Object Detection on Raspberry Pi

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Abstract

Internet of Things (IoT) refers to the billions of edge devices around the world connected to the internet for various applications such as collecting and analyzing data. Data analytics on these edge devices can protect user privacy and reduce communication costs. Specifically, computer vision is a core technique to build such applications on these devices, where object detection is an imperative task that is to recognize categories of objects and label their locations. This paper presented a senior design project that implemented object detection on Raspberry Pi via machine learning models. It is to employ Raspberry Pi Kits and a web-camera to detect predefined objects by running mobile deep learning models. Moreover, it was extended to recognize weapons in images with transfer learning techniques, which is to fine-tune the models on new annotated datasets collected from Internet. Specifically, it applied a Google USB accelerator to improve the detection speed. Preliminary validation results demonstrate that the models can effectively detect general objects such as person, keyboard, and laptop, as well as predefined weapons on Raspberry Pi.

Introduction

The Internet of Things (IoT) refers to the billions of edge devices around the world connected to the internet for collecting and analyzing data, which is evolving rapidly and widening existing communication systems. It was predicted that more than 50 billion IoT devices will be involved in IoT[1] after 2020 and these devices will be linked with each another to exchange and generate data to make everyday life easier in different aspects such as healthcare[2], military[3], smart home[4], and agriculture[5] by developing various applications. Specifically, computer vision is a core technique to build these applications, where object detection is an imperative task in this field that is to recognize categories of objects and label their locations.

This paper presents a senior design project that implemented object detection on Raspberry Pi by running deep learning models, where the edge devices include Raspberry Pi 3 and 4, Model B+ (Plus) Complete Starter Kit[1] and a web camera. It consists of three steps: 1) hardware configuration: it is to configure the Raspberry Pi and mount the web-camera on the Raspberry Pi; 2) software installation: it is to install necessary software such as TensorFlow and OpenCV; 3) deploying mobile deep learning models on Raspberry Pi to run object detection. Experimental results demonstrate the effectiveness of this implementation. Moreover, we leverage the USB accelerator to improve the detection speed.

[1] https://www.canakit.com/raspberry-pi-3-model-b-plus-starter-kit.html

Finally, we extend this implementation to weapon detection through fine-tuning pretrained deep learning models on data samples collected and annotated manually.

Project

This project implemented object detection on Raspberry Pi. As a core task in the field of computer vision, object detection is to detect instances of visual objects with a certain class (such as airplane, car, or animal) in digital images. It is implemented by developing computational models and techniques to recognize objects and their locations, which can be applied to many downstream computer vision tasks. Recent years have witnessed the breakthrough of object detection with the emergence of deep neural networks (DNNs)[6], especially, convolutional neural network (CNN)[7]. Compared to traditional techniques, the CNN can extract more specific and advanced features with deeper architectures layer by layer. Moreover, the expressivity and robust training algorithms allow CNN to learn informative object representations without the need to design features manually[8]. However, these models need to run with many computational resources, which cannot be afforded by edge devices for IoT. To overcome this challenge, mobile deep learning models have been implemented on these devices. With this advanced technique, this project is implemented as Figure 1. Web camera took pictures as input images to the mobile deep learning models that run on an edge device. Once completing detection, it will output object classes and corresponding locations on the image.

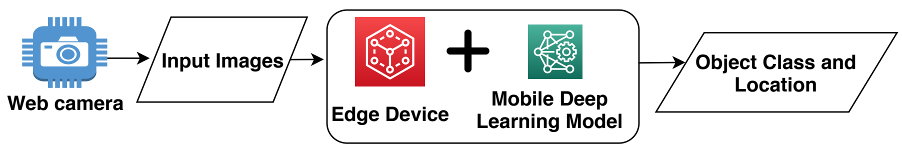

Figure 1. Object detection on an edge device with a mobile deep learning model

Moreover, this project is extended to detect weapons. It is observed that a large amount of population reconciles violence related to various weapons such as guns and knives all over the world. Therefore, it will be a good proactive solution to detect these weapons in public area to protect citizens. In this work, we implemented weapon detection on images, which is designed as Figure 2. Camera will help obtain the input data that would be video streams. Then, it will process the video and isolate images with image acquisition. Afterwards, we will apply mobile deep learning model to detect weapons with image recognition, where the output is to confirm if there is a weapon. If there is a weapon, it will send a notification. Otherwise, it will process the next image.

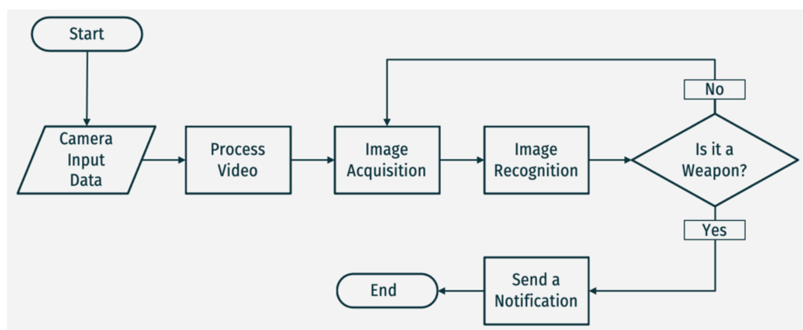

Figure 2. Flow of weapon detection

Implementation and Preliminary Validation

Implementation:

We employed specific a deep learning model and an edge device to implement this project. For deep learning model, this paper employed SSD-MobileNet[13] to implement object detection on edge devices.

