HIGH SCHOOL EDITION
Journal of Student Research

Volume 10 Issue 4 (2021)

# Aggressive Driving Detection and Alert System Leveraging Current Signal Light Infrastructure

Brian Li[1], Emma Li[1] and Hui Li[#]

[1]Mission San Jose High School, Fremont, CA, USA
[#]Advisor

## ABSTRACT

According to the National Highway Traffic Safety Administration, aggressive driving behaviors are responsible for 54 percent of annual traffic accidents from 2007 to 2019. These accidents cost our society billions of dollars economically. Additionally, hundreds of thousands of innocent lives are taken away and a profound psychological impact is placed on survivors. Existing research on aggressive driving detection mostly relies on devices mounted on vehicles for collecting the data when driving. Such approaches, however, will be hard to enforce in real life because of consumer privacy concerns. Also, not all existing vehicles can have the monitoring system, thus the overall effectiveness is limited. The approach that we propose here is to leverage the existing infrastructure of traffic lights to enforce the detection of aggressive driving behaviors for all vehicles at all times. The undertaken approach introduces centralized detection and alert systems that can work with an existing traffic light control system and a real digital map system as a real-world application. The detection system utilizes both traffic lights and speed sensors mounted alongside to detect aggressive driving behaviors at intersections. The alert system adopts an efficient specialized graph traversal algorithm to pinpoint impacted traffic lights and alert only the drivers nearby those lights. To demonstrate the approach, we prototyped both a detection system and an alert system running on an Arduino board. We verified their consistent high accuracy and real-time response by applying them to an experimental setup that consists of streets and intersections with traffic lights and infrared sensors.

## 1. Introduction

Aggressive driving has consistently been the leading cause for traffic accidents. The statistics published from the National Highway Traffic Safety Administration shows that over 54 percent of the annual traffic accidents are caused by aggressive driving from 2007 to 2019[1]. Not only do these accidents create a heavy toll onto society, with billions of dollars as an economic cost, but more profoundly they often lead to the loss of innocent people's lives, and a psychological impact on those who manage to survive.

Some interesting research efforts have been devoted to enhancing the techniques of detecting aggressive driving behaviors.
Haike Guan et. al. [2] applied a machine learning method to automatically detect certain aggressive driving behaviors based on the video recording collected from a surveillance camera mounted on taxis or trucks.

HIGH SCHOOL EDITION
Journal of Student Research
Volume 10 Issue 4 (2021)

**Figure 1.** Recorded video image on a night time traffic light in Japan

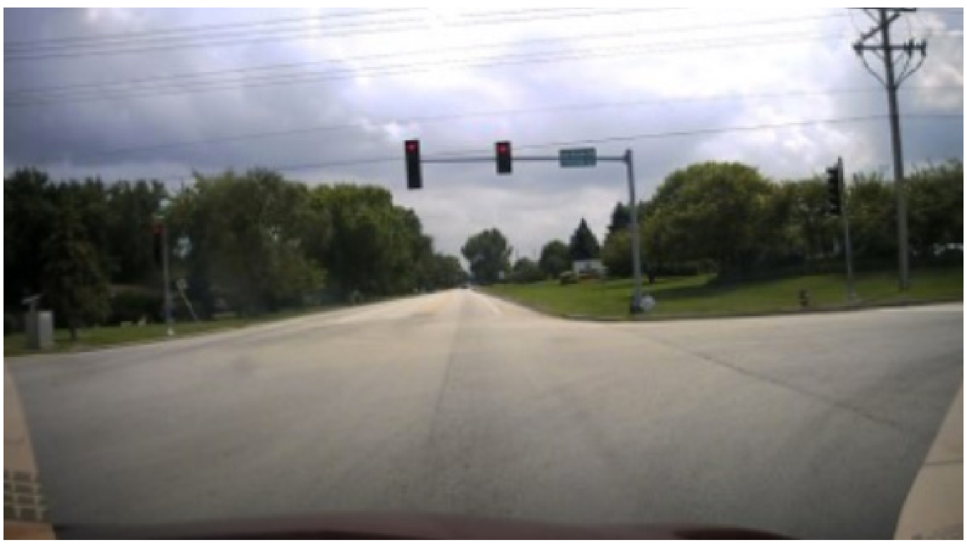

**Figure 2.** Recorded video image on a day time traffic light in USA

Figures 1 and 2 show that this machine learning system is capable of detecting traffic lights either in day time or at night and in Japan style or USA style. Figure 3 shows how the neural network-based machine learning algorithm works. The system can detect the engine and vehicle speeds. Based off of histogram modeling, it is able to classify if the vehicle is aggressive or not.

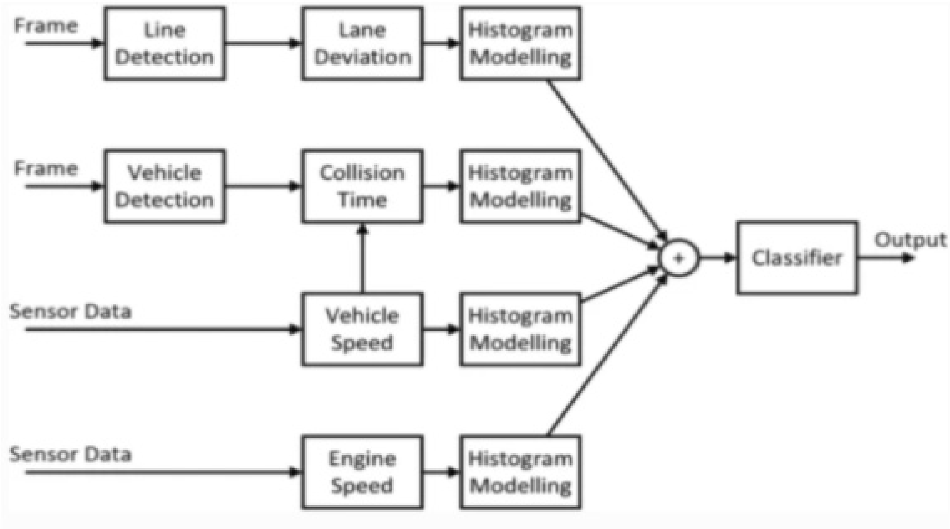


**Figure 3.** Neural network flowchart

Such technique can help insurance companies identify whether or not certain drivers have aggressive driving behaviors. However, for general purpose application, they have the following limitations:

- Privacy Concern: not all drivers will be willing to allow surveillance cameras mounted in their vehicles as shown in Figure 1.
- System Installation Requirement: at minimum, video capturing and recording device installation on vehicles is required, so most existing vehicles likely will not equip it and thus cannot be applied.
- Not Real-Time Detection: a driving journey is recorded first and then the recorded video is fed into the learning system to detect any aggressive driving behaviors offline.

