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Machine Learning-Based Car Specification Mismatching System for Pre-Crime Detection

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Abstract: Even with the installation of security systems and video cameras in residential buildings, the number of complexes and crimes in the neighborhood continues to worry residents in the modern era. For instance, the latest statistics show that the rate of vehicle theft was the highest among the crime rates in Malaysia from 2010 to 2017. It is common for criminals to take advantage of security flaws, such as when a phony license plate is put on a car and the security system misses it, allowing the criminals to enter the facility with ease. Hence, this paper intends to close the loopholes that criminals exploit by developing a system to identify car specifications such as the vehicle type, license plate, logo, and color using machine learning. This data will then be used to match the information of the car's owner, allowing the security system to discover and prevent any crime before it happens. Machine learning and deep learning models such as MobileNet SSD, YOLOv4, OCR and TensorFlow Lite color models are used to predict the car specifications. When mounting security cameras perpendicularly on the front-sides of vehicles to capture high-resolution photos, the proposed system is able to achieve a considerable performance accuracy of 100% for vehicle type, 97% for license plate, 74% for logo, and 68.5% for color predictions, respectively.

Keywords: *Car specification detection, machine learning, security system, vehicle crime*

1. Introduction

The advance of technologies in the 21st century has contributed to a better and safer living environment for human beings compared to the past decades. Technologies such as wireless communications, multimedia services, high-processing computers, etc., have not just been used to protect users from danger but also to fight crimes within the community. The common way to combat crime is to introduce a multiple-tier security system to commercial or residential buildings and areas. For example, the security system may include the installation of surveillance cameras, radio-frequency identification (RFID) access cards, and also the registration of car plate numbers when entering the buildings [1]. However, the rapid increase in population in the communities requires more complicated security management and higher human resources to maintain the efficiency of the security imposed on a certain confined area. Meanwhile, criminals are also utilizing the benefits of the latest technologies to commit modern crimes, such as using a fake license plate or identification card (IC) to enter a residential building.

The statistics obtained from [2] show that the number of crimes in Malaysia increased rapidly, with the total crime rate reported in Kuala Lumpur and Selangor approaching nearly 42% from 2010 to 2017. Among the crime activities, vehicle theft has the highest number of cases recorded, as shown in Fig. 1. On the other hand, another international statistic obtained from [3] indicates that the global vehicle theft rate has decreased rapidly since 2003, but saturated and then increased gradually from 2014 onwards. Thus, vehicles are indeed useful for allowing people to travel vast distances quickly, but they are also useful for allowing criminals to carry out their heinous crimes and robberies without being discovered by the police [4]. For instance, the simplest approach to trick the security personnel at the residential gate is to fabricate some car specifications, including changing the license plate numbers on a fake license plate. The thieves can then get past the security flaw that the entrance security guards are unable to notice since they do not have a proper detection system to identify vehicles with fake license plates.

As a result, more advanced systems have been proposed in various applications that utilize machine learning to prevent unwanted incidents or detect crimes. For instance, the paper in [5] created an integrated system named PerpSearch that takes a criminal description as

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information, such as the location, type, and physical description of suspects (personal traits or vehicles). With the assistance of machine learning for suspicious people's physical detection and matching, it focused on applying a crime pattern component to accurately assess criminals based on their criminal history. Another research paper applied convolutional neural networks (CNN) to predict crime using surveillance cameras [6]. The artificial intelligence (AI) system was able to capture and reveal images containing crime scenes such as blood or crime tools such as guns, rifles, knives, and other firearms or sharp objects via image processing. The surveillance camera was also used in [7] to detect a dispute or an intruder by utilizing sound signal processing for violence detection purposes and image processing for intruder detection purposes. Then, the system notified and sent alert signals to the system administrator.

