to a virtual account for ETC system to charge the users. Overall design of the system illustrated in figure 1.1. The system operation starts from the detection module identified coming vehicle and it triggers deduction module to send signals to the RFID tag on the vehicle. The credit will be deducted from user's virtual account when the deduction module transmitter received the response from the RFID tag. The enforcement module records front view image of the vehicles while the audit module records rear view image of the vehicles. Recorded front and rear-view image of the vehicles will be used for license plate recognition. Far Eastern Electronic Toll Collection used a parallel recognition mechanism and character pattern recognition to achieve automatic license plate recognition.

Singapore's Electronic Road Pricing system (2011) is an ETC scheme deployed to manage traffic in certain arterial road with heavy traffic. The ETC design is like MLFF toll collection system by Far Eastern Electronic Toll Collection, Taiwan which is illustrated in figure 1.1. The major difference between the two systems is the device on user's end.

Electronic Road Pricing system's users are required to install In-vehicle (IU) device to their vehicles to complete the toll collection payment. The In-vehicle device will receive the payment instruction from toll gantry and deduct from the users' cash card that attached to the device. The cameras equipped in this system have the license plate recognition capability to identify the vehicles passed by the gantry. Penalty will be issued to the road user if the cash card has insufficient credit.

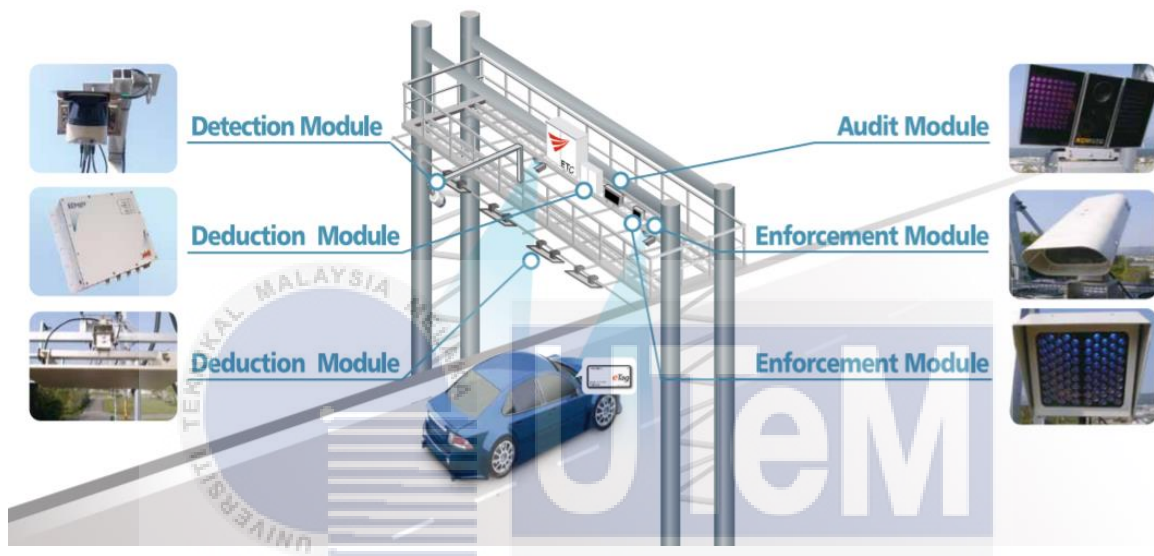


Figure 1.1: Far Eastern Electronic Toll Collection (2014) Multi-Lane Free Flow with RFID ETC