Deepika Chawla et. al. [4] also utilized a machine learning technique to detect abnormal driving behaviors based on the data collected from smartphone sensors. Figure 4 shows six possible aggressive driving behaviors, including weaving, swerving, side slipping, fast U-turn, turning with a wide radius, and sudden braking, all of which can be detected by this machine learning system.

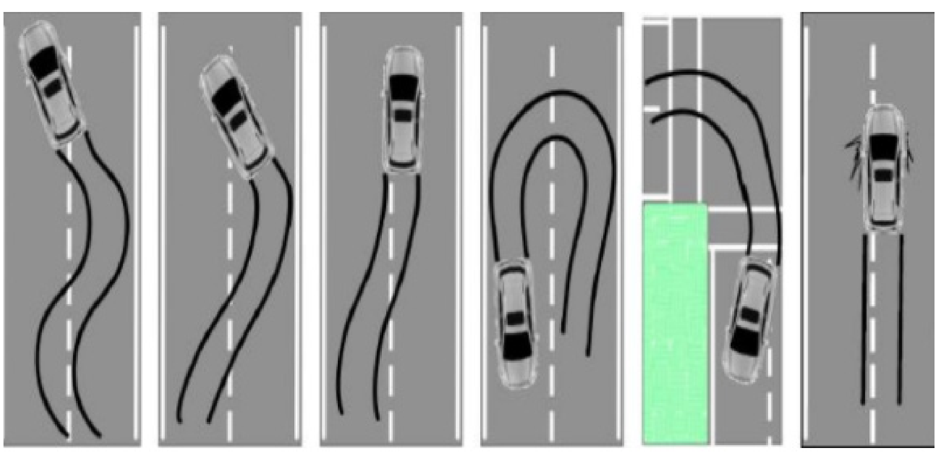

**Figure 4.** Six types of abnormal driving behaviors that can be detected by machine learning.

With the use of a smartphone, the approach eliminates the need for installing any special system on vehicles but it still suffers the following limitations:

- Privacy Concern: not all drivers will be willing to participate in such monitoring and may choose to turn it off.
- Not For Imminent Accident Threat Detection: the main purpose is for sober drivers to self-correct abnormal behaviors, not for irrational aggressive drivers with imminent accident threat.

In summary, most existing research focuses on *detection for correction* to help drivers to correct their behaviors. However, our approach focuses on *detection for prevention* to reduce or prevent the collateral damage from imminent accident threat. Our objective is to design an accurate real-time aggressive driving detection and alert system to effectively reduce or eliminate potential collateral damage on innocent drivers.

# 2. Approach

## 2.1 Overview

We developed centralized detection and alert systems that both leverage existing traffic light infrastructure to detect aggressive driving and then alert potentially impacted drivers at intersections. Figure 5 illustrates the overall concept. Such approach offers the following advantages:

- Enforcement on all drivers at all times
  - Does not rely on voluntary driving behavior monitoring.
  - Does not rely on drivers being sober and rational.
- Leverage existing traffic light system
  - Avoid huge infrastructure cost in real deployment.
  - Suit most geographic areas.
- Detection based on unique aggressive driving modeling
  - Focus on capturing imminent accident threat.
  - Introduce a simple mechanism to measure aggressiveness level.
- Smart alert based on efficient data structure
  - Identify impacted intersections with a novel alert decision graph.
  - Alert drivers with special light patterns at intersections.

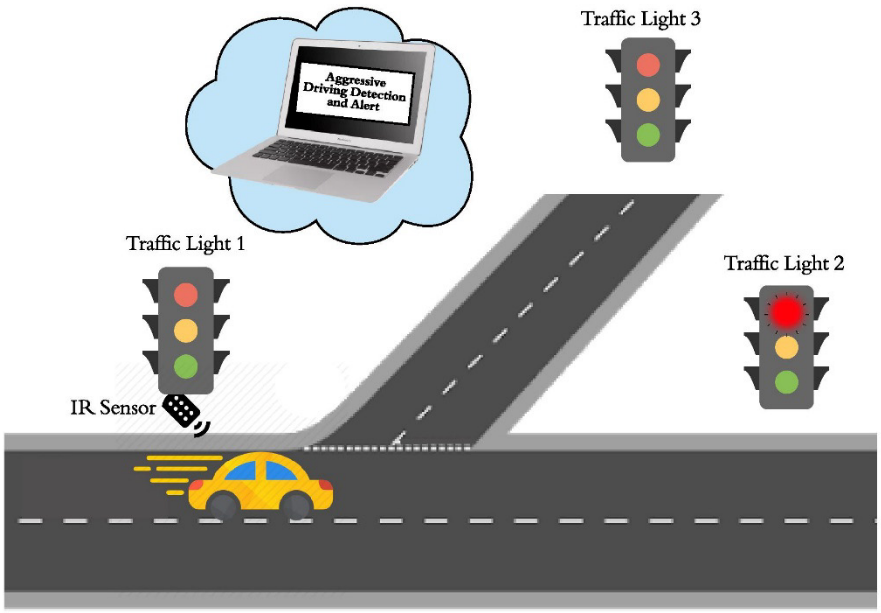


**Figure 5.** Aggressive driving detection and alert leveraging traffic light infrastructure

## 2.2 High-Level Design

Our project consists of two systems: detection and alert. Figure 6 demonstrates how the two systems can be deployed as a real-world application, where they integrate with two external systems: a digital map system such as Google Maps and a traffic light control system.

