An Edge-based Vehicle Surveillance System for Enforcing Vehicle Restriction Policies

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Abstract

Amount of the world's vehicular traffic has increased rapidly during recent years and cities all over the world are facing increased traffic congestion and environmental problems caused by vehicles. To reduce or avoid these problems, the authorities have been imposing traffic restriction policies such as lane restriction and time restriction rules over specific zones and areas such as city centers and highly populated areas. By imposing such restriction rules and policies on vehicles with large physical dimensions and high emission, severe traffic congestion problems and environmental impacts can be alleviated. In this paper, we propose an edge-based vehicle surveillance system that can enforce restriction rules and policies over a designated area where these rules and policies are imposed. The edge-based vehicle surveillance system can detect prohibited vehicles in designated areas and report this violation of restriction policies to the proper authorities.

1. Introduction

During recent years, the amount of vehicular traffic has greatly increased globally and around 75% of the cities around the world are facing increasing traffic congestion levels. In every major metropolitan city, vehicle congestion problems and traffic jams are one of the main reasons for the continually increasing transportation costs due to the wasted time and extra fuel [1]. Moreover, a major portion of the world's carbon dioxide emissions come from vehicles. Emissions from vehicles are the main cause for the degradation of ambient air quality around the world. Road traffic noise from vehicles is a major source of noise pollution in urban areas. Heavy traffic in urban areas can cause severe environmental problems in the form of air and noise pollution that can negatively affect the daily lives of the city residents.

Due to these reasons, an increasing number of cities around the world are imposing vehicle restriction policies on certain types of vehicles. City centers and areas with high population densities are imposed with vehicle restriction rules to increase the liveability for the city residents. Such restriction policies include space or lane restrictions where certain vehicles such as heavy trucks are restricted using designated lanes, and time restrictions in which certain vehicle types are restricted the usage of a road during peak periods such as rush hours. Imposing such restriction policies can reduce the number of vehicles in restricted areas and mitigate traffic congestion. Furthermore, many cities around the world are banning old vehicle models which have become fuel inefficient and are causing severe environmental pollution. By permanently restricting the entry of old inefficient vehicle models into city centers and urban areas, environmental impacts caused by these vehicles such as air and noise pollution can be alleviated and the liveability of the communities around the cities can be improved.

To increase the effectiveness of these restriction policies, surveillance of the entry of restricted vehicles into designated areas is required to enforce these policies. Manually monitoring restricted vehicles over a number of large areas can be highly complicated and costly. Due to the increasing advancement in IoT technology and machine learning techniques, edge-based vehicle surveillance system can be developed to enforce the vehicle restriction policies resulting in more efficient transportation networks, reduced pollution emissions and environmental impacts, hence improving the liveability standards of communities in highly populated areas.

2. System Model

In edge-based vehicle surveillance system, surveillance nodes can be spread around the restricted area or they can be placed at the entry points into the restricted area. In our system model in figure 1, surveillance nodes are placed at the entry points into the restricted area. In many cities around the world, most vehicle restriction policies are targeted towards heavy trucks, due to their sizable physical dimensions and emissions which have large impacts on traffic conditions and the environment. Due to these reasons, in our system model, trucks are chosen as the restricted

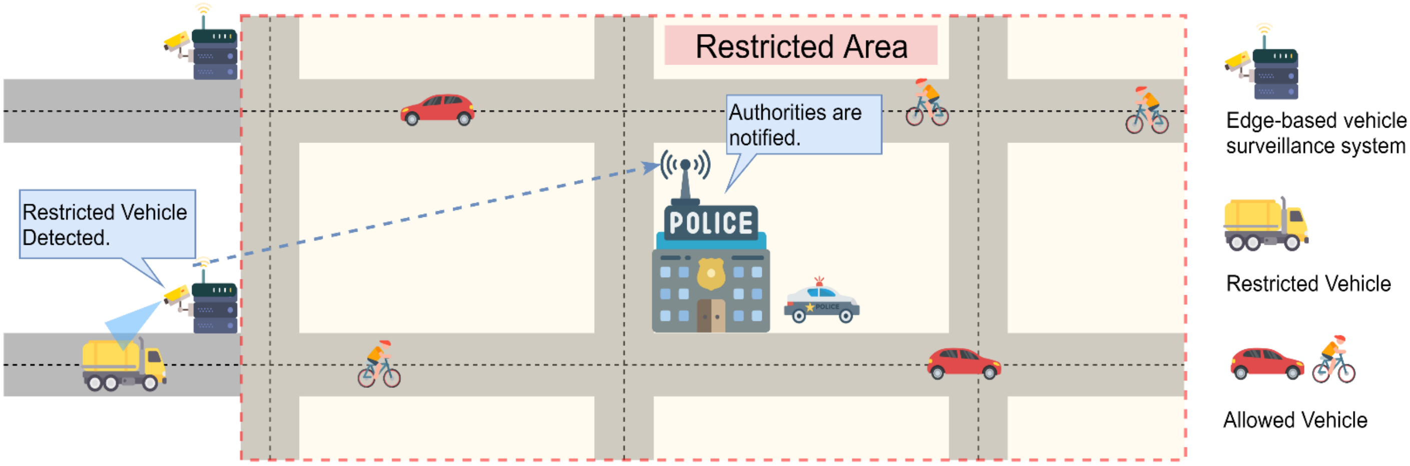

Figure 1. System Model

vehicle type for a designated area. The system can be easily reconfigured to change the type of restricted vehicle or add another type.

