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Malaysian Vanity License Plate Recognition Using Convolutional Neural Network

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Abstract. Convolutional Neural Network (CNN) is used to train a Malaysian vanity license plate recognition model to recognize vanity license plate available in Malaysia. A transfer learning method is applied in this project to train the model. The type of transfer learning used is finetuning. A modified pretrained ResNet18 network architecture is used to train the Malaysian vanity license plate recognition model. Some hyperparameters such as batch size, learning rate, step size, gamma and momentum are set before training. The optimizer used in this project is SGD (Stochastic Gradient Descent). The available Malaysian vanity license plate images provided by Tapway Sdn Bhd consist of 3 types of Malaysian vanity license plates, which are MALAYSIA, PUTRAJAYA and NORMAL LP (known as Normal License plate). All the images are randomly split into training set (70 % of the total images), validation set (20 % of the total images), and testing set (10 % of the total images) for training. After that, the images are cropped, normalized and transformed into tensors for training. The training is carried out for 70 epochs. Both models trained from original and modified pretrained ResNet18 network architectures are compared and discussed. The accuracy for both models of Malaysian vanity license plate recognition models is 92%. Both training models using the original ResNet18 and modified ResNet18 network architecture approach can be used to train the Malaysian vanity license plate recognition model and obtain similar results.

Keywords: Convolutional neural network; Malaysian vanity license plate recognition; Resnet18

1. Introduction

In Malaysia, it is mandatory for every car to have a car license plate. The purpose of having a car license plate for every car is to identify the cars in Malaysia. Malaysian license plates can be categorized into two types, which are Normal License Plates and Vanity License Plates. Normal License Plates are car license plates that contain uppercase letters in a particular format of letters and digits as per the state code. Vanity License Plates are special car number plates that need authorized permission by the Malaysian government before making the plates available to the public. Examples of vanity license plates include SUKOM, 1M4U, PATRIOT, and G1M.

Deep Learning is a branch of machine learning dealing with artificial neural networks, which are algorithms inspired by the function and structure of the brain (Brownlee, 2019). There are many types of deep learning applications that can bring convenient to the human, such as designing offline Arabic handwritten isolated character recognition system using

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artificial neural network approach written by (Abdalkafor, 2017) and developing a model of toll road service quality using an artificial neural network approach written by (Zuna et al., 2016). Deep learning architectures like Convolutional Neural Network (CNN) are gaining popularity in real-world applications (Shaheen et al., 2016). The major reason for deep learning becoming famous is because it can automatically extract and categorize features, eliminating the need for manual feature extraction and selection. Under deep learning, there is a technique called transfer learning which is first trained on a problem similar to the one being solved. Subsequently, the layers of the trained model are then utilized in a new model that is trained on the problem of interest. There are several benefits of using transfer learning method to train a model, such as higher learning rate, faster training, better initial model, and higher accuracy after training (W. by C. Dilmegani, 2020).

There are many different types of vanity license plates in Malaysia. Therefore, it is important to have a vanity car license plate classifier to recognize as well as characterizing the different vanity license plates in Malaysia. The recognition model to recognize the different vanity license plates in Malaysia can be used on applications such as fraud detection, toll plaza, and smart city.

2. Methods

CNN network architecture is chosen to be used in this project because of its in-built convolutional layer which decreases the high dimensionality of images with no loss of information (Lang, 2021). Moreover, CNN perform better in character recognition compared to traditional character recognition methods (Elhadi et al., 2019) such as Template Matching Kashyap et al., 2018) and Histogram Equalization (Pangestu et al., 2017). Transfer learning method is applied in this project to train the Malaysian vanity license plate recognition model. The type of transfer learning used is finetuning. In finetuning, a pretrained network is selected, and the whole model is retrained to update all the model's parameters according to the dataset provided (Inkawhich, 2022).