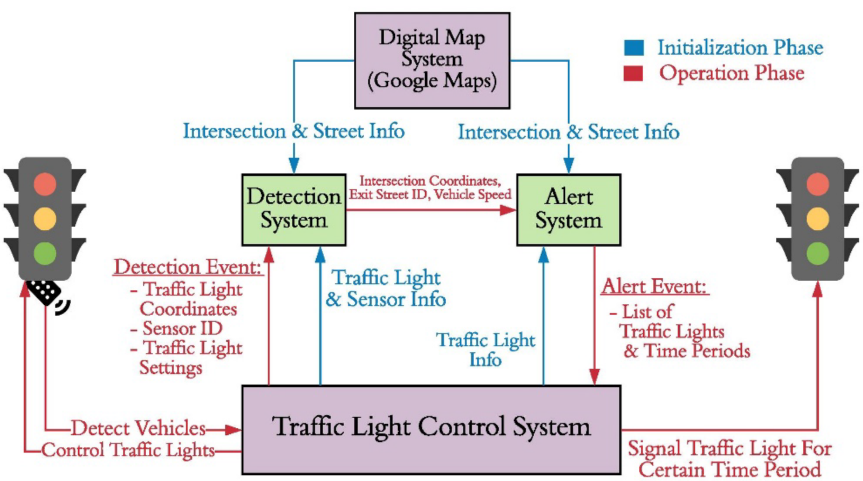


**Figure 6.** The high-level design of our systems as a real-world application.

In the initialization phase, the digital map system and traffic light control system pass in the intersection and street information, as well as traffic light and sensor information, to the detection and alert system. In the operation phase, whenever a sensor installed alongside with a traffic light detects a vehicle, a detection event consisting of traffic light coordinates, sensor ID, and traffic light setting is sent to the detection system. If aggressive driving is detected, then the detection system sends the intersection coordinates, exit street ID, and vehicle speed to the alert system. Once the alert system determines the impacted traffic lights, it sends the list of traffic lights and time periods to the traffic light control system, which then signals each traffic light for their corresponding time period.

## 2.3 Detection System

### *2.3.1 Motivation*

Our goal is to detect aggressive driving that poses imminent accident threat, not to detect aggressive driving for behavior correction.

### *2.3.2 Aggressive Driving Modeling*

The goal of the detection system is to detect various aggressive driving behaviors. As a start, the system focuses on tackling the two most prominent aggressive driving behaviors according to NHTSA statistics: speeding and red-light violation. It is true that both speeding and red-light violations have been defined by the traffic law of each state, but that's not sufficient here, for another important factor is the level of aggressiveness, which serves as a strong indicator of how likely such a violation could lead to an accident down the road and how big the collateral damage the accident may cause. With that said, here is how we model the two aggressive driving behaviors:

<u>Aggressive Speeding</u>

- Average speed passing through an intersection is above the speed limit by a certain percentage point. The percentage point markup amount depends on if it is a straight line pass-through or turning pass-through. Straight-line pass-through has a higher percentage point than turning pass-through. Left turn pass-through has a higher percentage point than right turn one. By default, we set the straight line pass-through with a 30% markup over the speed limit, 25% for a left turn, and 20% for a right turn. So, for example, if the speed limit of an intersection is 40 mph, the average aggressive speed threshold for straight-line pass-through is 52 mph; for a left turn pass-through is 50 mph; for right turn pass-through is 48 mph.
- The vehicle's speed profile passing through an intersection is non-decreasing, meaning that the vehicle maintains or increases its speed during the course of passing through an intersection.

<u>Aggressive Red-Light Violation</u>

- Pass over an intersection entrance line after the traffic light has turned red and after a markup time period. A markup time period is introduced here to incorporate the aggressiveness effect. The rationale is that once the traffic light has turned to red, even after the amount of markup time period, a vehicle still passes into the intersection, then that driving behavior is regarded as an aggressive red-light violation. The larger the markup time period is added, the more aggressive the level is regarded. By default, we set the markup time period as 5 seconds.

### *2.3.3 Infrared Sensor Based Speed Detection*

Infrared (IR) sensors are low-cost and easy to install. We use multiple IR sensors corresponding to each driving lane to obtain vehicle average speed and speed profile.

Two IR sensors are placed at a known distance facing a direction perpendicular to the passing direction of a vehicle, as shown in Figure 7. As the vehicle passes the two IR sensors one after another, the time difference is captured and the average passing speed is the distance between the two sensors divided by this time difference.

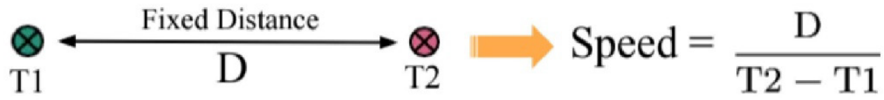


**Figure 7.** IR sensor-based speed detection.

### *2.3.4 Design for Single-lane 4-way Intersection*

First, we consider the design for a typical 4-way intersection with each street allowing two opposite traffic flows. For the simple illustration purpose, we assume all traffic flows are single lane-based. 2 IR sensors are placed at each of the four streets with a total of 8 sensors. Each IR sensor is attached somewhere at a traffic light fixture and oriented such that it points towards the center of a street lane and its detection circle is aligned with either the intersection entrance line from that street or intersection exit line into that street. Among the 8 IR sensors, 4 of them detect the traffic flow into the intersection and they are called inflow detection sensors, and the associated streets are called traffic inflow streets. The remaining 4 sensors detect the traffic flow out of the intersection and onto an exit street. They are called outflow detection sensors and the associated streets are called traffic outflow streets. Figure 8 provides a schematic illustration.

