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# Deep Learning-based Image Recognition for Disaster Prevention Application

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**Abstract:** *Nowadays, with the rapid development of cities, the traffic volume has also increased. Although Taiwan prohibits motorcycles from going on national highways, traffic accidents of motorcycles straying into national highways still occur from time to time. This research uses CCTV images as the research data set to intercept the film into images every second as training data for the research and uses image recognition technology combined with deep learning skills to improve the recognition precision of vehicles. According to the analysis and verification results of the research analysis, the precision of the trained vehicle identification can reach over 95%, and the recall rate can reach over 90%; combined with the prototype of the vehicle warning system, if the results of the research can be applied to the entrance of an expressway ramp, It can be immediately identified violating vehicles which Inadvertently, such as motorcycles can be given and blocked in advance, to avoid accidental intrusion of illegal vehicles on national highways.*

**Keywords:** Car Detection; Deep Learning; Disaster Prevention; Vehicles Warning System

## 1. INTRODUCTION

Motorcycles are one of the most common means of transportation in Taiwan. Therefore, related traffic accidents are also emerging in an endless stream [1]. According to the road traffic accident handling method, traffic accidents have been reported. It is divided into A1, A2, and A3. A1 is a traffic accident that causes death on the spot or within 24 hours, A2 is a traffic accident that causes injury or death in more than 24 hours, and A3 refers to traffic where only the vehicle's property is damaged. According to the statistics of the Freeway Bureau from 2015 to 2020, It showed that there were 122 accidents involving motorcycles accidentally riding into national highways and causing major accidents, of which A1 accounted for 12%, A2 accounted for 68% and A3 accounted for 20% [2], the number of related incidents is also increasing year by year. The data also shows that intruding motorcycles are undoubtedly a major threat to driving on national highways, and the risk of driving is also increasing. The scale of the accident is usually more serious when the vehicle is moving at high speed. Currently, when the traffic control center receives a report of motorcycles entering the national highway illegally, the National Highway Police Bureau will assist in guiding them to leave the national highway safely. This method of processing takes a long time to wait for assistance, and if there is a deliberate violation, it will be more difficult to handle. In order to prevent and reduce the occurrence of such possible major traffic accidents, the research and development of an intelligent vehicle identification system are necessary.

## 2. LITERATURE REVIEW

In order to reduce road traffic accidents, Xin He and Delu Zeng, used deep learning combined with image recognition to detect pedestrians in potentially dangerous areas of expressways. The research results show that the workload of traffic monitoring personnel can be reduced, and the monitoring accuracy can be improved to achieve an effective early warning effect [3]. Tomoyuki Suzuki et al. have used deep learning to train a large-scale vehicle accident data set, using this method to predict traffic accidents in each period, and analyze their risks, thereby reducing road traffic accidents [4]. Ankit Parag Shah et al. proposed a new traffic accident data set. In the study, it was found that the size of the vehicle and the scene of the traffic accident will affect the accuracy of identification; in the study, they also trained traffic accidents in different scenes. Combined with Faster R - CNN [5] is trained, which confirms the importance of preventing traffic accidents [6]. Dinesh Singh and Chalavadi Krishna Mohan used deep learning to detect traffic accidents in traffic surveillance images and predicted the traffic accidents by identifying the trajectory of the vehicle. In the study, they imported a real accident in Hyderabad, India for verification, and obtained good accuracy and recall in the research results [7]. Shuvendu Roy and Md. Sakif Rahman used deep learning combined with CCTV to detect emergency vehicles, such as ambulances, etc., and classified them into emergency vehicles and conventional vehicles through label classification to track emergency vehicles and reduce social disasters [8]. From the above, it can be seen that deep learning and neural networks have become the main methods of vehicle identification. Although there have been many studies on vehicle identification, few of them are the application of intensive training for specific scenarios such as motorcycles and national highways.

## 3. RESEARCH METHODS

This research intends to use vehicle identification combined with a warning system to establish a vehicle warning system. It is expected that illegal vehicles can be tracked accurately through the warning system In order to achieve the purpose of preventing the casualties of passers-by**.**

### 3.1 YOLO Networks

Machine learning (ML) is one of the most popular techniques for analyzing images and allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction [9]. Deep learning (DL) extends classical ML by adding more complexity into the model as well as transforming the data using various functions that allow data representation in a hierarchical way, through several levels of abstraction [10,11].
YOLO (You only look once), a popular deep learning library is used to implement the proposed work [12]. The