An original pretrained Resnet18 network architecture and a modified pretrained Resnet18 network are discussed and used to train the Malaysian vanity license plate recognition model. The number of output classification classes for both models are changed to match the number of Malaysian vanity license plate types available in this project so that the models can recognize the available Malaysian vanity license plate in this project. The training and dataset setup for the model are discussed. The design flow for this project is shown in Figure 1.

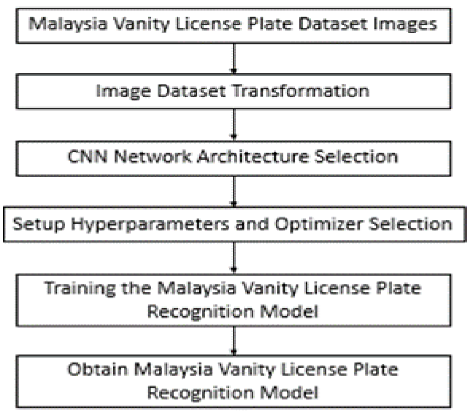


Figure 1 Design Flow

Firstly, a dataset of Malaysian vanity license plate images is obtained, and then some transformation is performed on the images to make them suitable for training. Next, a CNN network architecture is selected for training the Malaysian vanity license plate recognition model. After that, the network architecture hyperparameters are configured and an optimizer is selected for training. Furthermore, the classification model training is performed. Then, the Malaysian vanity license plate recognition model is obtained.

2.1. Modified ResNet18

An original ResNet18 pretrained network architecture is selected to be modified for training the Malaysian vanity license plate recognition model in this project. The ResNet18 is pretrained on the ImageNet dataset that has 1000 categories (Resnet.Py, 2022). A nonlinear activation function and a dropout function have been added to the fully connected layer of the ResNet18 pretrained network. Figure 2 shows a diagram of the modified ResNet18 network architecture. The diagram is constructed by referring to (He et al., 2016) from their 34-layer residual network architecture diagram for ImageNet.