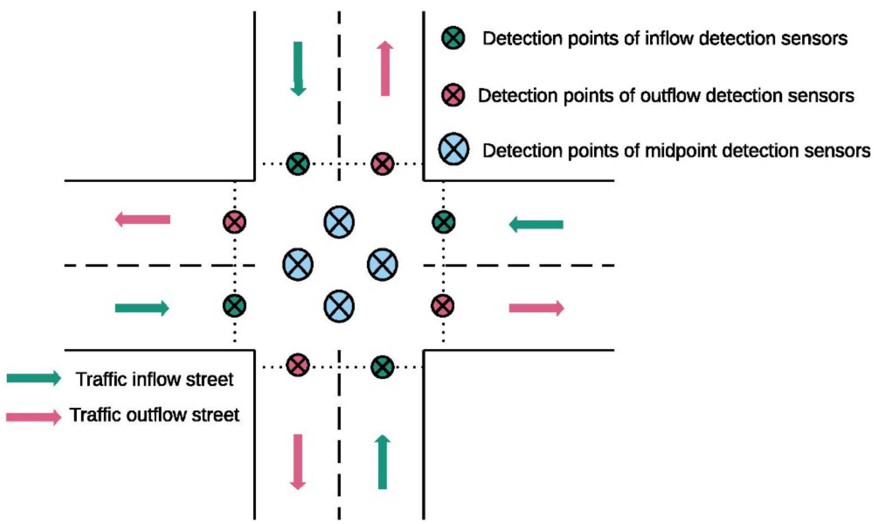


**Figure 8.** Sensor placement of a typical single-lane intersection.

The 8 sensors work in coordination with the traffic lights to detect vehicles' average intersection passing speeds. Each traffic light typically controls a straight-line traffic flow and a left turn traffic flow. Here we assume there is no traffic light control on right turns. For each such traffic flow, a pair of an inflow detection sensor and an outflow detection sensor and a pair of a traffic inflow street and traffic outflow street can be uniquely identified and are used in tandem to calculate the average speed of each vehicle in the traffic flow. Below describes how the distance between the paired sensors is determined for each such traffic flow:

- For a straight-line traffic flow, the distance is the width of the crossing street that the traffic flow passes through.

- For a left turn traffic flow, the distance is the half-width of the traffic inflow street plus the half-width of the traffic outflow street.
- For the right turn traffic flow, the distance is the half-width of the traffic outflow street.

Each inflow detection sensor is associated with a queue and whenever it detects a vehicle, it enqueues an initial timestamp. Whenever an outflow detection sensor detects a vehicle, the system identifies the inflow detection sensor based on the traffic light and extracts the initial timestamp from its queue. Then, it obtains the time difference of passing the paired sensors by subtracting the current timestamp by the initial timestamp, and lastly, it calculates the average passing speed of that vehicle with the obtained distance and the time difference.

To further obtain the speed profile of each passing vehicle, we place 4 more IR sensors with each detection circle close to the center area of the intersection as shown in Figure 8. With the 4 additional sensors, we can record the timestamp when a vehicle reaches the middle point of its passage through the intersection. These 4 sensors are named as midpoint detection sensors. They allow our system to obtain additional average speed data points as the following:

- For a straight-line traffic flow, one additional timestamp is obtained by the midpoint detection sensor, which gives the average speed of the first half and the average speed of the second half. To be considered as an aggressive speeding, the second-half average speed needs to be equal or higher than the first-half average speed.
- For a left turn traffic flow, two additional timestamps are obtained by two midpoint detection sensors, which gives 3 average speeds for the first straight segment, turning segment, and second straight segment. To be considered as an aggressive speeding, these three average speeds need to be equal or higher in sequence.

To facilitate the detection of an aggressive red-light violation, each inflow detection sensor is associated with a separate queue called a red-light violation queue and a timer called a red-light violation timer. Once a traffic light switches to red, the corresponding inflow detection sensor's red light violation timer is kicked off. The timer is set with the markup time period which is 5 seconds by default. The timer turns off once the markup time period passes. During the period after the timer goes off and before the traffic light switches to green, whenever the inflow detection sensor detects a vehicle passing through, the system will add a timestamp into the red-light violation queue. Once an outflow detection sensor detects a vehicle passing through, it will first check if the red-light violation queue of the paired inflow detection sensor has an entry or not, and if the queue is non-empty, the system considers the detection of an aggressive red-light violation.

Whenever the system detects an aggressive speeding or red-light violation instance, the vehicle exiting street is simply the traffic outflow street corresponding to the outflow detection sensor. The detection system passes the coordinates of the intersection, the vehicle exiting street and the detected vehicle speed to the alert system to determine which nearby traffic lights to be signaled.

### *2.3.5 Design for Multi-Lane 4-way Intersection*

Next, we will consider intersections with multiple lanes. Multi-lane traffic flow means there are two or more lanes in one traffic direction. The above-described design for intersections with single lane traffic flows can be easily extended to multi-lane traffic flows. Basically, for each additional lane, we need an additional pair of inflow and outflow detection sensors to detect the traffic flow on that lane. The coordination between the paired sensors along with traffic lights is similar to the single-lane traffic flow case. Figure 9 provides a schematic illustration on the IR sensor layout for a 4-way intersection with one street having 2-lane traffic flows and one street having single lane traffic flow.

HIGH SCHOOL EDITION
Journal of Student Research



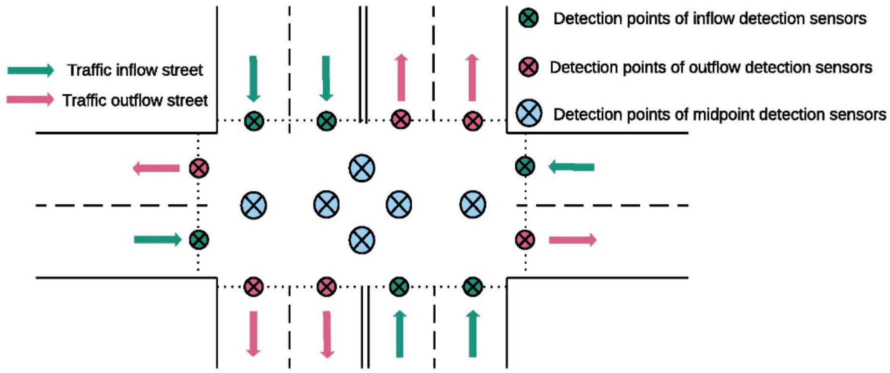


**Figure 9.** IR Sensor layout for multi-lane intersections.

### *2.3.6 Design for 3-way Intersection*

For a typical 3-way intersection with each street allowing two opposite traffic flows, 2 IR sensors are placed at each of the three streets with a total of 6 sensors. Among the 6 IR sensors, 3 of them are inflow detection sensors that detect the traffic flow into the intersection and the remaining 3 are outflow detection sensors that detect the traffic flow out of the intersection and onto an exit street. Two midpoint detection sensors are added to obtain the speed profile of each passing vehicle. The above-described detection mechanism designed for a 4-way intersection can be applied here for detecting aggressive speeding and red-light violations. Figure 10 provides the schematic illustration on the layout of IR sensors for a typical 3-way single lane intersection.