SSD-MobileNet is a single-shot detector with high performance for multiple categories of objects, where the architecture contains MobileNet[9]. To improve detection accuracy, it generates predictions of different scales from feature maps with different scales, and explicitly separates the predictions by aspect ratios. For edge device, Raspberry Pi was selected as the edge device to run SSD-MobileNet for object detection. It is designed as credit-card-sized single board computer for stimulating the teaching of basic computer science in schools. It supports Debian and Arch Linux ARM distributions and Python as the main programming language. In addition, NumPy, SciPy, Matplotlib, IPython, and PyLab can be used for computational mathematics as well as the analysis of experimental data or control systems[10]. It is widely used in many areas, such as for weather monitoring[11] because of its low cost, modularity, and open design. In addition, it is used by computer and electronic hobbyists, due to its adoption of HDMI and USB devices.

For weapon detection, implementation design is shown in Figure 3. In addition, we build a data set for weapon detection, where Figure 4 shows four examples of knives held by a person, where the white box is the ground truth. Although we collected 900 samples, the number of samples is not big enough to train the SSD-MobileNet from scratch. Therefore, we employed deep transfer learning[12] to resolve this challenge. It tries to transfer the knowledge from the source domain to the target domain by relaxing the assumption that the training data and the test data must be independent and identically distributed (i.i.d). It is to fine-tune SSD-MobileNet on the data collected for weapon detection.

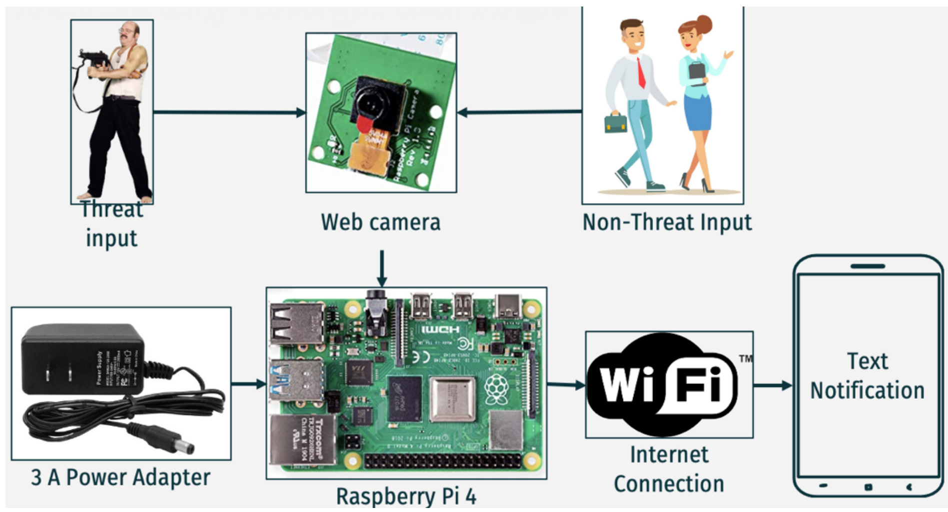

Figure 3. Implementation design of weapon detection

Figure 4. Examples of data samples for weapon detection

Preliminary Validation:

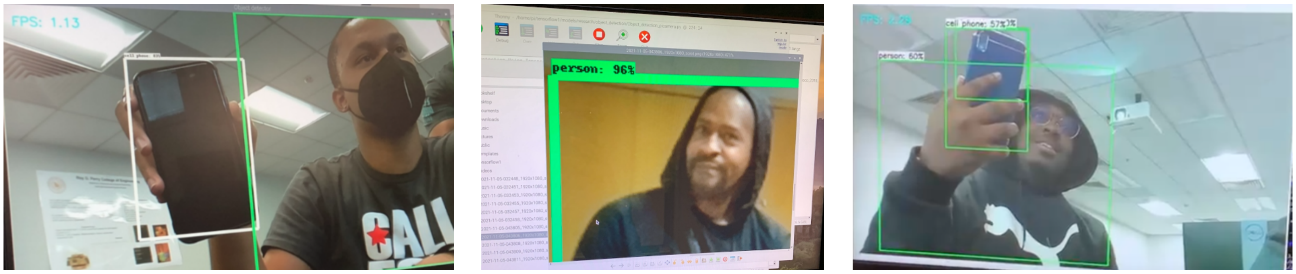

Figure 5. Examples of results of object detection on Raspberry Pi

For object detection on Raspberry Pi, we ran SSD-MobileNet on Raspberry Pi 3 to implement object detection. In addition, we employed accelerator to speed up the detection. Compared to the detection without this accelerator, the detection speed can be improved from 1.13 frame per second from to 10.51 frame per second on averages. Figure 5 presents three examples of detection results. The left example indicates that the implementation can detect multiple objects including a person and a phone even if the person was wearing face mask. In addition, the locations of these two objects are accurate in terms of bounding boxes. The middle example shows that the implementation can detect the object with high confidence (96%). The right example presents a more complex case that the locations of objects have overlaps. For instance, although the phone's location has overlaps with that of the person, the implementation can still detect these objects correctly.

For weapon detection on Raspberry Pi, we ran fine-tuned SSD-MobileNet on Raspberry Pi 4, where Figure 6 presents one example of detection results. Currently, we utilized the camera on laptop for this validation. In terms of the preliminary detection results, current version of implement is able to detect certain weapons such as handgun. However, the detection speed is not high enough for real-world applications. In addition, it is still limited with predefined weapons.

Figure 6. An example of detecting weapons

Conclusion

This paper presents preliminary work of the implementation of object detection on Raspberry Pi for a senior design project. We run a mobile deep learning model, SSD-MobileNet, on Raspberry Pi to detect various objects. Preliminary valudation results demonstrate the effectiveness of this implementation. Moreover, the on-going work is to improve weapon detection. Future work will focus on completing comprehensive and systematical validation on weapon detection in different testing scenarios.

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