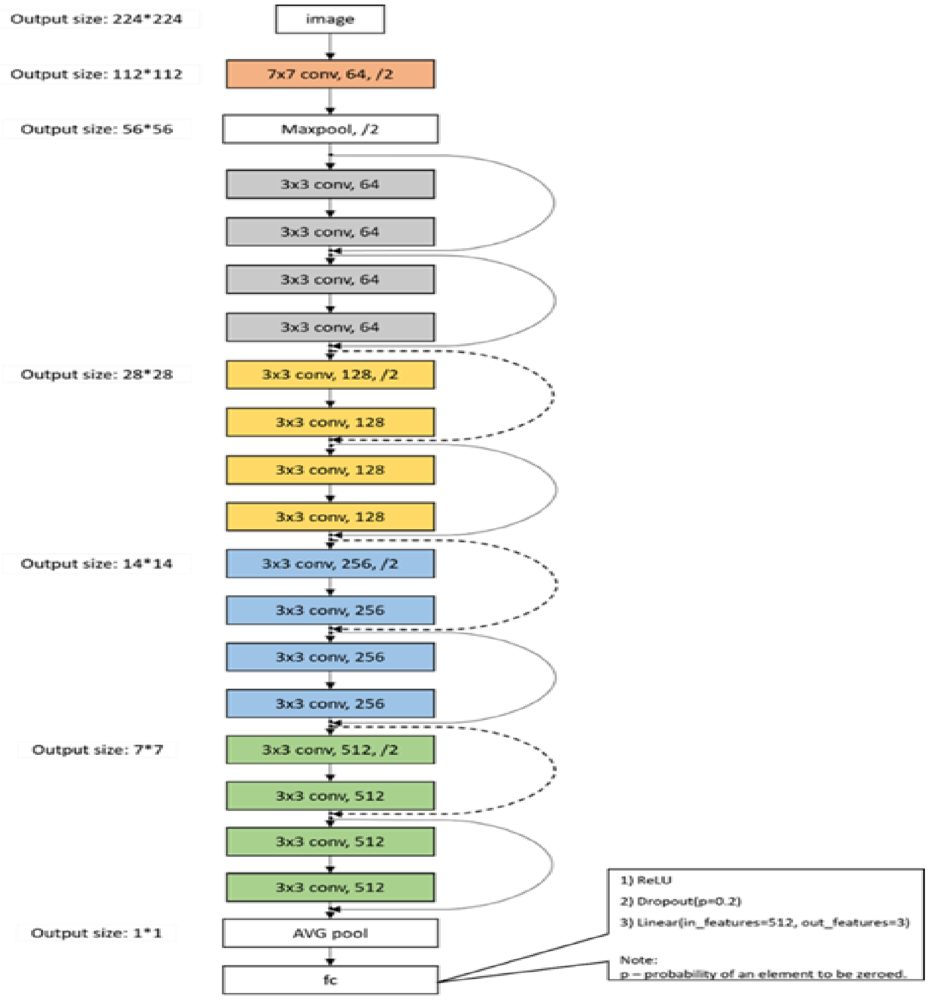


Figure 2 Modified ResNet18 Network Architecture

Nonlinear activation functions can allow the network to learn more complex data (Alzubaidi et al., 2021). ReLU (Rectified Linear Activation Function) is one of the nonlinear activation functions. ReLU is frequently used in CNN. In addition, the advantage of ReLU over the other functions is it consumes lower computational load.

Dropout is a commonly used method for generalization (Alzubaidi et al., 2021). Neurons are randomly dropped in each training epoch. Therefore, the model is forced to learn different independent features and the feature selection power is allocated equally to all the neurons. The dropped neuron will not involve in forward-propagation or back-propagation during training. However, the full-scale network is used to carry out a prediction in the testing process.

2.2. Optimizer and Hyperparameters

The optimizer used in this project is SGD (Stochastic Gradient Descent). SGD is a gradient descent algorithm that allows the parameters of the model to be updated on every training sample (Alzubaidi et al., 2021). This algorithm is faster and more memory effective compared to BGD (Batch Gradient Descent) for a big-sized training dataset.

There are several hyperparameters being set before training the Malaysian vanity license plate recognition model, such as batch size, learning rate, step size, gamma, and momentum. The learning rate is the parameter update step size (Alzubaidi et al., 2021) and it is set to 0.005. Momentum is a method that improves the training speed and accuracy by totalling up the calculated gradient at the previous step (Alzubaidi et al., 2021). The momentum is set to 0.9 for the training (Bushaev, 2017). A learning rate scheduler called lr_scheduler.StepLR is used. It decays the learning rate of each parameter group by gamma every step_size epochs. Step size is the period of learning rate decay and it is set to 10. Gamma is the multiplicative factor of learning rate decay and it is set to 0.7 for the training. Batch size indicates the number of training samples used in an epoch (Murphy, 2017). Some training experiments have been conducted using small batch sizes such as 4, 8, 16, and 32 to get a suitable batch size value. After conducting the experiments, the number of batch size chosen in training is 32 because the loss plot of the training using the batch size of 32 gives the least fluctuations in training loss over epochs. A very small batch size value is not suitable to be used in training as it may cause fluctuations in training loss over epochs (Hameed, 2021).

