Deep learning model for predicting traffic accident risk on an expressway

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1. Background

This study develops a deep learning model for predicting the likelihood of the occurrence of a traffic accident on an expressway. Traffic accidents are a big concern of society in many countries because the accidents cause severe losses on economy due to damages on road facilities and induced traffic congestions. In reducing the number of, or in minimizing the losses by traffic accidents, prediction of the likelihood of traffic accident occurrence is essential for devising appropriate traffic management in timely manner. The likelihood of accident occurrence, or the "traffic accident risk" hereafter, dynamically changes depending on various factors, such as traffic conditions, road environments and road geometries [1]. Recent development in measuring and storing traffic flow data has enabled the evaluation of the impact of such factors on accident risks as well as estimating traffic accident risks under various conditions considering the factors [1].

In traffic accident analysis, the statistical method has long been a major analysis approach. Shankar, et al [2] identified that number of traffic accidents have linear relationship with road geometries, such as number of curves and maximum slopes. Not only the static factors, but also the contribution of dynamic factors have been analyzed. Andry and Yagar [3] demonstrated that accidents are more likely to occur under rain weather. There have been many attempts to include the traffic flow conditions as a risk factor of statistical regression analysis, and revealed that accident risk tends to be higher in congestion [4] and also when variation in speed and/or occupancy are higher [5]. However, it is challenging to carry out statistical regression analysis techniques when considering interactions among factors. Neural Network (hereafter, 'NN') is applied to the analysis instead of statistical analysis. NN models are computational ones defined as a set of processing units, represented by artificial neurons. They can handle nonlinear relationships and interactions among factors [6].

This study aims to predict the crash-type accident risk in the future, i.e., in the next two hours, by utilizing a type of deep learning model, the convolutional neural network. This study also demonstrates that the engineering knowledge gained from the past research based on statistical methods and traffic flow analysis can be a useful input in developing a deep learning model.

2. Methodology

2.1 Deep learning model for accident risk prediction

Input data

This study develops a convolutional neural network (CNN) model for predicting the accident occurrence on an expressway route. The model input consists of two layers: the first layer for traffic flow features; and the second layer for weather condition feature. The traffic flow features in the first layer consists of time-series traffic detector data along a study route for the past one hour. This study utilizes three major measures of traffic flow: speed, traffic volume and time-occupancy data aggregated every 5 minutes. Further, in order to incorporate the engineering knowledge that traffic accidents are more likely to occur in shockwaves where the occupancy dynamically fluctuates, this study utilizes difference in occupancy value from the last 5 minute, "ΔOcc" hereafter. Each of the four variable is arranged in a matrix form with the dimension of $N \times T$, where N is the number of detectors on the study route. T is the number of time intervals; this study utilizes 5-minute traffic data of the past one hour, thus $T = 12$. The four matrixes of speed, volume, occupancy and ΔOcc are compiled in a tensor with the dimension of $N \times T \times 4$ to be an input from the first layer.

The weather condition feature in the second layer utilizes the finding that it is more accident prone in rainy conditions; therefore the layer inputs the precipitation in the past one hour.

Label data

Each input sample, which represents the traffic flow and weather feature in the past one hour, is associated with the accident occurrence in the next two hours on the study route. If traffic accidents occur in the next two hours, the corresponding input sample is labeled as "Accident (1)"; otherwise "No accident (0)". Regarding the accident types, only crash and sideswipe accidents are considered in the present study.

Model structure

The proposed CNN model structure is presented in Figure 1. The first input layer is fed to convolution layers with the 3×3 filter. Then the second input layer is added after flatten operation. In the output layer, the model gives a real value between [0.0, 1.0], which represents the accident risk; the higher the output is, it is more likely for accident to occur in the next two hours.

