Poster: Enhancing Autonomous Vehicles Safety through Edge-based Anomaly Detection

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Abstract

With the growth of vehicular computing capacity, there is an increasing demand for real-time data processing. However, data is sometimes not optimal for purposes such as storage or training. To address this issue, we propose a solution to enhance vehicle safety by generating abnormal image data. We then leverage machine learning algorithms to detect and classify these anomalies while vehicles are in operation. An edge-based anomaly detection approach will be applied to prevent accidents and enhance the safety of connected vehicles.

Keywords: Edge Computing, data analysis, data processing, image anomaly detection, connected and autonomous vehicles (CAVs)

1 Introduction

In recent years, edge computing has become widely recognized, with the notion that everything is at the edge. Where previously computations were solely performed on central servers, now edge devices possess the computational capabilities and accelerate the pace of the Internet of Things (IoT) integration[5]. As edge devices are more powerful for training and inference tasks than previous years ago, we have seen many light weighted models were deployed on IoT devices. In this trend, computation of hardware become more powerful and makes connected vehicles not only serve as transportation but also a mobile computing platform[4]. It aims to enable connected and autonomous vehicles processing and analyzing data without transmitting them to a physical server. It is not efficient and safe to send the data back to server. Also, our existing technologies could not guarantee data transmission with no information losses or communication latency. Electronic vehicles nowadays even have more than 100 sensors to detect and collect data. A huge amount of data will be generated by these sensors. Sensors generate approximately 25 GB of data per second. Under the situation, connected vehicles play a big role on analyzing data in a timely manner.

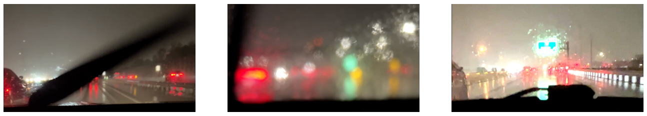
In a real world, many complex scenarios might be occurred on connected and autonomous vehicles. CAVs do not have time to wait for server response. Images captured by camera might be blurring, occluded, brightness, noisy etc. This is more likely happened while vehicles are driving in severe weather. Deep Neural Network models may not detect it since models are not intelligent enough to handle these corner cases. For instance, a lane detection model is designed for recognizing lanes specifically. If something covers the front camera of a vehicle and take up half of its field of view, even a detection model with a high accuracy would be failed. Failures in connected and autonomous vehicles can result in life-threatening dangers. In this case, it is not because of weakness of a model but it has never trained such abnormal data. To ensure safety of connected vehicles, we proposed that generate and simulate some abnormal images based on normal images to augment data. This approach could improve the success rate of anomaly detection model and warn the connected or autonomous driving vehicles before accidents.

Our motivation for this work stems from the pressing question: How to guarantee the input image data have good quality be sent into a model for the prediction on the CAVs? Advanced machine learning algorithms or what we called deep neural network hardly answer this question. They are likely to get some vague prediction while they were not pre-trained with these unseen patterns. However, we want make our CAVs as safe as possible as we minimize the risk of failure of predictions. Without image anomaly detection, even high accurate models are meaningless if it encounters any corner cases. As Figure1 1shows three corner cases will potentially cause failure of model prediction. Original images were trimmed by ourselves from a self-recording video tape.

In this paper, we consider using edge-based image anomaly detection model to beat this challenge. First, we generate abnormal data from existing datasets. We use Ford AV dataset[1] and Zenseact open dataset[2] to generate different types of scenarios. Anomalies including blurring, occlusion, brightness etc. will be generated from the original images for the training purpose. Finally, we will apply anomaly detection models on this combined dataset to see the performance.

2 Related work

Recently, many works related to synthetic data have been done for autonomous driving. In this Virtual KITTI2[3], the author presented an enhanced version of the esteemed Virtual KITTI dataset. This updated compilation encompasses five replicated sequences derived from the benchmark KITTI tracking dataset, further augmented with variations



(a) occlusion **(b)** blurring **(c)** brightness

Figure 1. Figure 1 shows three examples of image degradation: occlusion, blurring, and changes in brightness.

in weather conditions and alternate camera configurations. Also, some topics was gathered into a survey[6]. It shows the works through single synthetic data to multi-task synthetic data.

3 Methodology

3.1 Dataset

The Ford AV dataset[1] was collected from vehicles that traversed an average route of 66 km in Michigan during different seasons. This route included a mix of driving scenarios such as the Detroit Airport, freeways, city centers, university campuses, and suburban neighborhoods, among others. Each car has 7 cameras distributed at various angles(center, front-left, front-right, side-left, side-right, rear-left, rear-right) to provide comprehensive visual coverage. The other open source dataset called Zenseact[2] provides multi-modal scenarios These open source dataset has been formatted and annotated by experts. Their data were collected across 14 European countries with diverse scenes.

3.2 Hardware Devices

In the table1 **??**, three different devices AGX Xavier, Fog Node and GPU Workstation will be used to do inference. Experimental devices are equipped with either AMD x86_64 or Arm_64. We will use GPU workstation for data generation and model pre-training. All of them will be used for stage of inference.

Table 1. HARDWARE CONFIGURATIONS OF DEVICES

Devices	CPU	GPU	Memory
AGX Xavier	8-core NVIDIA Carmel Arm®v8.2	512-core NVIDIA VoltaTM	32 GB LPDDR4x
Fog Node	8-core Intel Xeon	-	32 GB DDR4
GPU Workstation	28-core Intel Core i9	4x NVIDIA RTX 8000	64 GB DDR4

3.3 Methods

First, we make a set of abnormal images based on open source libraries or tools. From original datasets, we should generate different types of images with anomalies. They will be stored into each sub-folder for annotations. This task we proposed using deep neural network to classify these images into categories of anomalies which we have designed for connected and autonomous vehicles. Figure2 **??** shows a structure of convolutional neural network as an example.

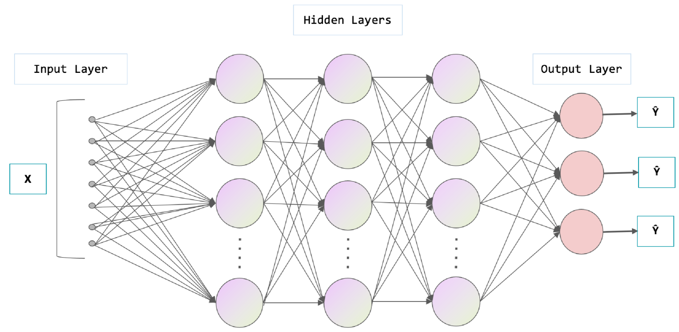


Figure 2. Example: Anomaly detection model using CNNs

4 Future Work

In the future, we should consider how to process these whole dataset and get correct bounding box for model training. After make sure these data are generated on the right track and well prepared, we can move to edge-based image anomaly detection model building and training. We plan to use deep neural network to achieve final classifications. Results evaluation will be performed to reflect training and inference.

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