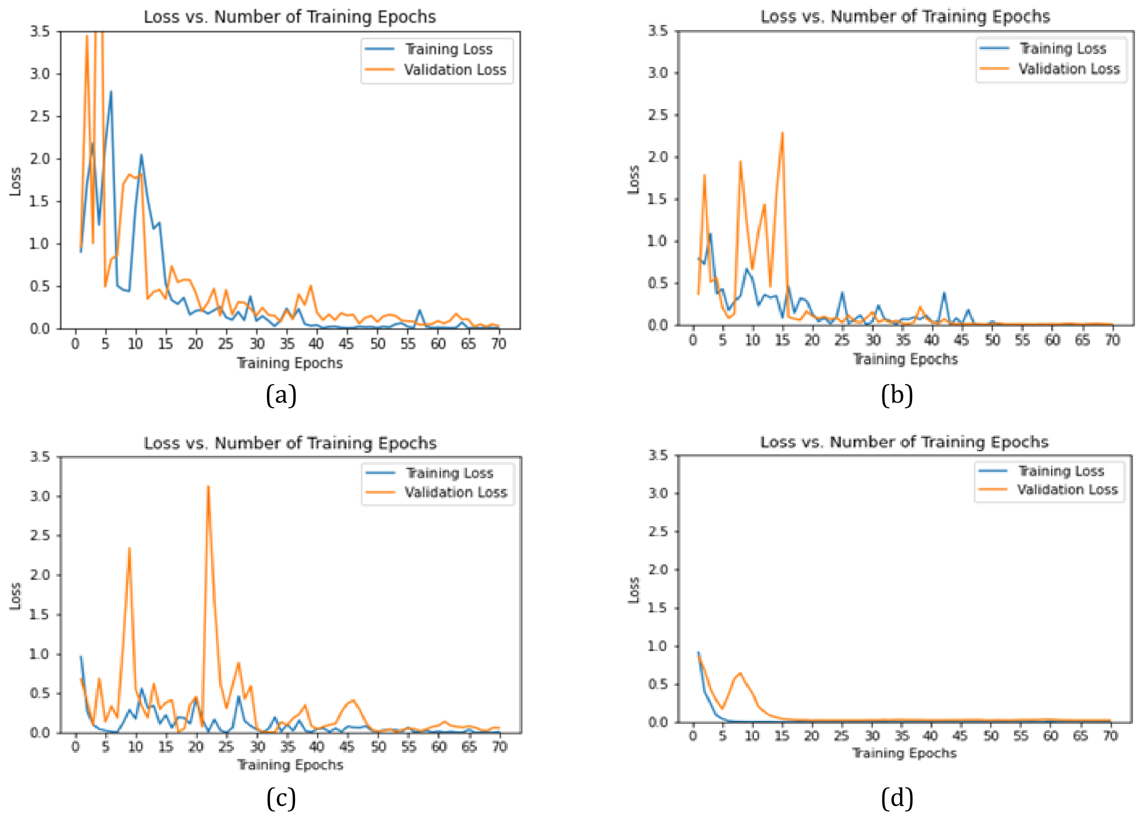


Figure 3 Loss plot obtained with: (a) Batch Size of 4; (b) Batch Size of 8; (c) Batch Size of 16; and (d) Batch Size of 32

Table 1 Summary of optimizer and hyperparameters

Optimizer	Learning Rate	Step Size	Gamma	Momentum	Batch Size
SGD	0.005	10	0.7	0.9	32

2.3. Training

Google Colab is a web IDE for python programming, and it has a free version for everyone to use it. The free version of Google Colab is used in this project to do the coding and training. Pytorch framework is used to do the training, applying, and modifying the pretrained ResNet18 network architecture. The original ResNet18 and modified ResNet18 network architecture will be used to train the Malaysian vanity license plate recognition model. The training for both models is carried out for 70 epochs. The optimizer and hyperparameters will be configured for the training.

Repetitive training of 10 times or more is performed on the same training setup for both original and modified ResNet18 pretrained network architecture to obtain the best model based on the results after training.