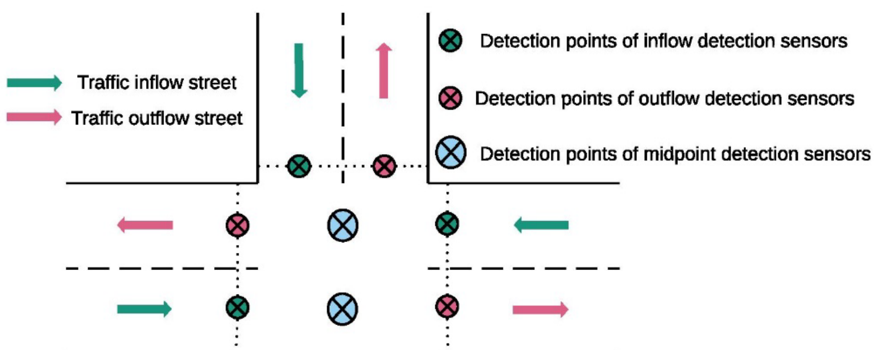


**Figure 10.** IR Sensor layout for three-way intersections.

### *2.3.7 Detection Algorithm*

Based on the above-described aggressive driving modeling, the designs for various types of intersections, we developed the detection algorithm. Figure 11 illustrates the details of its workflow.

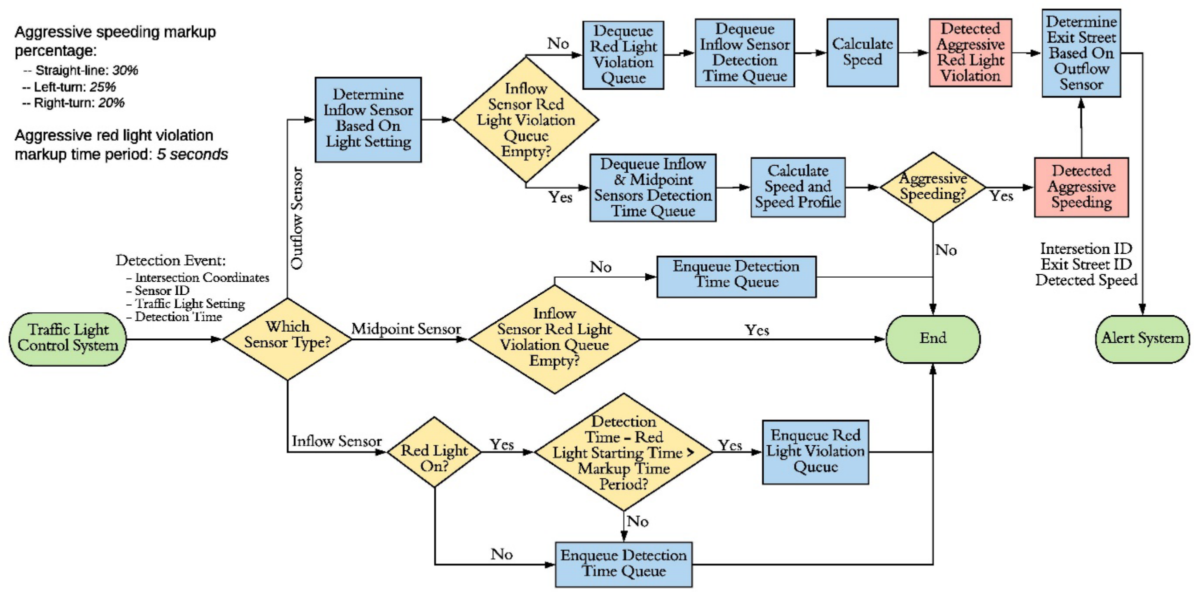


**Figure 11.** Flowchart describing the detection process.

### *2.3.8 Limitations*

There are a few limitations that our detection approach possesses. Because IR sensors cannot track individual objects, this detection system can only be applied to vehicles staying within its traffic lane while passing through an intersection. For an intersection with multi-lane traffic flows, in case a vehicle crosses to a different lane while passing the intersection, the sequence of the timestamps stored in the queues associated with the inflow detection sensors of the two lanes will be messed up, and thus will not be able to detect driving behaviors for both lanes correctly.

Once such a situation occurs, the detection system enters a remediation mode. During the remediation mode, the system will put the detection of driving behaviors on hold until all the timestamps in the two queues are extracted out by the corresponding outflow detection sensors - in other words, all the vehicles in the intersection have exited. This should usually happen upon the next red light after the remediation mode is on and the traffic flow stops. Once the system exits the remediation mode, it resumes its normal detection workflow.

## 2.4 Alert System

### *2.4.1 Motivation*

Our goal is to determine the next possible traffic lights that an aggressive driving vehicle can hit, and alert them so nearby drivers can take precautionary steps.

### *2.4.2 Alert Decision Graph*

The main task of the alert system is to determine which nearby traffic lights to be signaled based on the location of the intersection where aggressive driving is detected and the vehicle's exit route. To achieve this, the alert system needs to have knowledge about the network of streets, their intersection points, and whether each intersection has traffic lights or not.

For this, we introduce an alert decision graph data structure constructed and maintained by our alert system, as shown in Figure 12.

