AI Model for Stolen Vehicle Identification and Tracking

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*Abstract*-As the theft of vehicles is common in the urban cities. This project aims to develop a system integrated with AI model trained with Convolution Neural Network(CNN) algorithm for stolen vehicle identification and tracking. The advancing AI development motivates the use of neural network, machine learning and artificial intelligence in vehicle identification for a high accuracy. After feeding the AI model with 5000 annotated photos as input, it was found that the AI model can recognize most of the vehicles with the average accuracy of 65.4%. It has a precision and recall of 0.612 and 0.622 respectively. In some times, although it may not be able to distinguish the license plate number due to its relatively small size, it can still recognize the vehicle by combining with characteristics of a vehicle like appearance or color. The AI model will be integrated in a system with the information of stolen vehicles in a camera to test its accuracy in the future. Last but not least, this project proposes a new way to track down the stolen vehicles with the help of trained CNN model.

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1. Introduction

Background, objective and timeline will be discussed in this section. A brief background of vehicle theft situation in Hong Kong will be covered and the objective behind this project is to create a system integrated with AI model for vehicle identification and tracking.

**1.1 Background**

In 2020, statistic shows that there are 1366 reported cases of theft from vehicle in Hong Kong [1], approximate 4 vehicles were stolen every day back in 2020. Theft from vehicle is a common problem in urban cities like Hong Kong. It contributes to about $7.4 billion in total motor vehicle theft in the world in 2020[2]. Although there is an urgent need to identify and track down the stolen vehicle in a fast and reliable way, some countries like UK still rely on the inefficient and time-consuming methods for tracking down the stolen vehicles. The police in UK relies on methods like random checks of vehicles on the streets, keeping the watchlist of stolen car, checks of license in a parking lot, etc[3]. They require a lot of labor force and time when compared to the use of AI model for identification. The AI model can handle large amount of traffic in a short time and increase the chance of finding the stolen vehicles. Details like time, location and color of the stolen vehicle can also be provided to facilitate the catching of stolen vehicles.

**1.2 Objective**

This project aims to create a system integrated with AI model for vehicle identification and tracking to detect the stolen vehicles running on the streets. The system can deliver two main goals including real-time vehicle detection and creating route for the stolen vehicles.

* By setting up the cameras in the highways and traffic lights, real-time videos will be passed to an AI model to do identification and comparison with the stolen vehicles. If the AI model successfully identifies a stolen vehicle, an alert will be sent to the police for further investigation.
* By aligning the spots of a stolen vehicle found in different camera, a route can be mapped and used to predict the direction of the stolen vehicle for tracking and interception of stolen vehicles.

**1.3 Timeline**

We are currently on track and at the Preliminary Model Testing and Tuning stage. After this stage, we can continue working on the stage of system integration.

|  |  |  |
| --- | --- | --- |
| Milestone | Expected Completion Date | Estimated Learning Hours |
| Proposal Creation | 02/10/2022 | 4 |
| Website Creation | 02/10/2022 | 6 |
| Data Collection | 23/10/2022 | 15 |
| Model Creation | 25/10/2022 | 10 |
| Data Labeling | 30/10/2022 | 15 |
| Preliminary Model Testing and Tuning | 30/11/2022 | 10 |
| Interim Report | 30/11/2022 | 6 |

Tab. 1 Timeline for stages

It is concluded that the vehicle theft situation in Hong Kong is severe and there is a need to track down the stolen vehicle in a fast and reliable manner.

2. Literature Review

**Algorithm of the AI model**

We decided to use Convolutional Neural Network (CNN) algorithm to train the AI model. CNN is best in processing graphic data which can be represented by pixels. Pixel with higher value means the brighter color in a graph. The layers in CNN are placed in an order (Fig 1) such that it detects markings like lines or curves first, then more convoluted patterns like objects or vehicles can be detected next.