2.4. Dataset Setup

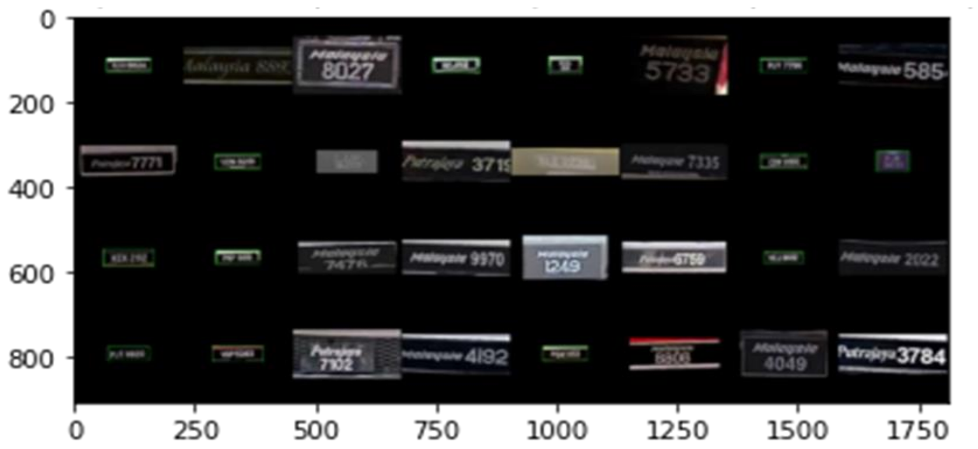
In this project, three types of Malaysian vanity license plates have been selected to be used in training the Malaysian vanity license plates recognition model and they include MALAYSIA, PUTRAJAYA, and NORMAL LP (known as Normal License plate). The vanity license plate dataset images are supplied by Tapway Sdn Bhd for training the Malaysian vanity license plate recognition model in this project. A total of 119 images is used as the vanity license plate dataset images. There are a total of 38 images for vanity license plate type MALAYSIA, a total of 21 images for vanity license plate type PUTRAJAYA and a total of 60 images for normal license plates. There are 44 clear normal license plate images and 16 blur normal license plate images within the normal license plate images.

All the images are then randomly split into training set (70 % of the total images), validation set (20 % of the total images), and testing set (10 % of the total images) for training. The summary of the Malaysian vanity license plate image dataset distribution is shown in Table 2.

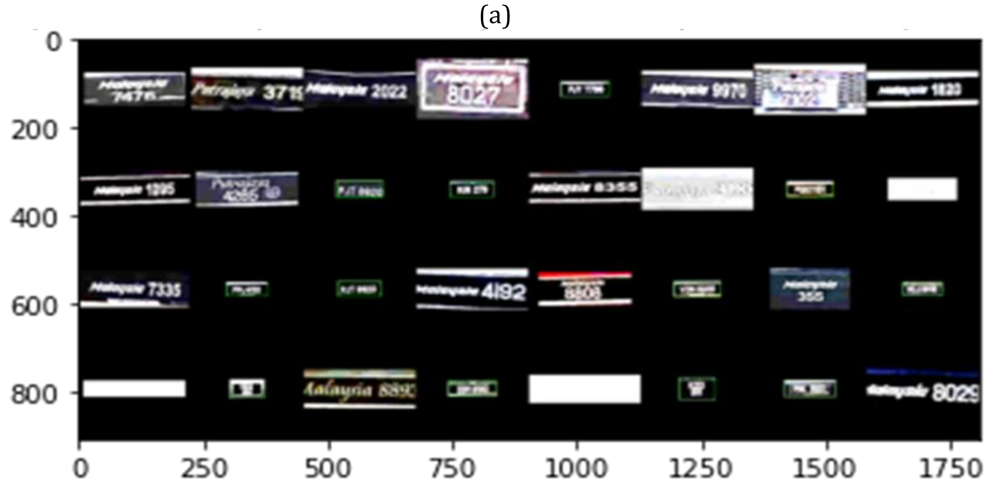
Table 2 Summary of Malaysia vanity license plate image dataset distribution

<table>
<tr><th>Dataset</th><th colspan="2">Total Images</th><th>Train (70%)</th><th>Val (20%)</th><th>Test (10%)</th></tr>
<tr><td>MALAYSIA</td><td colspan="2">38</td><td>26</td><td>8</td><td>4</td></tr>
<tr><td>PUTRAJAYA</td><td colspan="2">21</td><td>15</td><td>4</td><td>2</td></tr>
<tr><td rowspan="2">NORMAL LP</td><td colspan="2">60</td><td>42</td><td>12</td><td>6</td></tr>
<tr><td>Clear images: 44</td><td>Blur images: 16</td><td>Clear images + Blur images 31+11=42</td><td>Clear images + Blur images 9+3=12</td><td>Clear images + Blur images 4+2=6</td></tr>
</table>

