Traffic Sign Localization and Detection

Progress Report

University of Toronto

Faculty of Applied Science and Engineering

Artificial Intelligence Fundamentals

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Brief Project Description

There are around 2700 people die every year because of car crashes in Canada, reported by the *Hamiltonlawyer* [1]. According to CNN, the 8th most common death reason in the world contributes to traffic-related accidents. Among all reasons towards the traffic accident, not following the traffic signs is one of the leading causes for car accidents [1]. Therefore, our motivation for this project is to develop a safer and more reliable driving assistant system, and further, to assist with the future implementation of autonomous driving systems. The goal of our project is to detect and recognize the upcoming traffic signs from the driver's driving recorder. Machine learning is a reasonable approach for this project since we are able to train a model to learn the pattern of each traffic sign and therefore distinguish every sign with low delay and high accuracy.

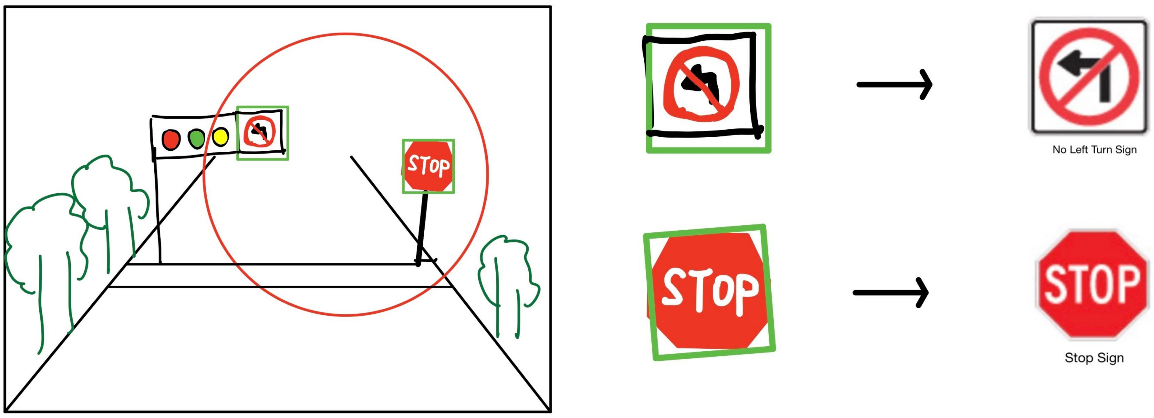

Figure 1. Goal -- localize and identify the traffic sign on a driving recorder

Data Processing

Content	Data processing skill	Data size	Remark
Driving recorder	Python video processing related library	25,728 images with size (1280 * 720 pixels)	Collected from real world driving recorder
Online Dataset from Mapillary	Applied and waiting for approval	40+GB, 100,000+ images	Contains traffic signs from North America
Traffic sign Augmentation	skimage lib, rotation, adding noise, flipping	around 150 images	Used to test a small CNN model that should identify traffic signs

Table 1. Summary of the data processing progress

The project contains two models, which are localization model and classification model respectively. We applied different data processing approaches to each dataset. In the localization model, we have two datasets sources: one is from our driving recorder, and another is from online. For the data from the driving recorder, one photo was captured every half second by a python script using video related libraries for each video and they were resized to 1280 x 720. For the data that we acquired from Mapillary [2], we organized and selected the appropriate images that were filmed in North America.

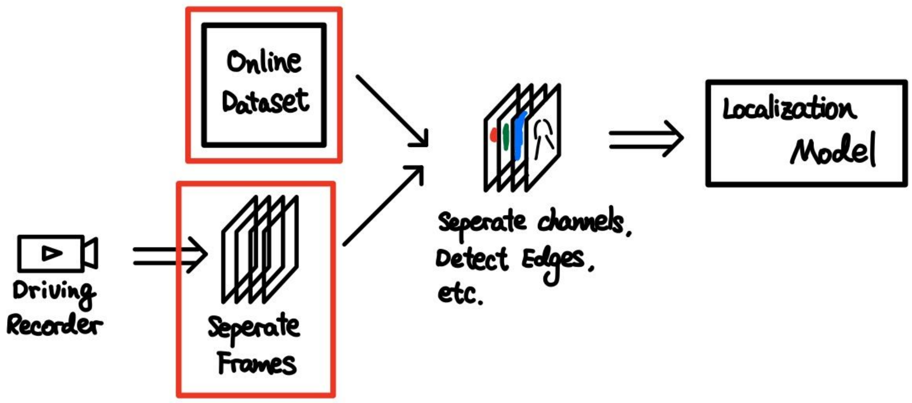

Figure 2. Online dataset and driving recorder processing steps

Figure 3(a). driving recorder data

Figure 3(b). online data

In the classification model, we downloaded the high resolution traffic signs from Ontario MTO[3]. Considering that traffic signs in real life are not always clear and standardized (e.g. distortion, faded colors), we generated training data by rotating, changing colours, and adding random noise from clear signs using skimage, which increases the accuracy of the model.

