

Artificial Intelligence Application in Automated Odometer Mileage Recognition of Freight Vehicles

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Abstract. Transportation cost management is necessary for entrepreneurs in industry and business. One way to do this is to report the daily mileage numbers read by the employees of a company, but still encountering errors in human mileage reading, resulting in incorrect information received and difficulties to plan effective revenue management. As well as, increasing workload and creating complications for employees in checking mileage information. Therefore, the objective of this research is to create a machine learning model for detecting and reading the mileage numbers 2 types of freight vehicles: Analog and Digital. It can be divided into 2 parts: 1) detect mileage is used to identify the position of the mileage in the image and cut only the mileage by removing the unrelated background from the image 2) detect numbers and reads miles. Both use object detection with the Faster-RCNN. The results show that to detect the position of the miles and cut only the number of miles to read the numbers correctly, 187 images from 220 test images, which is correct for the model, representing 85%. The results of the study achieve satisfactory performance that meet the requirements needed for real-life applications in the transportation and logistics industry.

Keywords: Object detection · Mileage reading · Faster-RCNN · Freight vehicles

1 Introduction

The advancement of Artificial Intelligence (AI) technology has played an important role in the digital era. It has been extensively used to facilitate convenience and enhance operational efficiency in various businesses and industries. Moreover, it helps to create business opportunities in competitiveness for the industry. Applications of AI have been applied widely in transportation to drive the new perspectives in innovative solutions and to support performance transportation operations.

Freight transportation is one of the backbones of industrial systems and it is also a major component of the supply chain. Energy consumption has significant effect on operating costs of freight vehicle. It can be estimated from the number of miles/kilometres traveled on an odometer which is an instrument for indicating the distance traveled by

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a vehicle. Auditing daily mileage is an approach to monitor the length of journeys and keep controls for avoiding fuel fraud.

Therefore, the objective of the research is to develop the learning model based on AI to automated mileage detection and reading from an odometer on freight vehicles. We applied to the company operating in the industries of beverages consisting of several distribution centers. In which each way of transporting the products, the mileage will be manually read before leaving the distribution center and the mileage will be recorded when freight vehicles arrive at the point of delivery and after the freight vehicles return to the distribution center. The aforementioned data was used to calculate and verify the amount of oil used in each trip to use for managing logistic costs. However, the problem was found that the inaccuracy and completeness of the data was the result of human record errors.

2 Literature Reviews

2.1 Artificial Neural Network

The Artificial Neural Network (ANN) is based on the simulation concept of the human brain's activities with creating computers to be intelligent in learning as well as humans. Moreover, it can practice and deploy knowledge to solve various problems. Therefore, many researchers have applied the concept of neural networks to several applications ranging from easy to complex tasks.

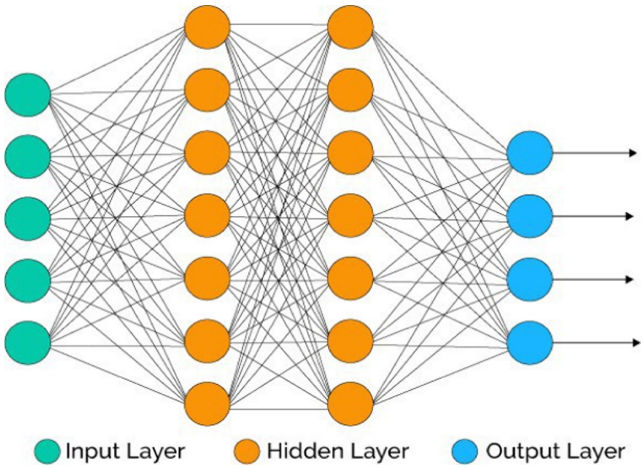


Fig. 1. Neural network architecture [6]

The architecture of the neural network is showed in Fig. 1. In principle, it can be divided into 3 layers as follows:

1. The input layer is the first layer of the neural network. It has a neuron that acts like a human neuron to receive and transmit information. The number of neurons in this

layer is equal to the number of input data. This layer is responsible for receiving data into the neural network model.
2. The hidden layer is an intermediate layer of the neural network, which has an effect on the model's learning efficiency. It serves the functions to combine the multiplication of the input data and the weight, and then convert to the result in the output layer.
3. The output layer is the last layer in the structure of the neural network model. It consists of output neurons. The number of neurons in this layer is equal to the number of output variables that represent the model's output of the model.