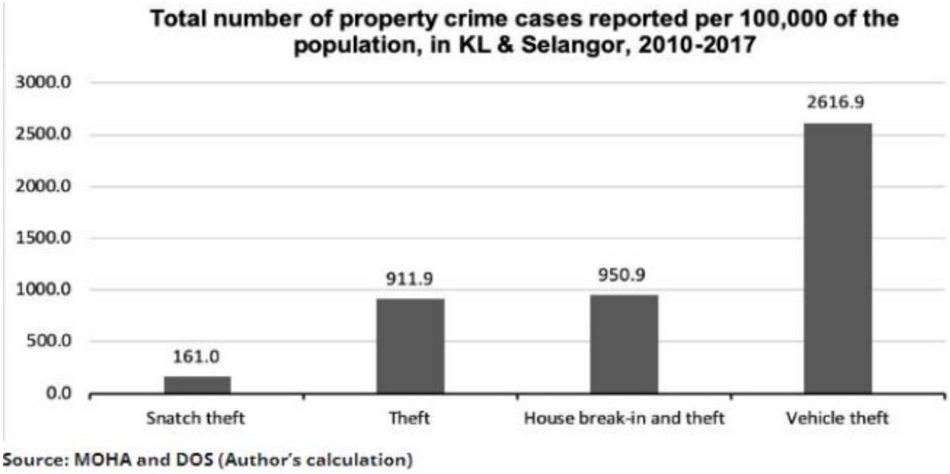

Fig. 1. The statistic of crimes rates reported in Kuala Lumpur and Selangor [2]

On the other hand, various machine learning and deep learning models have been proposed for vehicle detection [8-10]. These models include Xception, VGG, Inception, MobileNet. DenseNet, NASNet and their newer versions of vehicle detection and identification for determining the type of vehicle. The purpose of vehicle detection is to control traffic and parking lot gates [8], detect cars on highways, and count vehicles that exceed speed limits [9,10]. Another purpose is to locate and identify the license plate of the car using image text processing, so that the system can determine whether the vehicle is stolen or not [11]. The enhanced image processing technology delivers the details of the average distance of the automobile plate to the digital camera at a certain standard or resolution. The bigger the picture output, the greater the distance between the camera and the vehicle's license plate [12]. Meanwhile, a single-stage deep learning-based object detector named YOLO has been implemented in self-driving cars [13]. In this case, YOLO was used to recognize all objects surrounding the vehicle as well as measure the distance of moving cars for controlling the speed of the vehicle.

Although some machine learning models have been developed to detect license plate numbers on vehicles, there is no guarantee that the security system can identify the actual forged car plate used by the criminal. This is due to the fact that vehicle thieves can use a registered license plate on a different car model or duplicate the ID of the car owner to trick the security guard. Hence, in this paper, we propose to develop a car mismatching system by detecting several car specifications, such as the vehicle type, license plate, logo, and color of the vehicle using a surveillance camera placed in front of a guard toll. A few machine learning and deep learning models are combined to detect the car specifications. For instance, the MobileNet SSD model is used to predict vehicles and determine the type of vehicles. YOLOv4 is used to detect license plates and car logos, whereas the TensorFlow Lite color model is used to predict the color of the car. The learning models are trained using a limited set of data obtained from some free online resources. The accuracy of the prediction models is tested under several situations, such as the position of the vehicle and the resolution of the photos, in order to verify the performance of the proposed system. At the end, the information contained in the car's specifications is collected and matched with the data of the owners of the cars to determine the actual car owner and to detect possible pre-crime activities.

2. System Architecture

Fig. 2 shows the proposed system model, which consists of a total of four phases: formation, data, design & implementation, analysis, and matching. Phase 1 is the formation of the research methodology, which includes the initiation of the project and its requirements. Phase 2 collects the images or videos of the vehicles and performs the necessary image filtering. Phase 3 develops the codes for detecting the car specifications using machine learning and deep learning. Phase 4 tests the learning models and generates the performance analysis. Last but not least, Phase 5 completes the project by matching the predicted data with the information of the car owner. The details of each phase are presented in the following section.

2.1. Phase 1: Formation

In the first phase, the requirements of the project are determined. The system requires considerable high-speed computer processing since extensive image processing and machine learning have to be implemented. In this case, the Google Colab online platform [14] is chosen as a common tool to build the programme codes in the Python language [15] for machine learning. It also supports multiple programming libraries for image processing and analysis with high processing power.