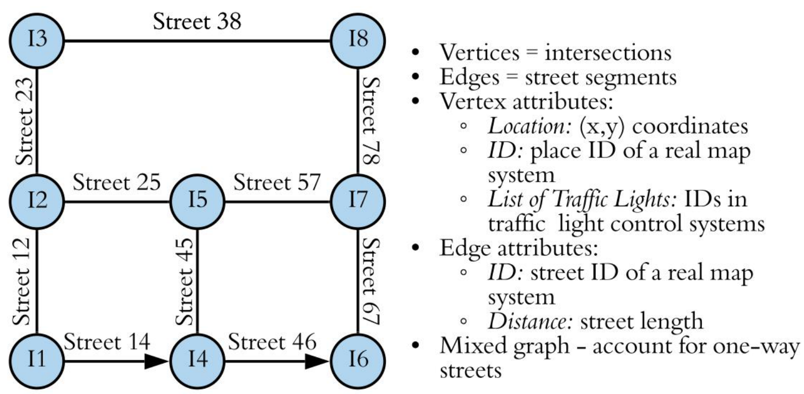


**Figure 12.** Our alert decision graph.

An alert decision graph captures only necessary information for the alert system to make its decision, where the vertices are intersections and edges are street segments. Each vertex has the following attributes:

- Location: (x,y) coordinates.
- Place ID: place ID of a real map system.
- Traffic light flag: whether there are traffic lights or not.
- Speed limit: maximum allowed speed.

In order to account for both unidirectional and bidirectional streets, an edge can be directed or undirected one. So, the graph is a mixed graph. To align each alert decision graph to the real-life street network, it is constructed based on a real map system like Google Maps. Each vertex stores real intersection coordinates and the place ID of a real map system. Each edge is tagged with a real-life street name. In case traffic light information is missing, a separate manual input mechanism is offered for amending it. Our alert system constructs an alert decision graph region by region. A region is defined by the area covered by a central traffic light control system.

Once the alert decision graph is constructed, our alert system caches all the vertices in a hash table with key equal to a hash function of its real coordinates or place ID. Whenever an aggressive driving instance is detected at an intersection, the detection system sends its coordinates or place ID, the vehicle's exit street name and detected vehicle speed to the alert system. With the fore-mentioned cached information, the alert system can quickly identify the starting vertex and starting edge of the alert decision graph and kick off its depth-first search traversal algorithm to determine impacted intersections that have traffic lights.

### *2.4.3 Alert Duration Period*

Once any traffic light is alerted, we need a mechanism to reset them at an appropriate time later. Considering the situation where traffic lights at multiple next-hit intersections are alerted, if the aggressive driving vehicle hits one of the intersections, it seems a reasonable time to reset all the alerted traffic lights including the ones at other intersections. But the problem here is that, what if the vehicle for whatever reason never hits any of those intersections as expected? For instance, it could stop in the middle as the driver arrives home. The solution that we are undertaking is to introduce an alert time period for each alerted traffic light. Once the alert time period elapses, the alerted traffic light will be reset. The alert time period starts when a traffic light is alerted. The value of the time period is the driving distance between the detected intersection and each searched next-hit intersection divided by the speed of the detected aggressive driving vehicle. The workflow presented in Figure 13 shows how such time duration is calculated. The driving distance is essentially the total edge distance between the starting intersection vertex to each searched intersection vertex.

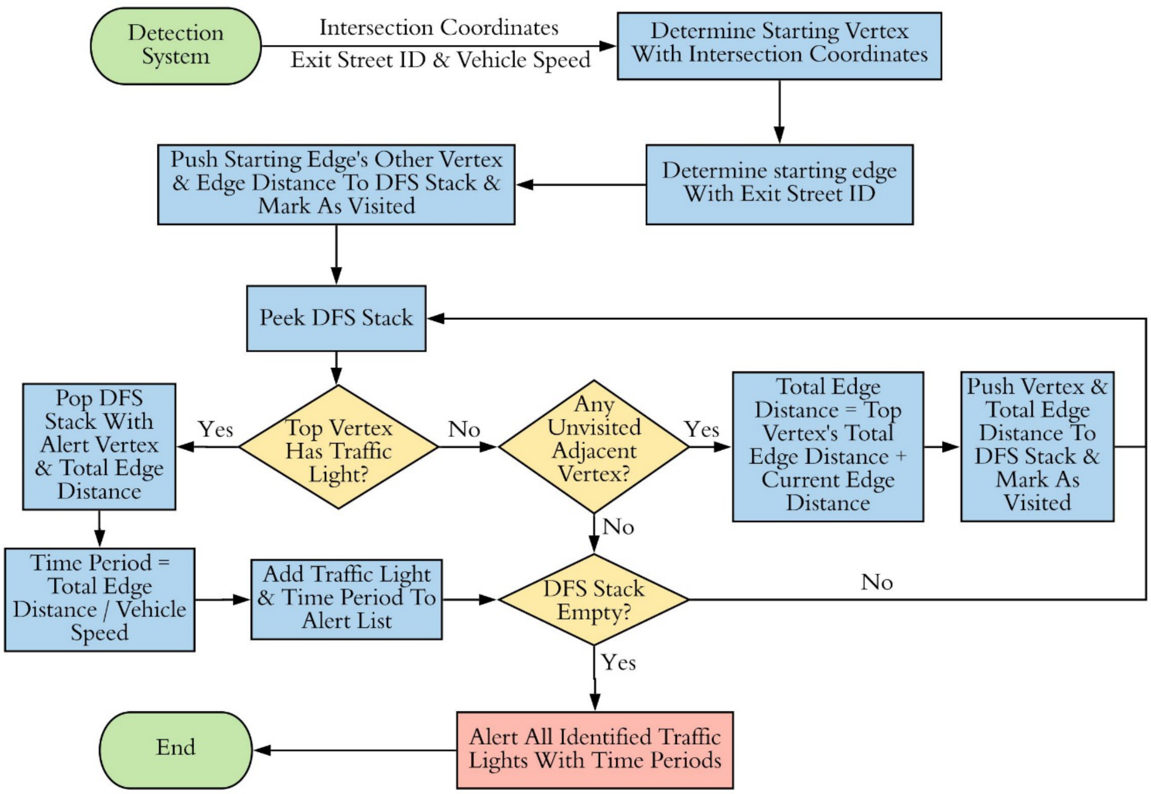


**Figure 13.** Flowchart describing the alert process.

### *2.4.4 Graph Search and Alert Algorithm*

Our alert system adopts a specialized depth-first search traversal algorithm. The specialization lies in two aspects:

- When the top vertex in the stack has traffic lights, it is popped out from the stack right away without further looking at its adjacent vertices.
- When determining the adjacent vertices of a top vertex in the stack, in case of a directed edge, treat the other vertex as an adjacent one only if it can be reached from the top vertex.