2.2 Convolutional Neural Network

Convolutional Neural Network (CNN) is very similar to the neural network. The difference is that the convolutional neural network is designed specifically for the task that uses images as an input. The layer of a convolutional neural network is different from that of the artificial neural network. The convolutional neural network has neurons arranged in three dimensions consisting of width, height and depth. It is used in object detection, identifying locations objects in images.

The most common layers of the convolutional neural network consisted of 5 layers, each of which is detailed as follows:

1. An input layer is often used to express visual data as a matrix. For a color (RGB) image, there will be 3 matrices associated with the image. For example, the color image is 32×32 (width $\times$ height), so the input layer will have an input dimension of $32 \times 32 \times 3$.
2. A convolution layer consists of a filter or kernel to calculate the weight of the area which the filter has moved through. The filter can have multiple layers to increase the number of feature maps. Each feature map learns different information about the image, such as border or dot pitch.
3. An activation layer is composed of a function that is in between the input feeding and the output connected to the layers. A popular activation function in convolution neural networks is the Rectified Linear Unit (ReLU) function, where all the negative value is turned to 0, while the positive value is still retained and the size does not change. In addition, one popular function, the softmax function which is a classification function, is used in the last layer of the network to classify inputs into multiple categories based on considering the maximum probability as in Eq. 1.

$$f(x)_j = \frac{e^{x_j}}{\sum_{i=1}^{k} e^{x_i}} \tag{1}$$

4. The Pooling layer is a layer that reduces the width and height of the image but retains the depth of the image. The popular pooling techniques consist of 2 types: Max pooling and Average pooling.
5. The fully connected layer is the last layer for classification. Namely, the neurons in this layer connect to the activation of the neurons in the previous layer.

The concept of R-CNN is to use a Selective Search (SS) approach to propose around 2000 Regions-Of-Interest (ROI), which are then fed into a convolutional neural network to extract features. These features were used to classify the images and their object boundaries using Support Vector Machines (SVM) and regression methods.

[1] studied the mileage extraction from odometer images for the automating auto insurance process. The company provides customers with an easy and flexible way in order to provide all the information they need when reporting a claim or request for a quote. It also reduces human errors and speeds up the process of data collection, where accurate mileage readings are essential to apply to car insurance quotes and process claims in sequence. Therefore, the study objective was to extract the mileage from the odometer image using object detection which will be divided into two parts to locate the miles in the image by using the structure of Faster R-CNN and Single Shot Detector (SSD), As a result, the Faster R-CNN structure was more accurate than the model built with the Single Shot Detector (SSD) structure.

[2] and [5] improve accuracy on automatic license plate recognition (ALPR) systems.by applying the Convolutional Neural Networks (CNNs) to use of synthetically generated images. [3]. introduced the Faster R-CNN which use selective search for region proposals and convolutional feature maps as input. It can improve the speed of the object detection. [7] presented text detection method based on multi-region proposal network (Multi-RPN) to detect texts of various sizes simultaneously. As a result, the proposed Multi-RPN method improved detection scores and kept almost the same detection speed as compared to the original Faster R-CNN.

[8] studied Indian road license plate detection and reading using Faster-RCNN to detect and read Indian license plates. It is challenging due to the diverse nature of license plates such as font, size, and number of lines. It applied the structure of the Faster R-CNN and extracted the features with Resnet50 andVGG16. As a result, Resnet50 provided higher mAP than VGG16. The accuracy in detecting and reading car license plates was accounting for 88.5%.