YOLO algorithm [13] converts the detection into a regression problem, which can generate bounding box coordinates and the probability of each classification directly through regression in one evaluation without going through region proposals. Therefore, the detection speed is faster than Faster R-CNN [5], but it still has the problem of low detection accuracy of small objects. In order to improve YOLO, YOLOv2 [14] (also known as YOLO9000) has imported the DarkNet19 architecture. Through joint optimization of detection, more than 9,000 objects can be detected and classified simultaneously. The YOLOv3 [15] network is developed from YOLO and YOLOv2. YOLOv3 uses Darknet-53 as the backbone framework. Through 53 convolutional layers, the network architecture can be deeply constructed. Compared with previous versions, many updated technologies have been adopted, such as multi-label classification, different bounding box prediction modes, ResNet, and Feature Pyramid Networks (FPN) to improve detection accuracy of small objects, and YOLOv3 structure as shown in Fig.1 and Fig.2.

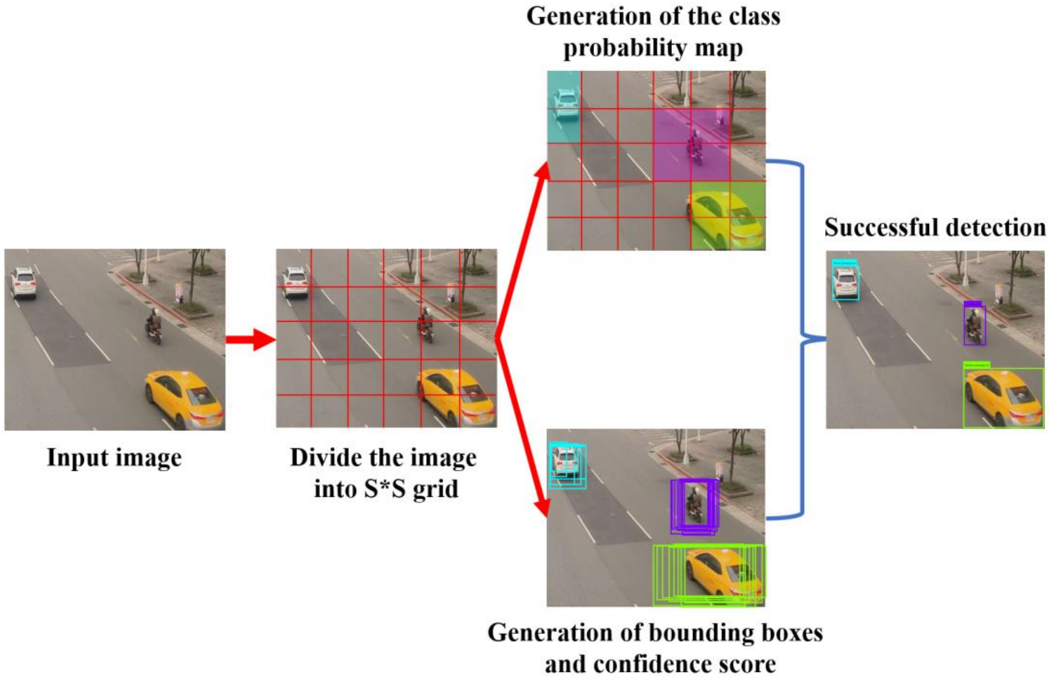


Fig. 1. YOLOv3 network architecture

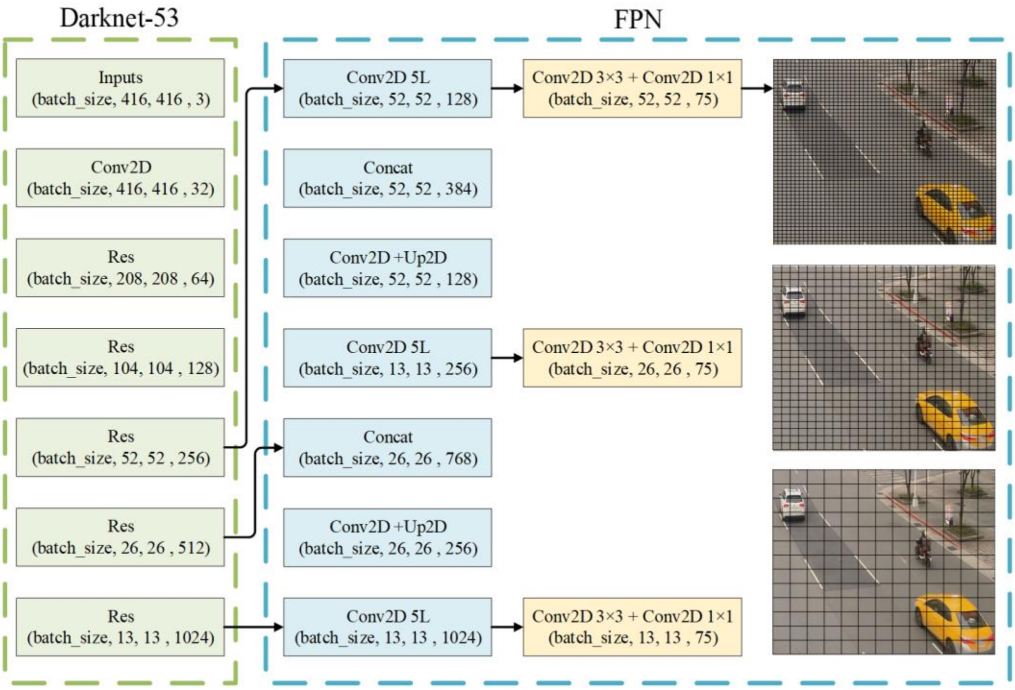


Fig. 2. YOLOv3 network algorithm

This research mainly focuses on simulating vehicle identification at the intersection of expressway and discussing its disaster prevention application. Therefore, the experimental plan of this research aims to identify the types of vehicles and motorcycles driving on national highways. There are four types of vehicles. In order to improve the accuracy of the training model of this research, we plan to shoot and record in different regions to increase the data diversity. The YOLOv3 will be used for training and verification and identification.

### 3.2 Vehicle image dataset development

In order to ensure the complexity and feasibility of the trained model, this research simulated CCTV photography techniques recorded in multiple locations. To ensure the actual traffic conditions, this research also imported the existing CCTV surveillance equipment images. In the research, the actual vehicle images of different pixels, different traffic periods, and different traffic environments are divided into four classes: Motorcycle (Label 1), Private passenger car (Label 2), Business passenger car (Label 3), and Bus (Label 4).
Raw data is usually characterized by several irregularities, whose presence influences the performance of subsequent learning steps [16]. To obtain a more robust training model, it is important to pre-process the various data imported into the model and ensure that the data are clean. Data cleaning is a necessary step in many data-driven analytics [17]. In this study, many inappropriate training data were filtered out and data augmentation was used to increase data diversity and prevent overfitting. Data Augmentation encompasses a suite of techniques that enhance the size and quality of training datasets [18], the strength of the database can be improved by easily expanding the data in various ways, such as horizontal flip, brightness change, contrast, color filter, and random Gaussian adjustment will be randomly applied during the training phase to enhance the data set and improve the simulation of various conditions.