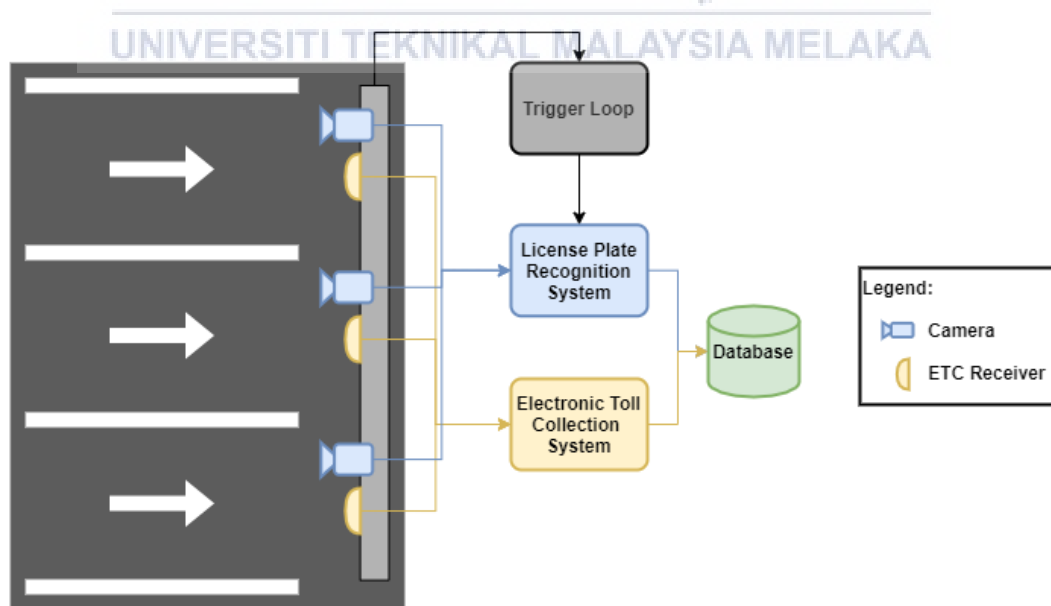


Figure 1.2: Backend system of Multi-Lane Free Flow

1.2.2 Multi-Lane Free Flow in Malaysia

Electronic toll collection (ETC) on the highways can be classified into 2 categories: the stop-and-go and the free-flow. Stop-and-go is the most conventional ETC system which highway users are stopped by a closed barrier gate, upon which the gate will open after the toll payment is done. Single-lane free flow (SLFF) system is similar to gated system where the lane separation islands are setup that guide highway users into the specific lane for radio-frequency identification (RFID) payment. SLFF systems do not have any gated structure, instead a RFID reader is mounted on top of the toll to detect that payment is done through a centralized cashless gateway while a highway user drives through. However, multi-lane free flow (MLFF) is different as it allows high speed traffic free flow without any guidance to the lane. MLFF will serve the purpose of reducing traffic jam caused by previous toll collection systems. It is anticipated that MLFF will overcome the necessity of having to slow down the vehicles for lane queuing with the gate open-close system and SLFF which generate unnecessary delay and traffic jam especially during high volume traffic. As of today while this report is being written, Malaysia highway authority has yet to implement the multi-lane free flow toll collection system in the country.

The Malaysian Association of Highway Concession Companies (LLM) targets to have all highways across Malaysia to adopt the MLFF system within the next three years. RFID ETC is the feature used as an early preparation for such transition. One of the present challenges faced by the highway concessionaires in implementing the MLFF is the vehicle identification on RFID tag that matches with the real vehicle that is driven on the highway. Therefore, a robust and fast license plate recognition system is necessary in order

to recognize the vehicle license plate and to match the information with the captured RFID information in every ETC transaction.

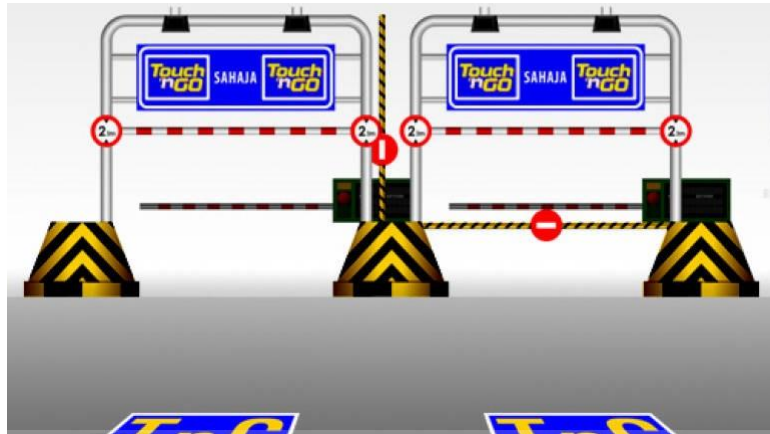


Figure 1.3: Malaysia stop-and-go electronic toll collection system

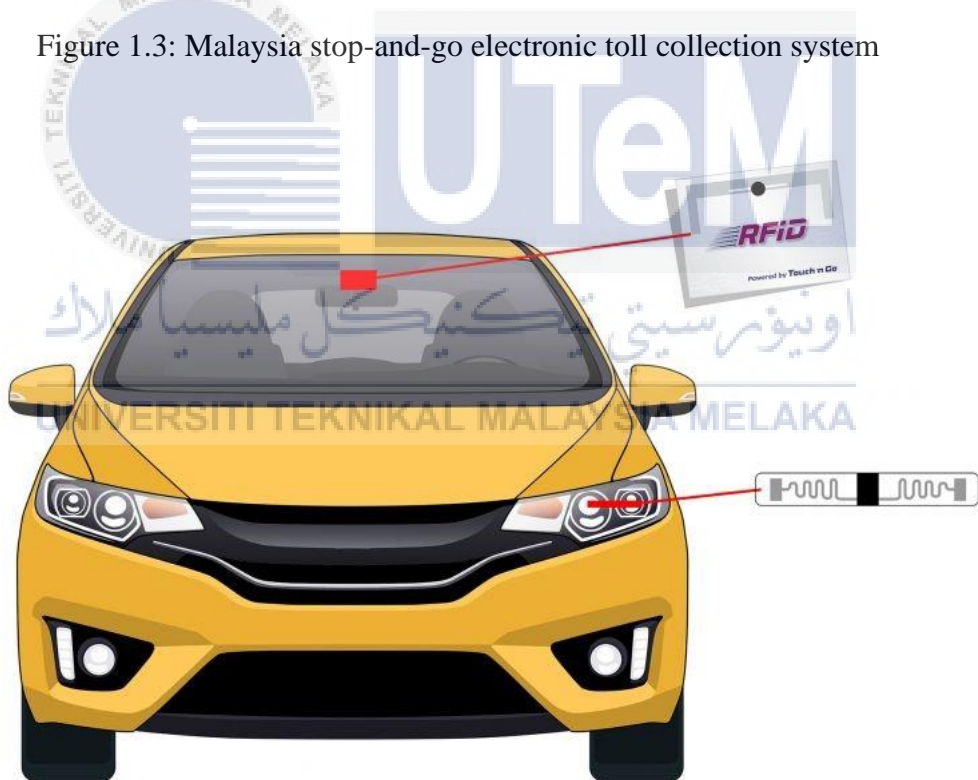


Figure 1.4: Malaysia RFID tag for electronic toll collection system