[9] studied traffic sign detection system using a convolutional neural network to train for extraction of the characteristics of traffic signs using You Only Look Once (YOLO), There were 9 types of mandatory traffic signs, including no overtaking signs, no u-turn signs to the right, no u-turn sign to the left, no right turn sign, no left turn sign, signs do not turn right or make a u-turn, signs do not turn left or make a u-turn, the sign prohibits changing the lane to the right and finally, the sign prohibits changing the lane to the left. The design of this traffic sign detection system consists of 4 parts: preparation of training data sets, building a model, testing the model and performance evaluation. The model was tested with a total of 108 traffic sign data sets and had a precision value of 0.87%, a recall value of 0.89% and F-Measure equals to 0.88%.

3 Research Methodology

Data used in this research are RGB images saved as a JPEG file format with a variety of resolutions starting from the resolution of 720 × 720 pixels to 2730 × 1536 pixels. The different types of freight vehicles are found in the company. However, there are two types of odometers in those various vehicles are used: analog and digital. Analog

odometer can be divided into two subtypes: blue and black (see in Fig. 2), while the digital odometer can be divided into 2 subtypes (see in Fig. 3).

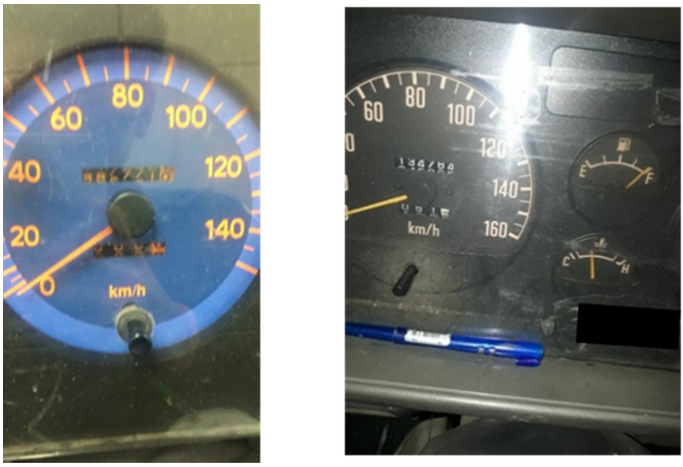


Fig. 2. Analog odometer (Color figure online)



Fig. 3. Digital odometer

There are a total of 635 images used in the study, divided into 390 analog images and 245 digital images. A simple random sampling (SRS) technique is used to divide images based on the type of odometers into two dataset: training dataset accounting for approximately 80% of the total of data and testing dataset accounting for approximately 20% of the total of data. Moreover, data augmentation is applied to build the various images such as number of pixels in images to make images lighter or darker, noise enhancement, image quality degradation, and image rotation to increase a size of training dataset for improving the model.

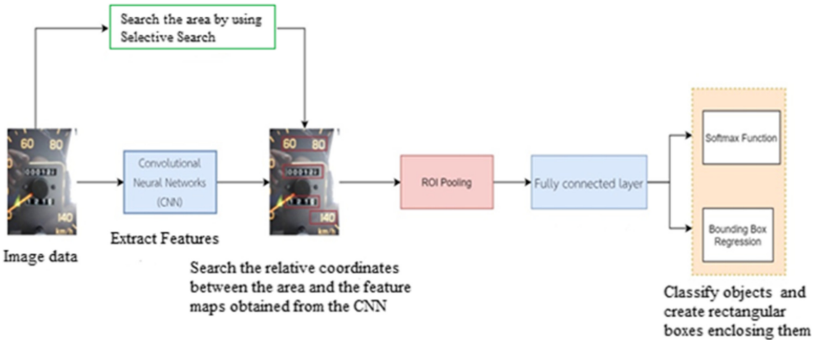


Fig. 4. The process of object detection

Figure 4 shows the process to detect the area of images containing the mileage based on the Faster-RCNN algorithms [4].