During the traversing, the alert system keeps all the visited vertices that have traffic lights - all the kept vertices are the impacted traffic lights. To signal an impacted traffic light, alert system uses blinking as the special signal pattern. Doing so should not disrupt the existing traffic control signals in most cases. Figure 13 illustrates the details about the workflow of the alert algorithm.

## 3. Experimental Setup

### 3.1 Setup Device

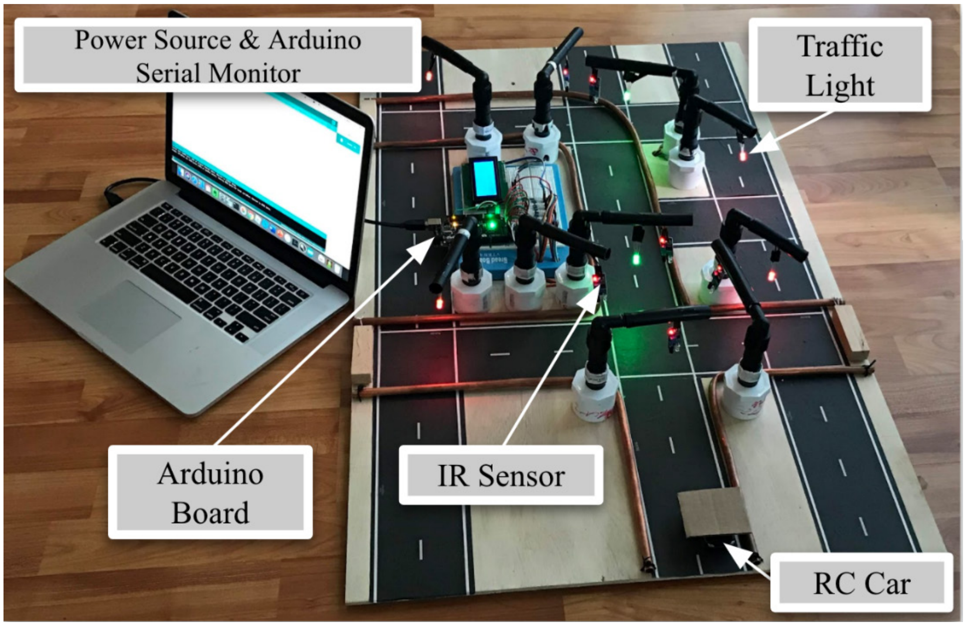


**Figure 14.** A picture of our experiment setup.

To demonstrate our idea and its underpinning design, we build an experimental setup as shown in Figure 14 that consists of a mockup map, an Arduino board, several IR sensors, LED lights, and remote-controllable toy cars. All sensors and LED lights are controlled by the Arduino board. Our detection and alerting systems also run on the Arduino board. LED lights serve as traffic lights. The mockup map contains a network of streets, intersections, and traffic lights. Even though our design can be applied to multi-lane traffic flows, for demonstration purposes, all streets in the mockup map offer single-lane traffic flows.

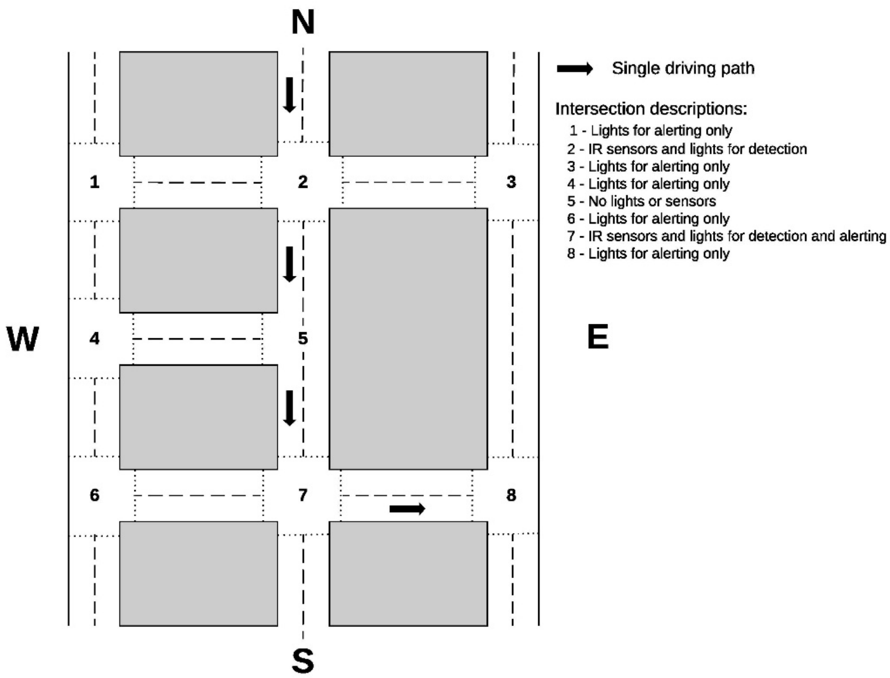


**Figure 15.** Layout of our mockup map.

Below clarifies some details about the mockup map. Also see Figure 15 for the illustration on the layout.