2.2. Phase 2: Data

The second phase of the model is to search for a dataset of vehicle photos or videos. The aim is to collect as many pictures of vehicles with Malaysian license plates as possible. Finding the necessary images can be difficult because most car shots have their license plates covered for security and privacy reasons. However, we are able to search and download hundreds of images of Malaysian cars for sale on the Paultan website [16]. After filtering the downloaded photos, a total of 60 images with both high and low quality are selected for training and testing the machine learning or deep learning models later. The pictures are then categorized into 35 images of front-side cars and 25 images of back-side cars.

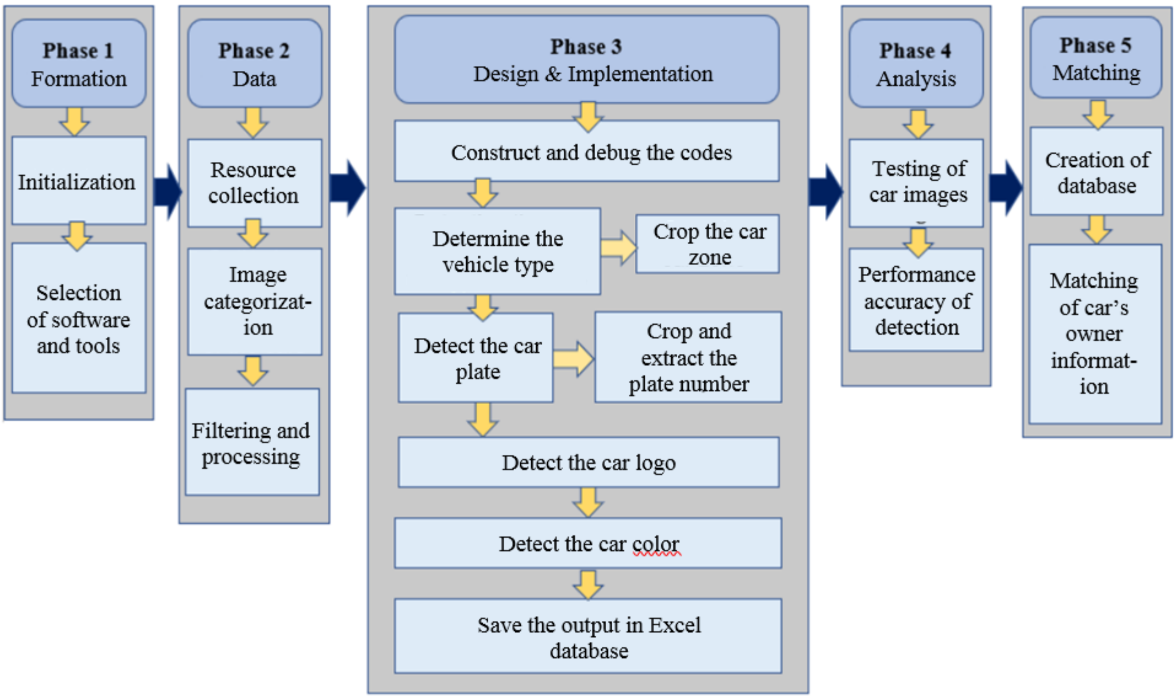

Fig. 2. System model

2.3. Phase 3: Design & Implementation

The third phase of the model is to design and develop the Python codes, describing the methods used in machine learning to identify car details such as vehicle types, license plates, logos, and colors using car images. Fig. 3 depicts the overall flow chart of the car detection procedure. There are a few machine learning and deep learning models implemented in this paper, which include the MobileNet Single Shot Detector (MobileNet SSD), You Only Look Once version 4 (YOLOv4) Tiny, optical character recognition (OCR), and TensorFlow Lite color.

Fig. 3. Flow chart of the car detection procedure.

First of all, the MobileNet SSD model is a part of the deep neural network (DNN) module implemented in MATLAB [17]. The DNN module enables the import of pre-trained models from Tensorflow, Caffe, Darknet, and Torch, among other deep learning frameworks and many different architectures, which are compatible with the Open-Source Computer Vision Library (OpenCV). It is well suited for detecting, processing, and identifying objects in the environment of an image. Therefore, it is used in this paper to detect the region of vehicles as well as the shape of the vehicles in our image samples. After successfully identifying the vehicle types, the images are then cropped according to the car zone.