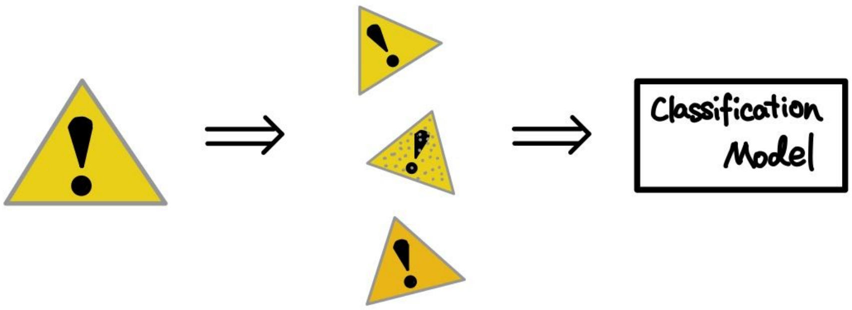

Figure 4. data argumentation from standard images

Figure 5(a)-5(d). Original sign, rotated sign, sign with random noise, and colour adjustment

Baseline Model

In the project proposal, we proposed a combination of sliding window and CNN as our baseline model. The sliding window algorithm is used for detecting the traffic sign. The "window" is moved around the image and makes small crops. Those crops will then be forwarded into CNN to classify. In the CNN model, the data will be processed by 2 convolutional layers, followed by 2 fully-connected layers and then passed to output layers. This CNN will be trained to categorize traffic signs into different types, such as warning and regulation.

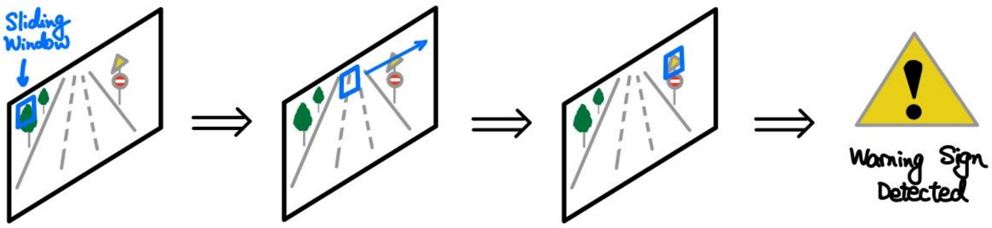

Figure 6. working principle of baseline model(using sliding window and CNN)

However, the sliding window algorithm will require a longer time to process as it moves around the images and makes crops. In the primary model, we will improve the performance of the data processing stage to reduce the runtime and adjust CNN to enhance the accuracy of classification.

Primary Model

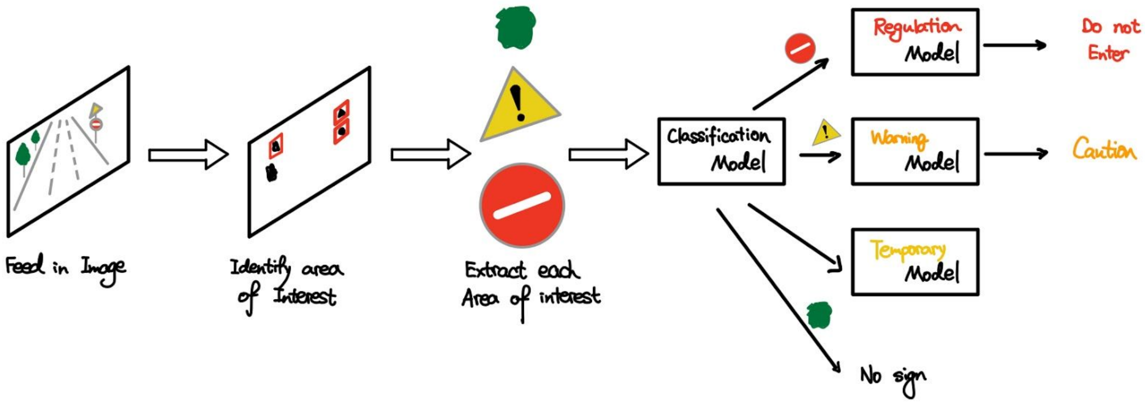

Figure 7. Diagram of the final designed model architecture

So far, we utilized a heuristic model of color detection for localization, combined with a CNN model to classify “Construction” signs and “Traffic Control” signs for now, so we can make sure that CNN works for traffic signs classification. We chose to use this architecture since most of the traffic signs have bright colors. Besides, CNN classification model is good at detecting different features in the input images, and it also keeps the spatial structure of images, making it fit our problem well.