After splitting the images into training set, validation set and testing set, all the images undergo transformation. Firstly, the images are center cropped to become a size of 224*224 because the Resnet18 pretrained network architecture accepts the input size of 224*224. Figure 4 (a) shows a batch of example images from the training dataset that has been center cropped. Next, the images are then transformed into tensors. After that, the images are normalized before training so that learning can speed up and leads to faster convergence (Stöttner, 2019). Figure 4 (b) shows a batch of example images from the training dataset that has been center cropped and normalized.



(a)



(b)

Figure 4 A batch of example images from the training dataset that have been: (a) Center Cropped; and (b) Center Cropped and Normalized

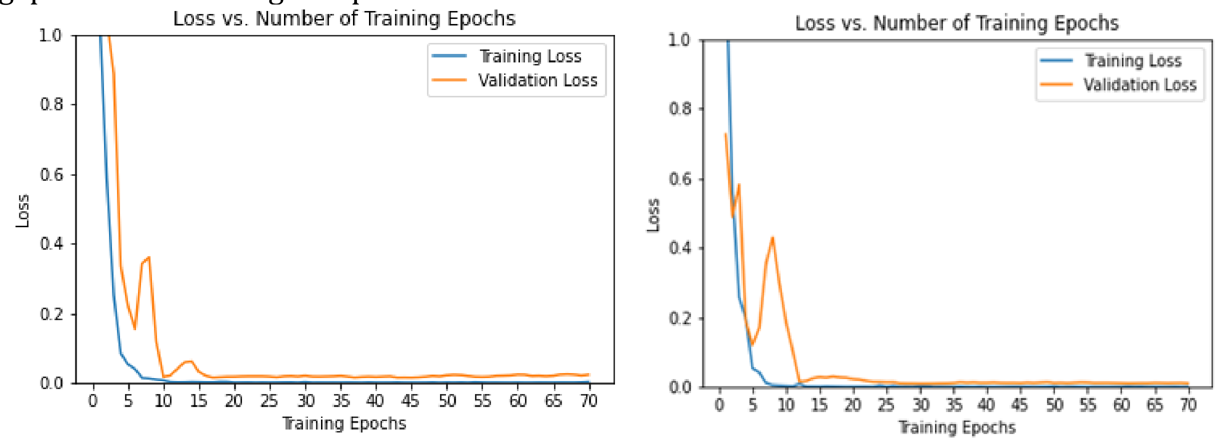
3. Results and Discussion

After running 70 epochs to train the Malaysian vanity license plate recognition model using both the original ResNet18 and modified ResNet18 networks, the loss plots of both models are obtained. The testing dataset is used to obtain the confusion matrix and classification reports of both models. The loss plot, confusion matrix and classification report are obtained to view the performance of the models. The training dataset accuracies for both the models are 100%.

3.1. Loss Plot

The loss plot of training Malaysian vanity license plate recognition model using original pretrained ResNet18 network architecture is obtained and shown in Figure 5 (a). The blue line represents the training loss plotting in which it decreases and then reaches a point of stability smoothly. The orange line represents the validation loss plotting and it fluctuates at the beginning of the training and then decreases until it reaches a point of stability smoothly. The gap between both losses is small after the 20th epoch. The obtained loss plot is an optimal fitting loss plot.

The loss plot of training Malaysian vanity license plate recognition model using modified pretrained ResNet18 network architecture is obtained and shown in Figure 5(b). The training loss plotting decreases and then reaches a point of stability smoothly. The validation loss plotting fluctuates at the beginning of the training and then decreases until it reaches a point of stability smoothly. The gap between both losses is small after the 25th epoch. The obtained loss plot is an optimal fitting loss plot. Optimal fitting is identified in Figure 5(b) when the training loss plot reduces until it reaches a point of stability. In addition, the validation loss plot reduces until it reaches a point of stability and has a tiny gap with the training loss plot.