Next, the YOLOv4 Tiny model is one of the most popular deep learning algorithms applied for object detection and recognition by using bounding box coordinates around the targeted objects [18]. It is fast in image processing, and it can anticipate many different classes of objects depending on the things that need to be detected, such as people, cars, logos, animals, books, phones, etc. In this paper, it is used to detect the licence plates from the crop. After recognizing the license plate region, OCR, a machine learning-based algorithm, is used to read and extract the texts and numbers from the plates [19]. It is a common tool for the translation of images of typed, handwritten, or printed text into machine-encoded text, such as a scanned document, a scene photo, or subtitle text overlaid on an image. The YOLOv4 Tiny is also used to detect the logos of the vehicles. In this paper, there are a total of 21 types of car branding chosen especially for Malaysia to be detected by the system. They are Audi, Bentley, BMW, Chevrolet, Chrysler, Citroen, Ferrari, Ford, Honda, Hyundai, Infiniti, Isuzu, Jaguar, Jeep, Renault, Mitsubishi, Nissan, Lexus, Mercedes-Benz, Volvo, and Suzuki.

Last of all, the TensorFlow Lite model [20] is used to detect the colors of the vehicles from the cropped images. It utilizes a pre-trained machine learning color model titled "color2.tflite", which is capable of recognizing only seven types of common color: black, blue, green, pink, red, white, and yellow.

2.4. Phase 4: Analysis

After extracting and storing all the car specifications in a comma-separated values (CSV) type of Excel file, the proposed system continues with testing the performance of the learning models in phase 4. Through the 60 collected images downloaded from the Paultan website, the performance accuracy is evaluated for each car's specifications, including vehicle type, license plate, logo, and color. In addition, the detection accuracy is also calculated and analyzed based on the position of the vehicles in the images (front-side or back-side) and the resolution of the images.

2.5. Phase 5: Matching

In the final phase, a dummy database is created in an Excel file to store the car owner's information. The system matches the owner's information with the car detection output to verify the identification of the car driver and get past the security guard toll. The system can notify the security guards if the detected car specifications do not match the true identity of the car owner.

3. Results and Discussion

3.1. Detection of Car Specifications

Fig. 4. presents an example of how the car specifications are being detected successfully by the proposed system. The width and length of the cropped image are represented as x-axis and y-axis scales in Fig. 4. Assume that the image of a vehicle is captured by a surveillance camera in front of the guard tower. It is then stored in the computer for image processing to detect the type of vehicle, license plate numbers, car logo, and color. Initially, the codes utilize the MobileNet SSD model to detect the region of the car in the image. Further image cropping will be performed to make the car region clearer if necessary.

The system then continues with the detection of license plates using the YOLOv4 Tiny model. If the plate is detected, the image is again cropped to a smaller zone showing only the car plate. The OCR algorithm is applied next to extract the letters from the plate. The extracted letters, MWV35, are printed on the screen as shown in Fig. 4. The color of the vehicle is also detected as white color using the TensorFlow Lite model, with a prediction of 93.8%. At the end, the YOLOv4 Tiny model is again implemented in the code to detect the car logo as Nissan with a confidence level calculated as high as 0.99 (the maximum level is 1). The percentage of predictions and the confidence level of the models indicate the probability of getting more accurate results. Therefore, in this example, the system has successfully detected all the car specifications correctly.