### 3.3 Experimental environments

The training and testing experiment environment of this study is Microsoft Windows 10 operating system, equipped with Intel [R] Core {TM} i5-10400CPU@2.90GHz, memory 16G, graphics card NVIDIA GeForce GTX 1060Ti 6G computer environment, and use Keras advanced neural network API (2.1.5) [19] combined with Tensorflow (1.15.0) [20] as the deep learning framework of this research is written in Python.

### 3.4 Design of warning system

At present, Taiwan's current measures to deal with motorcycles entering the national highway by mistake are to notify the traffic control center of the Freeway Bureau or the national highway Police Bureau to assist in guiding them to leave the national highway safely.
If the national highway police cannot clearly grasp the correct location of the violator, the rescue time will be prolonged, and if the violator acts deliberately, the risk of causing a major traffic accident will also increase. If a serious traffic accident occurs on the national highway, not only just the unpredictable number of casualties will also cause more traffic problems.
In order to reduce the number of traffic accidents caused by motorcycles straying into national highways and ensure driving safety, this study intends to use vehicle identification combined with a warning system to establish a vehicle warning system. It is expected that illegal vehicles can be accurately tracked through the warning system, and achieve the purpose of preventing injuries and deaths.

## 4. RESULTS

### 4.1 Evaluation Metrics

To evaluate the performance of models, different accuracy measures like precision (Eq. (1)), recall (Eq. (2)) and f1-score (Eq. (3)) were used to find out the effectiveness of classifiers [21].

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

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

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision+Recall} \tag{3}$$

Where $TP$ are true positive, $FP$ are false positive, $FN$ are false negative classifications.

### 4.2 Analysis of vehicle model inspection results

In this research, back-testing was performed on 1,000, 2,000, and 6,000 training sets, and 10% of the images were used as the test set for back-testing. The changes in precision and recall rate and the effects of the three training sets are shown in Table 1, Table 2, and Table 3.
At the beginning of training, the number of datasets is not sufficiently diverse, resulting in poor overall precision and recall, which cannot be applied in practice. The identification results of 1,000 training sets are shown in Fig. 3.