Diagram, engineering drawing

Description automatically generated

Fig 1. Architecture of CNN[8]

The input image is broken down into pixels and filtered by the convolution layer filter by taking the element-wise product of filters in the image and then summing those specific values for every sliding action and then maximum pooling layer to reduce the image’s dimension and noise of the input while keeping the features before the final classification layer to distinguish the dominating and low-level feature.

For setting the parameters in the CNN algorithm, comparison between CNN algorithm and AlexNet classifter by Jorge E. Espinosa et al. [7] was taken into consideration. He suggested that CNN algorithm worked best with a 0.6 NMS threshold value. Huansheng Song et al.[5] stated that the drastic change in the size of the vehicles is a huge challenge in vehicle detection. He suggested that visioning the surface of the street with image segmentation and algorithm for vision-based identification can overcome the challenge. A paper by Zhong-Qiu et. al.[4] focusing on an algorithm which uses deep learning to detect objects suggested that YOLOv5 and Fast R CNN perform better than R CNN. In this project, the accuracy of the CNN algorithm will be measured and compared with traditional methods.

3. Methodology

In this section, Data Collection and Processing will be discussed first, followed by Design Aims, Hardware Architecture and Software Architecture. Input Augmentation, annotation and split dataset were used to provide the input to feed the Convolution Neural Network model. This project aims to create a modular-based program, scalable and easy maintain system.

**3.1 Data Collection and Processing**

The training dataset of vehicles was collected with smartphone fixing on a point to do recording for a few hours. The smartphone was placed on different spots like parking lot, open streets, and traffic light to increase the variety of vehicles. The collected videos were framed and processed with augmentation first to increase the size of dataset to 5000 photos. Then the photos were annotated with classes of vehicle and position of license plate. Finally, the processed dataset was split into 80% for training and 20% for validation.

Text

Description automatically generated

Fig.2 steps of data processing

**3.2 Design Aims**

The Design of the system aims to achieve three more goals other than the project objective.

* A scalable project which can be upscaled in the future to include additional requirements. It is not only applicable to just one camera. It can accommodate new features and amendments without much effort.
* A modular based program so that it can run on multiple cameras independently. The parallel connected cameras can form a network to allow parallel computation in order to shorten the time needed.
* An easy-maintain project. The project can be managed with least effort, or even automatically.

**3.3 Hardware Architecture**

Cameras, computers, and GPU farm are required in this project. In order to mimic the quality of a street camera(which has a lower resolution when compared to smartphone), the resolution of the collected videos was downgraded with Gaussian blur. GPU farm provided by the Department of Computer Science, The University of Hong Kong, was used to increase the speed of training the AI model.

**3.3 Software Architecture**

The video feed from the cameras is processed and fed to a trained CNN model. This extracts the details of the vehicle such as make, model, color and license plate number. These details can then be compared against a database of known missing vehicles. If a search result has a very high probability of being a stolen vehicle then a POST request is sent to law enforcers to notify them of details concerning the vehicle and its sighting. The system will use Postgresql as a backend database engine. Data of the stolen vehicles is stored in database for matching.

4. Finding

With the above setup of hardware and software architecture, a system with live cameras programmed with a Convolution Neural Network model can be delivered to detect the stolen vehicles and alert the authorities. Although the AI model is expected to have a low recall and precision on recognizing the license plate number, the error can be addressed with the help of combining all features of a vehicle on determining the matching rate.

**4.1 Deliverable**

The final deliverable of this FYP will be a system with an interface in Fig 4 and an AI model to detect the stolen vehicles with the workflow of the following graph. The system will be implemented with mobile app interface for monitoring. The camera will be connected to the app showing the probability being a stolen vehicle (Fig.3).