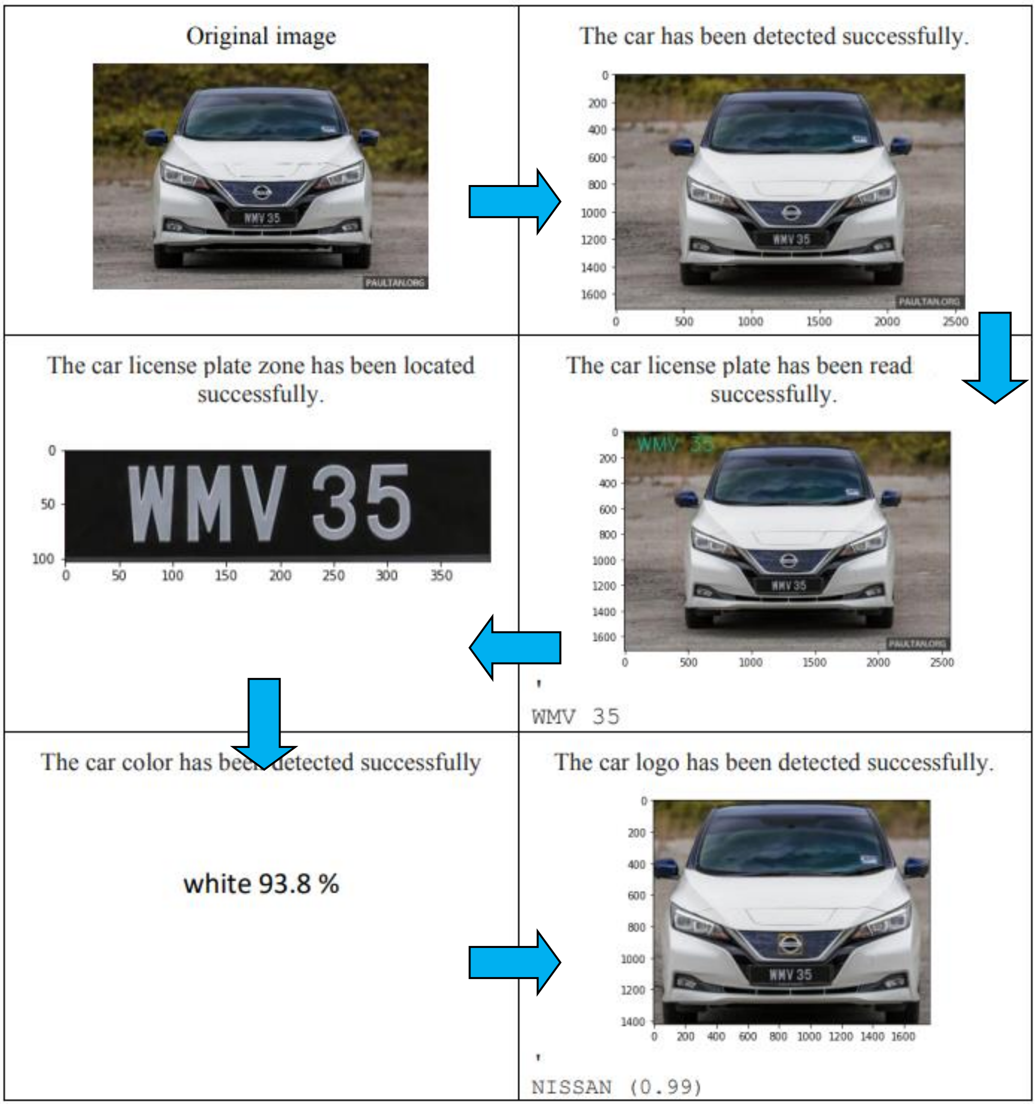

Fig. 4. An example of the car specifications detection

3.2. Performance Analysis of Car Detection

The performance accuracy of car detection, as shown in Fig. 5, is based on 35 images of front-side cars and 25 images of back-side cars. Based on the testing results, the system has successfully recognized and detected the vehicle types from all 60 images. On the other hand, the accuracy of extracting the correct license plate numbers is 97% for front-side cars and 88% for back-side cars, respectively. On the other hand, the system is able to achieve an accuracy of 74% and 68% for detecting the car logos and the car colors of the front-side cars. However, the accuracy of detecting the car logos and car colors is only measured at 12% and 60% for the back-side cars, respectively. This means that the car specifications, such as color and logo, are more difficult to detect when the camera can only capture the image of the back of the vehicle. The suggested solution is to only capture the image of the front of the vehicle at a nearly perpendicular angle to reduce the false detection rate.

In addition, we also analyze the performance of the proposed system based on the resolution of the images, as shown in Fig. 6. Due to resource limitations, only the back-side cars have low-resolution images. Out of the total of 25 back-side car images, there are 19 with high resolution and 6 with low resolution. The definition of a high-resolution image used in this paper is more than 1024 pixels, and the low-resolution image has a pixel count of less than 1024. It is clear that the accuracy of the car logo detection drops from 94% for high-resolution to 83% for low-resolution. However, there is no obvious conclusion that can be drawn since both the results of the car logo detection are considerably lower. Therefore, further analysis needs to be done by testing the proposed system with more vehicle images. The suggested solution to minimize the effect of image resolution on car specification detection is to use a high-definition surveillance camera to capture an image of the vehicle. If the vehicle is moving, then we have to consider implementing additional video processing in the system.