4 Experimental Results

The learning rate for detecting mileage is defined in a range of 0.0005 and 0.0002. The results shown in Fig. 5(a) and b are found that a total of learning cycles is equal to 24,046 iterations and take a time about 1 h 39 min 57 s with mAP (mean Average Precision) of 0.733 and mAP@iou0.5 equal to 0.996. Total loss is 0.0476.

From Fig. 6(a) and (b), the total time used to train the model for mileage reading is 3 h 30 min 6 s with mAP (mean Average Precision) of 0.835 and mAP@iou0.5 equal to 0.989. Total loss is 0.2898.

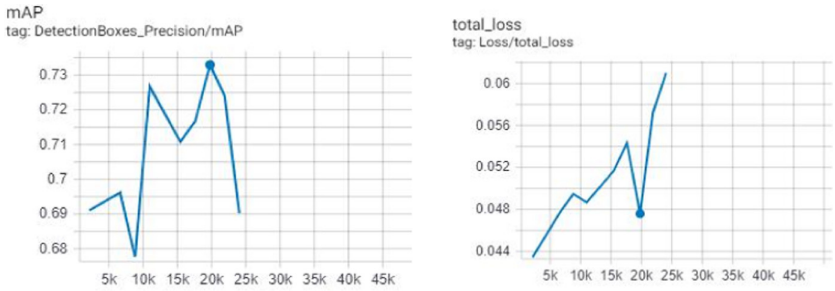


Fig. 5. The detection object model

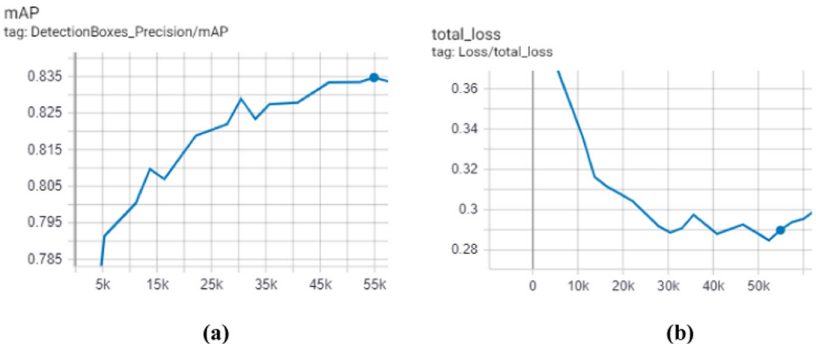


Fig. 6. The mileage reading model

Figure 7 shows an example of testing the object detection model (a) the mileage detection and (b) cutting specific area of mileage numbers. Figure 8 shows the rectangular frame to predict mileage numbers by the model.

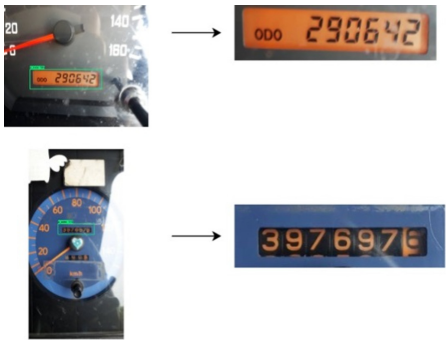


Fig. 7. An example of the result while training the model for mileage detection

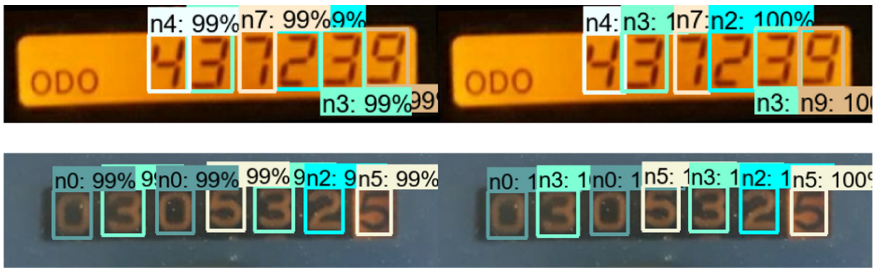


Fig. 8. An example of the result while training the model for reading mileage

The totals of 220 images are used to test the accuracy of object detection and reading the 6-digit of mileage in both the analog and digital odometer. The experimental results are shown in Table 1.