Table 1. Performances of the 1,000 training sets

| | Label 1 | Label 2 | Label 3 | Label 4 |
|---|---|---|---|---|
| TP | 22 | 195 | 60 | 36 |
| FP | 11 | 36 | 12 | 29 |
| FN | 82 | 206 | 19 | 20 |
| Precision | 67% | 84% | 83% | 55% |
| Recall | 21% | 49% | 76% | 64% |
| F1 score | 32% | 62% | 79% | 60% |

Table 2. Performances of the 2,000 training sets

| | Label 1 | Label 2 | Label 3 | Label 4 |
|---|---|---|---|---|
| TP | 326 | 789 | 241 | 173 |
| FP | 16 | 108 | 7 | 12 |
| FN | 188 | 406 | 39 | 36 |
| Precision | 94% | 87% | 97% | 93% |
| Recall | 63% | 66% | 86% | 83% |
| F1 score | 76% | 75% | 91% | 88% |

The overall accuracy has significantly improved in the middle of the training period. However, it is still found that the recognition results of nighttime traffic conditions are poor, and it is necessary to supplement the nighttime images. The identification results of 2,000 training sets are shown in Fig. 4.
The final test result has a certain accuracy. However, if the detected target reaches a certain degree of occlusion,

the target is too small, and the rendering effect of the light may cause incorrect recognition. It is also found that the accuracy rate during the day is higher than at night, the halo at night can cause incorrect identification. The identification results of 6,000 training sets are shown in Fig. 5.

(a) Nighttime (b) Daytime

Fig. 3. 1,000 training sets results

(a) Nighttime (b) Daytime

Fig. 4. 2,000 training sets results

(a) Nighttime (b) Daytime

Fig. 5. 6,000 training sets results

Table 3. Performances of the 6,000 training sets

| | Label 1 | Label 2 | Label 3 | Label 4 |
|---|---|---|---|---|
| TP | 1529 | 2193 | 609 | 396 |
| FP | 88 | 28 | 22 | 16 |
| FN | 113 | 138 | 46 | 46 |
| Precision | 95% | 98% | 97% | 96% |
| Recall | 93% | 94% | 98% | 90% |
| F1 score | 94% | 96% | 97% | 93% |

The performance of the changes in precision and recall rate of each vehicle type in the three training sets are shown in Fig. 6, Fig. 7, Fig. 8, and Fig. 9.

Due to the small size of the motorcycles and their different shapes under various traffic conditions, the performance of the recall rate is poor in the initial and middle training stages. In the final training stage, due to the rich training set, the precision and recall rate have better performance.

Since the body of the private passenger cars is similar to the business passenger car, there are many misidentifications during the back-testing phase. As a result, the recall rate of the private passenger cars was poor in the early and mid-term training stages.

Due to the research limitations of this study, all business passenger cars are set to be yellow, so in the early stage of back-test identification, it can have a better recall rate and precision rate. However, due to the similar body of business passenger cars and private passenger cars, there are still some identification errors in the back-testing stage.

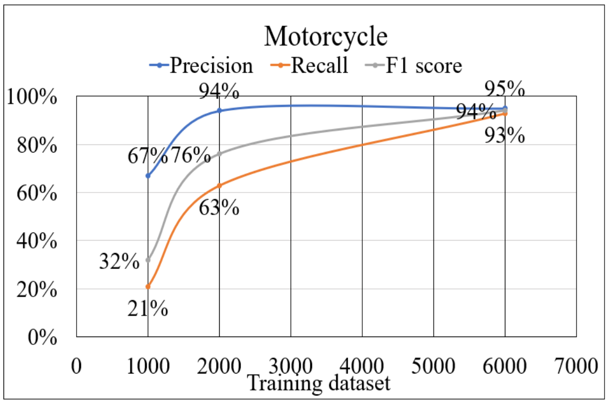


Fig. 6. Motorcycle index analysis

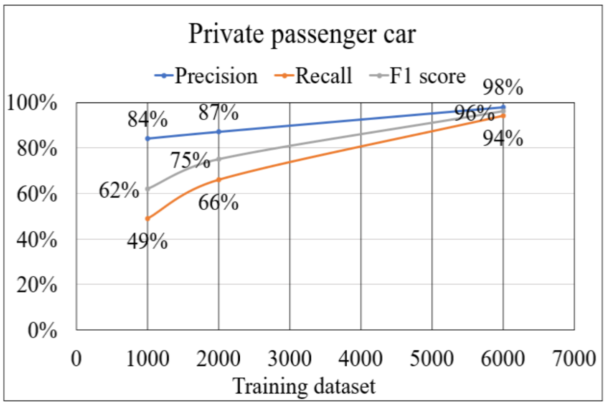


Fig. 7. Private passenger car index analysis

Although the body of the bus is large and conspicuous, the number of buses is less than other types of vehicles. As a result, it is more difficult for the bus to train during the training phase.