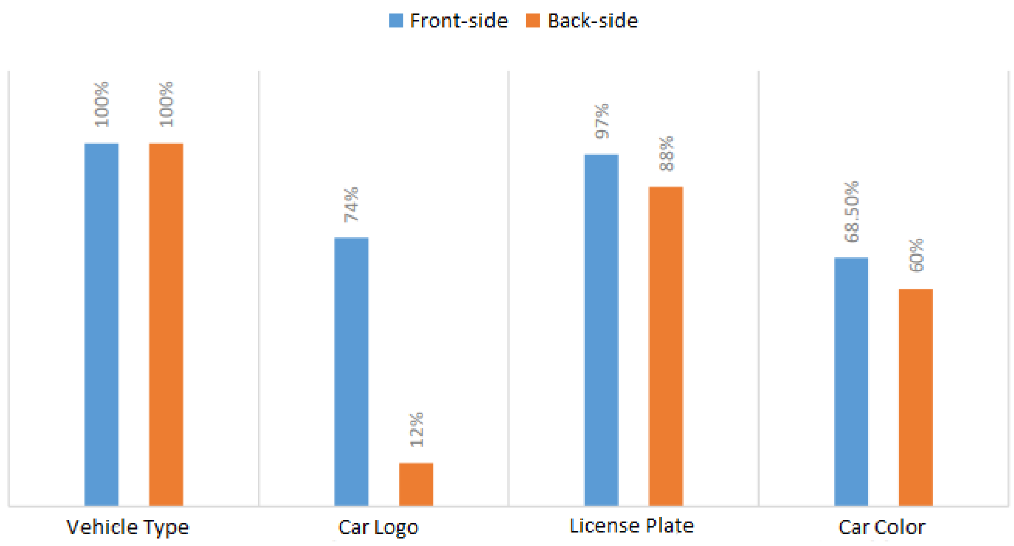

Fig. 5. Accuracy of the car specifications detection

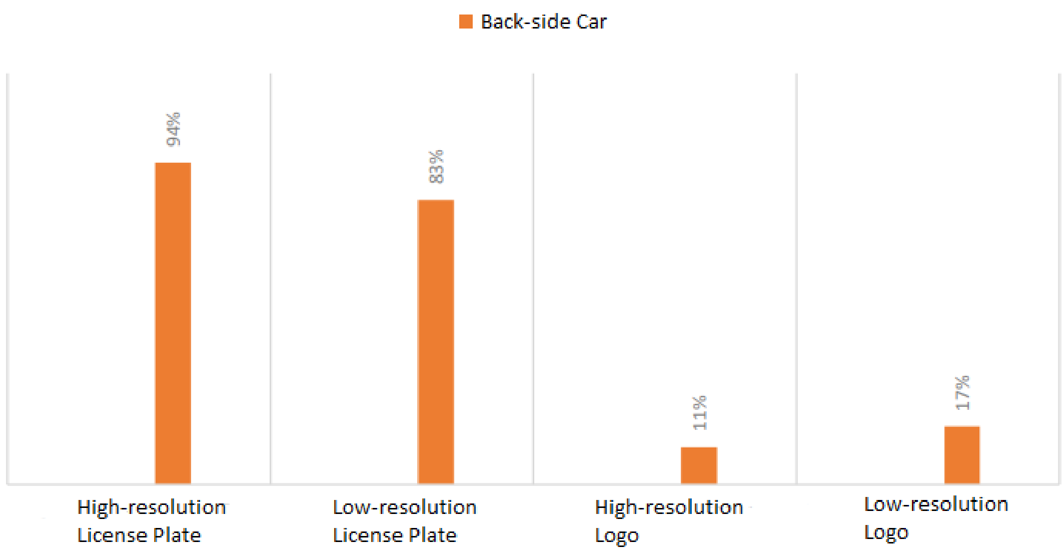

Fig. 6. Accuracy comparison of the high-resolution and low-resolution images

3.3. Matching of Car Specifications

After detecting and extracting the car specifications, such as the car plate numbers, color and logo, the system stores all the information in an Excel file. For instance, a vehicle with a brand of BMW, a color of black, and a plate number of VFL8928 is detected and stored in the Excel file as shown in Fig. 7. A database storing all the information of a true car owner is also created in the CSV Excel file. The system will then compare the detected output with the database. If there is a match between these two data points, the system will recognize the driver as the true owner. If not, the guard or authority needs to take further action to verify the identity of the driver before he can enter the premises. We did not set any conditions on how to determine whether the match is 100% or less since the detection of the car logo and color did not achieve a high percentage of accuracy. However, the proposed system is able to assist the guard in preventing possible vehicle crime before it happens if they can detect any suspects earlier based on the car specification detection.

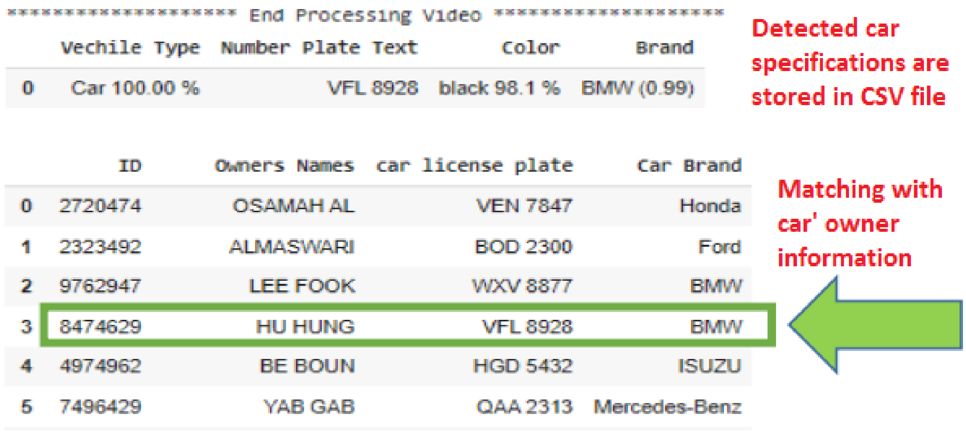

Fig. 7. Matching of car specifications

4. Conclusion

The proposed system in this paper has successfully detected the car specifications through the application of artificial intelligence technologies such as deep neural networks and convolutional neural networks. Several machine learning and deep learning models have been deployed to identify the vehicle types, license plate numbers, logos, and colors of the vehicles in the images. For instance, the MobileNet SSD and YOLOv4 Tiny models are able to detect the vehicle type as well as car plate numbers