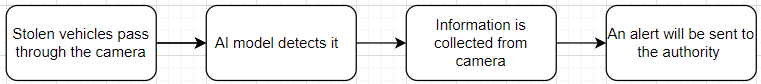


Fig.3 Workflow of the system

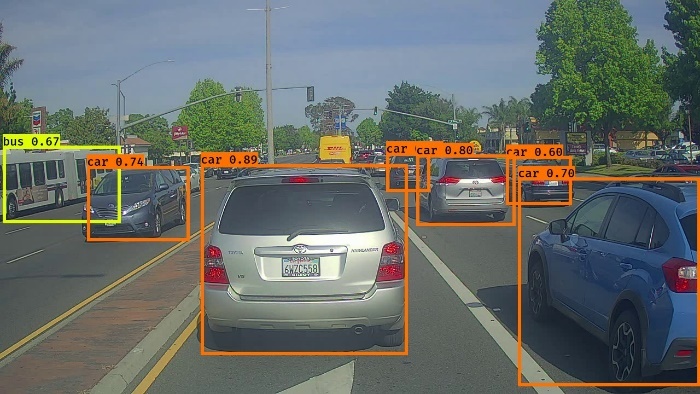


Fig.4 screen of the app[6]

The above image shows the proposed interface of the system where the orange and yellow boxes represent the matching rate of stolen vehicle.

**4.2 Error in the program**

It is expected that the AI model will have a low recall and precision on recognizing the license plate number. It cannot identify the stolen vehicles by just the appearance as vehicles may have identical brand, model, and shape. The most reliable reference of the stolen car is the license plate number. However, the match in license plate number does not guarantee the match with stolen car as there may be misinterpretations in the graph by AI. Other characteristics like color, brand, shape, etc. are needed to be considered for calculating the similarity to increase the accuracy of the model.

**4.3 Difficulty**

It is expected that the biggest difficulty is integrating the AI model with the system to do the real-time detection. As it is not feasible to run the AI model on the camera, the live video needs to be passed to the app. After analyzing the video, request needs to be sent back to the camera for capturing the screenshot, date, location, etc.

5. Discussion

Evaluation on the AI model

Runtime, recall and precision are three main factors for evaluating the algorithm. Runtime is defined by the time needed to process one frame of the video by the algorithm; Recall is defined by dividing the true positive number by the sum of all instances; Precision is defined by dividing the true positive number by the sum of correctly and incorrectly predicted instances.

Precision = TP/(TP + FP) (5)

Recall = TP/(TP + FN) (6)

True positive (TP)—total number of correctly identified stolen vehicles.

False positive (FP)—total number of incorrectly identified stolen vehicles.

False negative (FP)—total number of stolen vehicles not being identified.

AI model can recognize most of the vehicles with the average accuracy of 65.4%. It has a precision and recall of 0.612 and 0.622 respectively. However, the precision and recall on recognizing the license plate number are 0.521 and 0.517, which are comparatively low . It is expected the Al model based on CNN algorithm will yield a high precision and recall on recognizing the vehicle object if the size of input dataset is large enough. However, the precision and recall will be undesirably low on recognizing the license plate number due to the small size of the license plate when compared to the vehicle. The distance between the vehicle and the camera will also affect the performance of the model. The AI model will not be able to identify the vehicles until they reach a relatively close distance.

6. Conclusion

In conclusion, the AI model trained by Convolution Neural Network(CNN) algorithm can detect most of the stolen vehicles when they pass the camera. In some times, it may not be able to distinguish the license plate. Combining with other characteristics, the stolen can be highly distinguishable. Although there are some limitations and difficulties needed to be further solved. The further developed system can spot most of the stolen vehicles and prevent vehicle thefts.

**6.1 Limitation**

We can get access to the footages of CCTV monitoring the traffic of vehicles as there may be a risk of infringing personal privacy. We can only use camera to collect the necessary data for training and testing. Although the distance between the real CCTV and vehicle is long, we can still mimic most of the feature on a CCTV camera so that the system can be integrated with the CCTV in the future and the performance of the AI model will not vary.

**6.2 Future work**

In the future, the system can be further developed and implemented in a network of CCTVs. Every vehicle in the network will be checked by the model so the chance of catching a running stolen car will be much higher. To address the low recall and precision on recognizing the license plate number, it is recommended to use Optical Character Recognition (OCR) algorithm, which performs well in recognize text image, to analyze the license plate number of a vehicle to increase the accuracy.

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