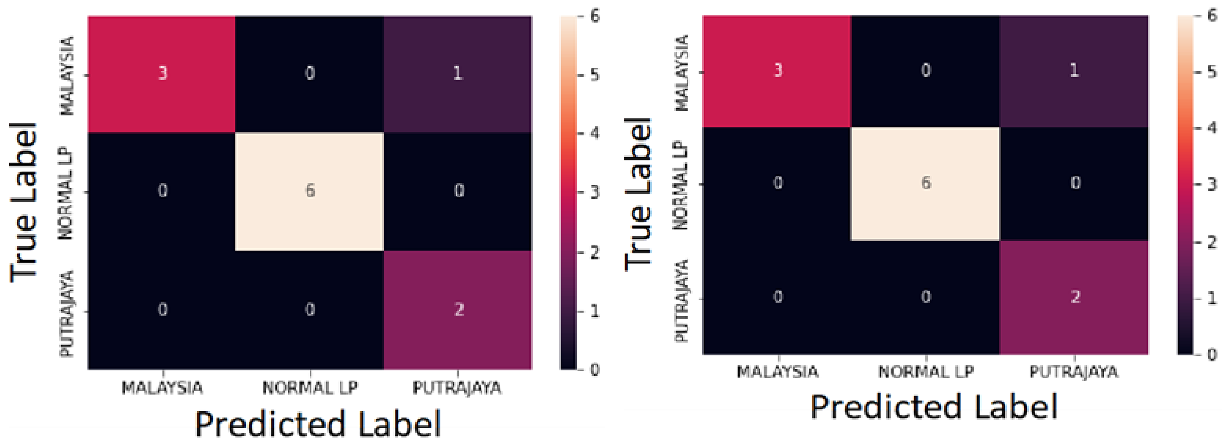
(a) (b)

Figure 5 Loss plot of the trained model using: (a) Original pretrained ResNet18 network architecture; and (b) Modified pretrained ResNet18 network architecture

The gap between the training loss plot and validation loss plot after they reach a point of stability is smaller for the loss plot of training Malaysian vanity license plate recognition model using modified pretrained ResNet18 network architecture compared to the loss plot of training Malaysian vanity license plate recognition model using original pretrained ResNet18 network architecture.

3.2. Confusion Matrix

The Malaysian vanity license plate recognition model is trained using three different Malaysian vanity license plates datasets which are MALAYSIA, PUTRAJAYA, and NORMAL LP (known as Normal License plate), so a 3-class classification confusion matrix has been obtained where the classes represent the different Malaysian vanity license plates type. The 3-class classification confusion matrix of the model can be obtained by using the confusion matrix function from sklearn library (Scikit-learn, 2022a). The 3-class classification confusion matrix of the trained Malaysian vanity license plate recognition model using both network architectures is shown in Figure 6.



(a) (b)

Figure 6 Confusion Matrix of the trained model using: (a) Original pretrained ResNet18; and (b) Modified pretrained ResNet18

The TP, TN, FP, and FN values for all the classes for the trained Malaysian vanity license plate recognition model using original pretrained ResNet18 network architecture are summarized in Table 3.

Table 3 TP, TN, FP, and FN values of all the classes of the trained model using original pretrained ResNet18 network architecture

Malaysia Vanity License Plate	TP	TN	FP	FN
MALAYSIA	3	8	0	1
NORMAL LP	6	6	0	0
PUTRAJAYA	2	9	1	0

The TP, TN, FP, and FN values for all the classes for the trained Malaysian vanity license plate recognition model using modified pretrained ResNet18 network architecture are summarized in Table 4. The obtained Confusion Matrix for trained Malaysian vanity license plate recognition model using original pretrained ResNet18 network architecture and modified pretrained ResNet18 network architecture are the same. The TP, TN, FP, and FN values of all the classes for both of the models are the same.