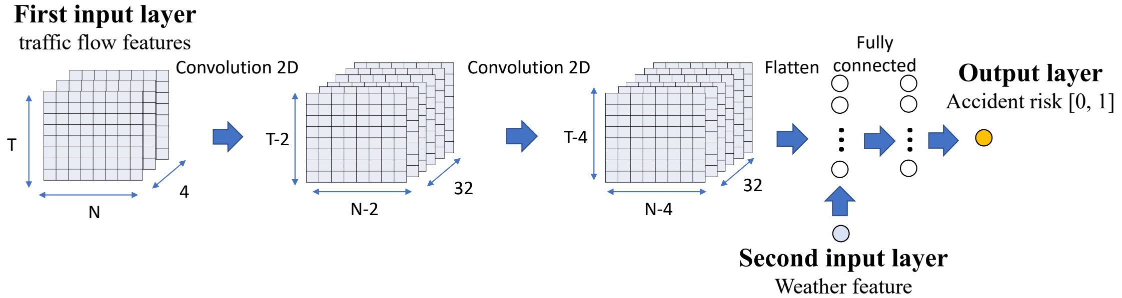

Figure 1. Illustration of the proposed CNN model structure

2.2 Evaluation of prediction accuracy

The output is evaluated by using the Aria Under the Curve (AUC) of Receiver Operating Characteristic (ROC) Curve. The model produces a value between [0.0, 1.0]; an accident alert can be released if the value exceeds a threshold. The relationship between the predicted condition and the true condition is summarized as shown in Table 1, based on which two accuracy criteria are calculated as shown in equation (1) and (2). It is fair to claim that the model is highly accurate if it produces lower False Positive Rate (FPR) while keeping higher True Positive Rate (TPR). The ROC curve illustrates the relationship between the FPR and the TPR under various threshold values, and the model with higher accuracy results in the larger AUC of the ROC.

$$False\ Positive\ Rate = \frac{FP}{FP + TN} \tag{1}$$

$$True\ Positive\ Rate = \frac{TP}{TP + FN} \tag{2}$$

Table 1. Contingency table of true and predicted conditions

	Accident alert (predicted condition)		
Accident occurrence (True condition)		Positive	Negative
	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

3. Result

3.1 Study site and data

The study site is the outbound of the route 3 on the Tokyo Metropolitan Expressway, Japan; the 11.7-km route is equipped with 18 ultrasonic detectors. The study period is 9 years from April 2010 to March 2019. The data is separated into two sets: the data of 2018 for validation data; and others for training data.

3.2 Model evaluation results

The CNN model is trained using the model structure presented in 2.1. As well, another model that does not include the variables suggested in the past studies is trained, i.e., the model without ΔOcc in the first input layer and weather feature in the second input layer. The results are presented in Figure 2. The model considering the engineering knowledge demonstrates higher AUC value.

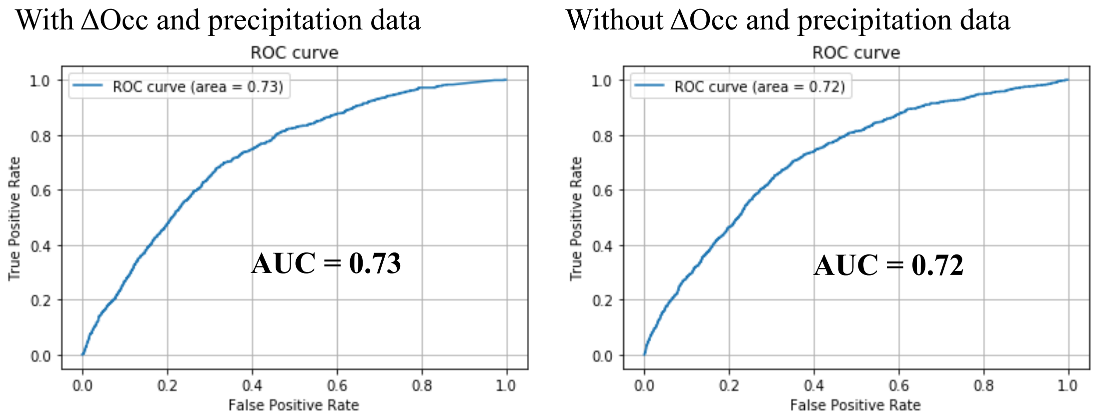

Figure 2. AUC of ROC with and without engineering knowledge

4. Conclusion

This study developed a CNN model for predicting the accident risk in the future, focusing on crash and sideswipe accidents. The input data consisted of time series traffic detector data as well as weather data, and the model outputs the probability of an accident occurrence during the next two hours. The CNN model was applied to a route in the Tokyo Metropolitan Expressway. The prediction accuracy was evaluated using the AUC of the ROC. The result showed that the accident risks on the next 2 hours have been well predicted in a high accuracy. Further, this study also demonstrated that the accident risk factors suggested in the previous studies could be a useful input in developing a model with higher accuracy.

Future research needs include comparison of the prediction accuracy with statistical models.

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