with a considerable high percentage of accuracy. However, the YOLOv4 Tiny and TensorFlow Lite models can only achieve more than 60% performance accuracy for color detection when the front-side of the vehicles is captured in the images. A matching system has been established in this paper too to detect crimes earlier by matching these car specifications to the identity of the valid car's owner, disallowing criminals to carry fake license plates to commit crimes.

Last but not least, there are some limitations in this research, where the collection of resources such as vehicle images at night, rainy days, etc. is challenging, and the system requires a huge dataset for training the machine learning models in order to improve the performance accuracy. Thus, the system can be improved further by collecting more high-resolution images to detect car specifications in any conditions, including time and weather. For instance, it can be tested under night mode or dim light conditions, as well as under heavy rain, which can make it impossible to see clearly. In addition, improving the quality of the images by installing a surveillance camera with a high-quality resolution can also improve the performance accuracy. Once the suggested improvement has been implemented, the proposed system can be applied practically to all commercial and residential buildings.

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Author contributions

Gwo Chin Chung: Conceptualization, Writing-Original draft preparation, Investigation **Almaswari Osamah Abdullah Hezam:** Methodology, Field study, Software, Data curation **It Ee Lee:** Visualization, Validation, Writing-Reviewing and Editing **Jun Jiat Tiang:** Visualization, Investigation, Validation **Khan Vun Teong:** Field study, Investigation, Data curation.

Conflicts of interest

The authors declare no conflicts of interest.

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