Table 4 TP, TN, FP, and FN values of all the classes of the trained model using modified pretrained ResNet18 network architecture

Malaysia Vanity License Plate	TP	TN	FP	FN
Malaysia	3	8	0	1
Normal Lp	6	6	0	0
Putrajaya	2	9	1	0

3.3. *Classification Report*

Classification report consists of precision, recall, f1-score, and support for all the classes. The classification report also has accuracy, macro average, and weight average of the trained Malaysian vanity license plate recognition model. Classification report of the model can be obtained by using classification report function from sklearn library (Scikit-learn, 2022b). The testing dataset is used in the classification report function to obtain the classification report for the model.

Precision computes the positive class that is accurately predicted by all predicted classes in a positive class (Alzubaidi et al., 2021). The mathematical representation of precision is in Equation 1.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall computes the ratio of positive classes that are accurately classified (Alzubaidi et al., 2021). The mathematical representation of recall is in Equation 2.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

The f1-score computes the harmonic average of the recall-to-precision ratio (Alzubaidi et al., 2021). The mathematical representation of f1-score is in Equation 3.

$$f1 \text{ score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

Support indicates the number of testing images for a class inside the testing dataset.

Accuracy computes the ratio of accurately predicted classes to the total number of samples evaluated (Alzubaidi et al., 2021). The mathematical representation of accuracy is in Equation 4.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The macro average can be obtained by averaging the unweighted mean per class (Scikit-learn, 2022a). In addition, the weighted average is obtained by averaging the support-weighted mean per class.

The classification report of the trained Malaysian vanity license plate recognition model using original pretrained ResNet18 network architecture and modified pretrained ResNet18 network architecture is obtained by using the classification report function in sklearn library. The classification report is shown in Figure 7. The obtained Classification Report for trained Malaysian vanity license plate recognition model using original pretrained ResNet18 network architecture and modified pretrained ResNet18 network architecture is the same. The accuracy for both models is the same, which is 92%.

Table 5 Classification Report of the trained model using: (a) Original pretrained ResNet18; and (b) Modified pretrained ResNet18

	precision	recall	f1-score	support
MALAYSIA	1.00	0.75	0.86	4
NORMAL LP	1.00	1.00	1.00	6
PUTRAJAYA	0.67	1.00	0.80	2
accuracy			0.92	12
macro avg	0.89	0.92	0.89	12
weighted avg	0.94	0.92	0.92	12

(a)

	precision	recall	f1-score	support
MALAYSIA	1.00	0.75	0.86	4
NORMAL LP	1.00	1.00	1.00	6
PUTRAJAYA	0.67	1.00	0.80	2
accuracy			0.92	12
macro avg	0.89	0.92	0.89	12
weighted avg	0.94	0.92	0.92	12

(b)

4. Conclusions

A Malaysian vanity license plate recognition model is developed in this project. The model is part of the Tapway Sdn Bhd's Automatic Number Plate Recognition (ANPR) system. Transfer learning method is applied in this project to train the Malaysian vanity license plate recognition model. An original ResNet18 and modified ResNet18 network architecture are used to train the Malaysian vanity license plate recognition model with the available Malaysian vanity license plate images provided by Tapway Sdn Bhd. The modification done in the modified ResNet18 network architecture is such as adding a nonlinear activation function called ReLU and a dropout layer in fully connected layer of the pretrained network. In addition, the output feature number of the linear layer inside the fully connected layer for both original ResNet18 and modified ResNet18 network architecture has changed to match the number of available Malaysian vanity license plates. This is so that the model can recognize car license plate images to the matching available Malaysian vanity license plate type. Due to the limitation of the small dataset provided, we are unable to observe a significant performance between the original model with the modified model. However, we can still observe that the performance of the modified model is better than the original model based on the training loss plot and validation loss plot.

Acknowledgements

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