When the edge-based surveillance system detects the incoming traffic, it takes the image of the incoming vehicle. In each surveillance edge node, a convolutional neural network model trained on a dataset of vehicle images is embedded to perform the vehicle classification task. The vehicle image taken is fed into the convolutional neural network model for vehicle type classification. If the vehicle is classified as a restricted vehicle type which in this case is a truck, the system will notify the authorities about the restricted vehicle in the designated area. Then the authorities can take appropriate actions based on the received notification.

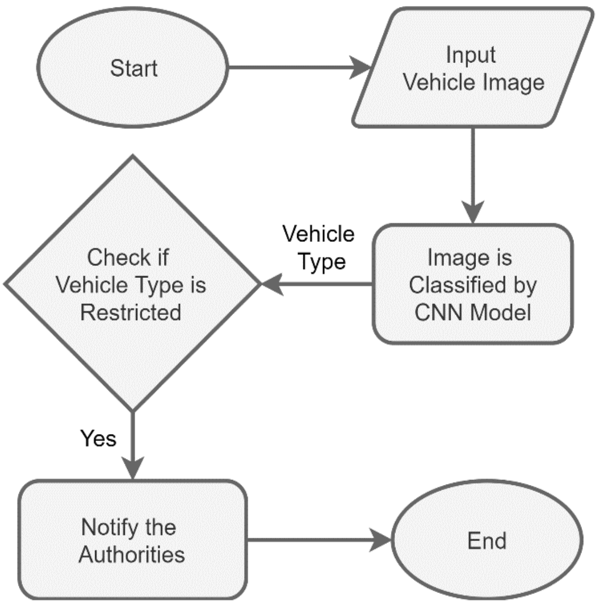

Figure 2. System Flow Diagram

Edge-based Vehicle Surveillance System Algorithm

1: Input: Image of the detected vehicle
2: Output: Whether the vehicle type is restricted vehicle type or not
3: Begin
4: Get input vehicle image
5: Classify the vehicle type using CNN model
6: Check if the vehicle type is restricted
7: If the vehicle type is restricted
8: Notify the authorities
9: End

3. Convolutional Neural Network Model

Convolution neural network is a type of deep neural network used mainly for analyzing visual imagery [2]. In the edge-based vehicle surveillance system, the most important process is the classification of the input vehicle image into vehicle type. Since the entire system depends highly on the classified vehicle type, it is imperative that the classification task is performed accurately. In our experiment, the vehicle classifier model is constructed using the convolutional base of the VGG16 model [3]. The resulting neural network model is fine-tuned on a dataset that contains four types of vehicles: bike, car, truck and cycle. The data set contains 200 images of bikes, 300 images of cars, 200 images of cycles and 300 images of truck for training. For validation, it contains 30, 50, 30, 50 images of bikes, cars, cycles and trucks respectively. To reduce the overfitting of the model, image augmentation techniques are applied to the training data set [4]. After training this neural network for 100 epochs, it can correctly identify over 80 percent of the restricted vehicles.

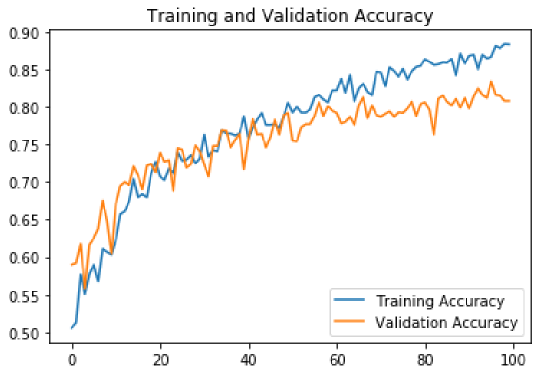

Figure 3. Accuracy of CNN model

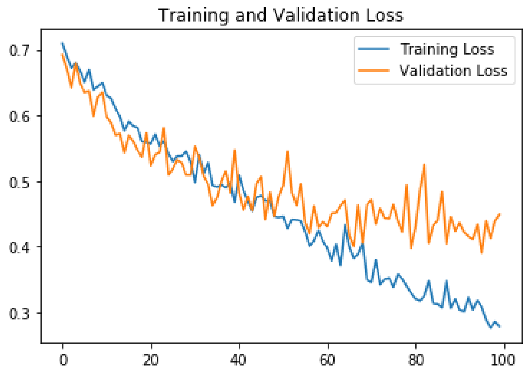

Figure 4. Loss of CNN model

4. Conclusion

By deploying edge-based vehicle surveillance system, violation of traffic restriction policies can be reduced in designated areas. Compared to manually monitoring the restricted areas, this system can cover larger areas and will also have reduced operation costs. Since it is an edge-based system with an embedded classifier model inside each node, vehicle image inferencing task can be done internally. By using edge-based inferencing paradigm, the system will have low latency response when performing the vehicle classification task compared to centralized cloud inferencing paradigm.

Acknowledgement

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