To localize the traffic signs, we transform images to HSV and YPbPr color space to detect vivid colors, such as red and orange. We have not yet combined the localization and classification, therefore we implemented data augmentation as described in the data processing section to build our own training and validation set for the CNN model.

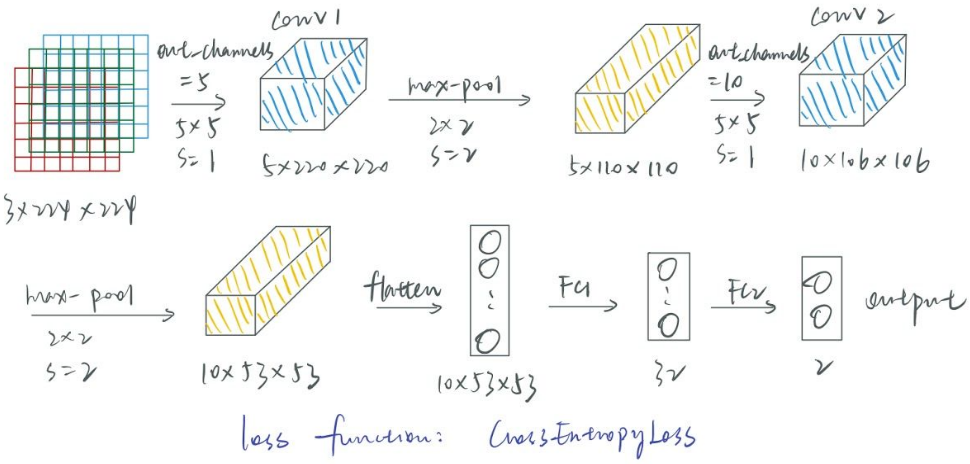

Figure 8. overall architecture of our current CNN model

Layer	Number of Parameters
Convolutional layer 1	(3*5*5+1)*5 = 380
Convolutional layer 2	(5*5*5+1)*5 = 1260
Fully connected layer 1	(10*53*53+1)*32 = 898912
Fully connected layer 2	(32+1)*2 = 66
Total	900618

Table 2. Number of parameters calculation of our current CNN model

Results

Result for localization model:

Figure 9(a), 9(b). Examples of localization result

Result for classification model:

We've tried different sets of hyperparameters for training the classification model:

Set I: batch size = 16, learning rate = 0.005, number of epochs = 10

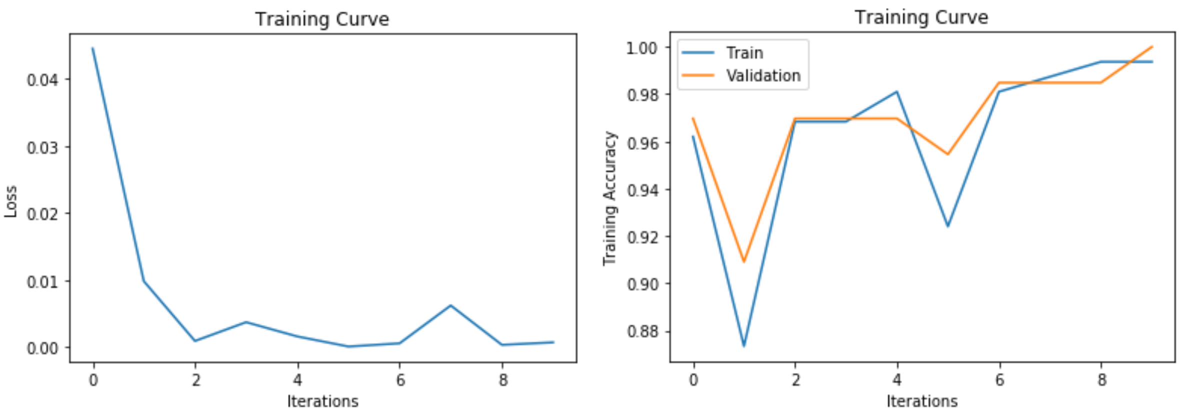

Figure 10. Training loss plot and accuracy plot for hyperparameter set I

Set II: batch size = 16, learning rate = 0.005, number of epochs = 10

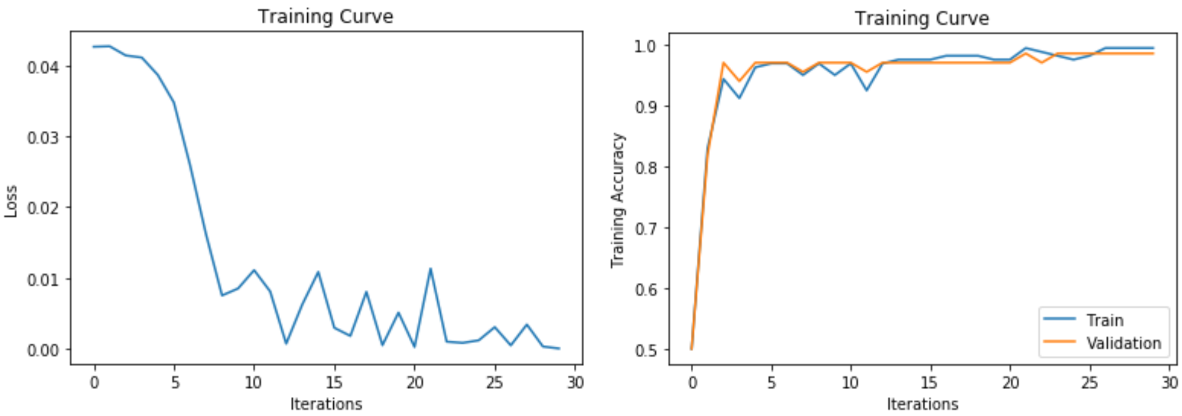

Figure 11. Training loss plot and accuracy plot for hyperparameter set II

Below is the traffic sign we cropped from a driver's recorder, and we put it into our classification model.

Figure 12. construction sign cropped from driver's recorder

Our model shows there is a probability of 87.48%(*) that this sign is a construction sign, which means our model can distinguish it from "Traffic Control" signs with high confidence. It proves that our data argumentation method and classification model work.

*: output from the model is: tensor([[0.9247, -1.0191]], grad_fn=<AddmmBackward>)
softmax calculation: exp(0.9247) / (exp(0.9247) + exp(-1.0191)) = 0.8748

Project Progress

Due to the COVID-19 outbreak and the transition of work from in-person to online, the progress of our team is now slightly behind what we scheduled in our project proposal. Currently, we completed the preprocessing heuristic method that can localize the area of interest. However, the accuracy is lower than we expected and we are trying to use a CNN model to boost the accuracy. Also, we completed and tested a classification model that can identify temporary traffic signs. Based on the current pace, we decide to mainly focus on our model and set audio output as an optional task if time allows. Detailed schedule and timelines are as follows:

Task	**Assigned team member**	**Due date**	**Progress Status**
Traffic sign localization (heuristic)	Siwei He	Already done.	Accuracy is lower than expected.
Traffic sign localization (machine learning with CNN models)	Xinru Li, Siwei He	Mar. 22nd (model testing) Mar. 28th (final model)	Work in progress.
Traffic sign classification (Temporary signs)	Xinru Li, Jiani Li	Already done.	Accuracy is good.
Traffic sign data augumentation	Jiani Li, Qihan Liu	Mar. 20th	Work in progress.
Traffic sign classification (All signs)	Jiani Li, Qihan Liu	Mar. 22nd (first layer) Mar. 28th (second layer)	Not yet started.
Link localization model and classification model, finalize project	All group members	Apr. 1st	Not yet started.
Presentation recording	All group members	Apr. 3rd	Not yet started.

Table 3. Tasks for each team member and the associated due date

Reference

[1]"What Are The Leading Causes of Car Accidents in Ontario?", *Lalande Personal Injury Lawyers*, 2020. [Online]. Available: https://www.hamiltonlawyers.com/car-accidents/leading-causes/. [Accessed: 15- Mar- 2020].

[2] Mapillary.com. (2020). Mapillary - *Street-level imagery, powered by collaboration and computer vision*. [online] Available at: https://www.mapillary.com/dataset/trafficsign. [Accessed 20 March 2020].

[3] Ontario.ca. 2018. *Traffic Signs And Lights*. [online] Available at: <https://www.ontario.ca/document/official-mto-drivers-handbook/signs>. [Accessed 20 March 2020].