### 4.3 Vehicle warning system function

The first function is arranged based on the main national highway route structure with reference to the real-time video monitor system of various counties and cities in Taiwan to facilitate the integration with the current traffic planning. The second function is the content block, which includes the latest notification of each road section, and related violation information. Through this hierarchical structure, the information is detailed layer by layer, so that law enforcement officers can clearly understand the information related to violations (see Fig. 10).

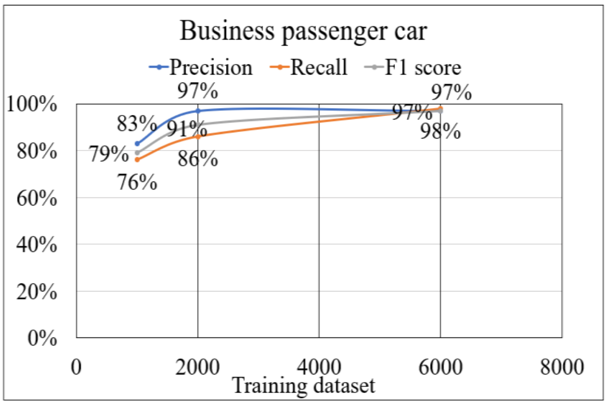


Fig. 8. Business passenger car index analysis

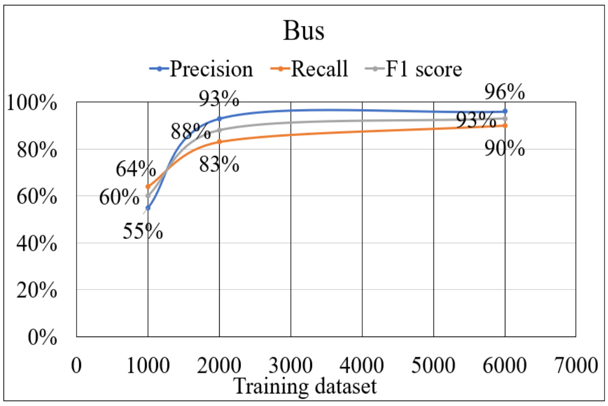


Fig. 9. Bus index analysis


(a) Navigation block (b) Violation information

Fig. 10. Vehicle warning system function

### 4.4 Extensible warning method

This study also proposes a warning method for motorcycles straying into a national highway. When the Vehicle warning system successfully identifies an illegal vehicle, the Freeway Bureau traffic control center will immediately use the warning system to notify the relevant law enforcement officers and take action to stop or warn at the first time. This method can effectively reduce the number of incidents of motorcycles straying into the national highway. This method can effectively reduce the number of incidents of motorcycles straying into the national highway. It can also be blocked by setting up flashing warning signs and fences to remind drivers of the entry of illegal vehicles on the national highway (see Fig. 11)., reducing the probability of major car accidents caused by illegal vehicles.

## 5. CONCLUSION

This study uses the neural network of YOLOv3 to achieve the purpose of vehicle detection and classification, which are Motorcycle, Private passenger car, Business passenger car and Bus. In addition, a back-test of 600 images in the training set of 6000 images, the precision of the training is above 95%, and the recall rate is all above 90%.

Fig. 11. Extensible warning method

Through back-testing at different stages of this study, it is known that there are many factors that affect the accurate recognition of deep learning, such as the change of vehicle volume in different traffic environments, the influence of light in the morning and night of the traffic environment, the halo and shadowing caused by equipment sampling objects and so on will affect the recognition rate.

However, in the results of the back-test, it was found that some objects were misidentified as vehicles, such as street lights. It is speculated that there are many factors that affect the accurate recognition of deep learning. As the training set increases, the influencing factor also increases and affects the accuracy of recognition.

The vehicle warning system was developed by this study institute; through the visual interface, the warning system is divided into navigation and content functions. Using this system, you can clearly know the time, location, and reason for the violation of the vehicle and combine the identification of the image to help law enforcement officers reach their location as soon as possible before a serious car accident occurs and solve the problem, which can further reduce the possibility of subsequent road disasters, thereby reducing the number of injuries and deaths, and achieving the effect of disaster prevention.

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