Table 1. Results of object detection and mileage reading

Type of odometer	# Images of testing dataset	Accuracy of object detection	%	Accuracy of mileage reading	%
Analog	68	67	98.53	57	83.82
Digital	152	148	97.37	130	85.53

As Table 2 of Chi-square hypothesis testing, it was found that the accuracy ratio in detecting and reading the miles on both analog and digital odometer is equal to 85:15 at the significant level of 0.05.

Table 2. Chi-square hypothesis testing

Test statistics	
Chi-square	0.074
df	1
Asymp. sig.	0.786

The Precision, Recall and F-Measure of reading mileages on analog and digital odometers are shown in Tables 3 and 4 respectively. The result shows the precisions of numbers 2, 4 and 8 in the analog odometer are equal to 1. It can say that the model is accurately and precisely detected and classified in every time it is predicted to be the numbers 2, 4 and 8 of the analog numbers as well as the digital numbers shown in

Table 3. Result of the precision, recall, F-measure for analog mileage

Number	Precision	Recall	F-measure
1	0.941	1.000	0.970
2	1.000	1.000	1.000
3	0.931	0.982	0.956
4	1.000	0.948	0.973
5	0.983	1.000	0.991
6	0.978	0.978	0.978
7	0.976	1.000	0.988
8	1.000	0.933	0.965
9	0.955	0.977	0.966
0	0.946	0.981	0.963
Average	**0.971**	0.98	0.975

Table 4, the 6 and 9 with precision of 1, while digital numbers 1 and 0 have less precision than other numbers. There is an error in the classification of numbers, for example the number 1 or 0 cannot be detected or classified properly in some images. Recall shows that the model can predict the numbers correctly with the solution relative to the total number of solutions of that number. From Table 1, it is found that the recall of the analog numbers 1, 2, 5 and 7 are equal to 1. Namely, the model is able to correctly detect analog numbers that contain numbers 1, 2, 5 and 7 as well as digital numbers consisting of 0 2 3 6 and 7 shown in Table 2, while recall values for analog numbers 4 and 8 are equal to 0.948 and 0.933 which are less than other numbers. Moreover, F-Measure is preferred to evaluate the performance of the learning model because it is the mean between precision and recall.

Table 4. Result of the precision, recall, F-measure for digital mileage

Number	Precision	Recall	F-measure
1	0.917	0.989	0.952
2	0.993	1.000	0.996
3	0.989	1.000	0.994
4	0.976	0.976	0.976
5	0.987	0.987	0.987
6	1.000	1.000	1.000
7	0.963	1.000	0.981
8	0.990	0.970	0.980
9	1.000	0.969	0.984
0	0.921	1.000	0.959
Average	0.974	0.989	0.981

5 Discussion and Conclusion

When comparing to the model of the company applied on the same dataset, it is found that our model for mileage detection and mileage read with the Faster-RCNN framework provides considerable accuracy. The accuracy of the model for detecting and reading analog and digital mileage was 87.5% and 93% respectively, while the accuracy of the company's model based on the commercial tools was 50% and 87% respectively. Thus, the developed machine learning model could replace the relatively expensive commercial software. This enables the company to detect errors in the mileage reading by drivers. The mileage figures are also used to provide time frame for fleet maintenance on time, and to plan efficient logistics management strategies. It can also be applied in conjunction with GPS data analysis to prevent fuel theft.

However, it is found that 33 images were incorrect mileage detection and reading the miles. Mistakes can be divided 3 types: errors in detecting mileage, errors to detect

numbers, and errors in reading miles. It is found that some images have interference in detecting mileage and reading mileage such as reflection on an odometer, scratches on an odometer. This is some external factors that cannot be controlled. Consequently, it causes an error in the mileage detection and reading of the mileage.

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