- The entire map is built on a baseboard. It has an (x,y) local coordinate system defined with the upper left corner as the origin with inches as the unit. To facilitate the description, we also label the upper edge, lower edge, left edge, and right edge as north, south, west, and east respectively. X-coordinate values increase from west to east; Y-coordinate values increase from north to south. With that, when we say "a vehicle is passing from north to south", it means we control the toy car to move vertically downwards.
- Each street has two lanes and one for each traffic direction. So, all streets offer single lane traffic flows.
- Each street is tagged with a name. The name is constructed based on the following schemes:
    - For a north-south street: Letter "A" + north end intersection number + south end intersection number. E.g. A25 is the street connecting intersections 2 and 5.
    - For a west-east street: Letter "S" + west end intersection number + east end intersection number. E.g., S78 is the street connection between intersections 7 and 8.
- There is a total of 8 intersections with IDs from 1 to 8.
- The following information is maintained with each intersection:
    - Location: (x,y) coordinates.
    - Traffic light flag: indicate whether there are traffic lights or not.
    - Speed limit: maximum allowed speed.
- Designate intersections 2 and 7 for detecting aggressive driving. There are IR sensors and LED lights installed at those intersections.
- Intersections 1, 3, 4, 6, and 8 all have traffic lights and thus equipped with LED lights only.
- Intersection 5 does not have traffic lights.

## 3.2 Materials

The project materials are listed below:

- 7 LED lights
- 6 infrared (IR) sensors
- 2 push-pin buttons
- 2 remote-controlled toy cars
- Baseboard
- Breadboard
- Arduino MEGA 2560
- LCD display
- Wood Blocks
- Wires
- Batteries
- Plumbing tubes and couplings

# 4. Experiments and Measurements

## 4.1 Procedures

We constructed two types of experiments summarized below to demonstrate all the key ideas behind what our detection system and alert system aim to deliver.

### *4.1.1 Progressive Detection and Alert*

For this experiment, we construct a driving path for a single remote-controlled car to drive through. The driving path consists of two intersections (2, 7) used to detect aggressive driving behaviors, one intersection (5) without any traffic light, three intersections serving as the alert targets (4, 7, 8). As a car drives through this driving path, its aggressive driving behaviors are detected at the two different intersections progressively, and the traffic lights being alerted are also updated progressively. Figure 16 provides the schematic illustration.

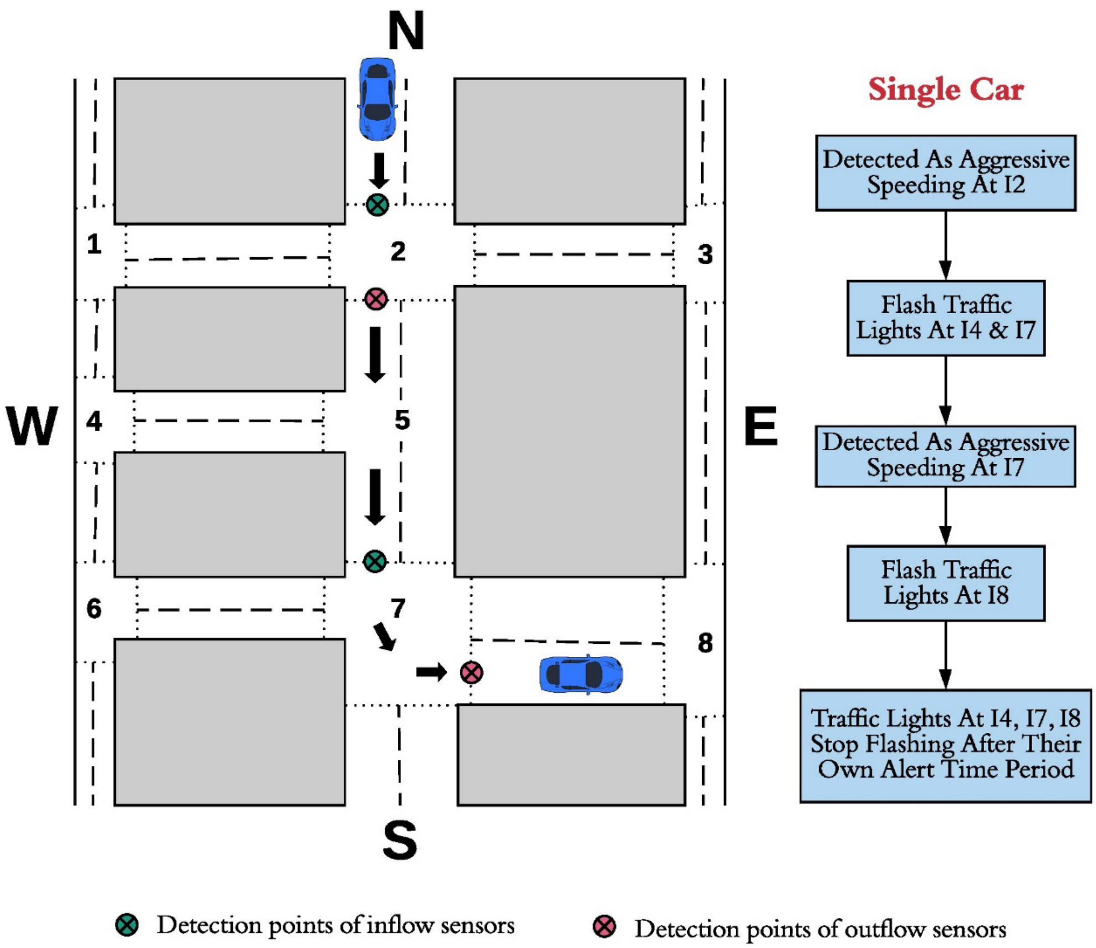


**Figure 16.** The trajectory of a progressive detection and alert experiment.

Below describes the steps in detail:

1. The car starts from the north edge driving towards the south and approaching intersection 2.
2. The car hits intersection 2 with aggressive speed over the speed limit by 30% and passes it with a straight line and exits onto "A25" street.
3. The detection system detects the aggressive driving instance at intersection 2. It sends intersection 2 coordinates, ID, the exit street name "A25" and detected car speed to the alert system.
4. The alert system determines intersection 4 and 7 are the impacted traffic light locations and flashes the LEDs located at those two intersections.
5. The car continues its aggressive driving passing through intersection 5 and exiting onto "A57" street.
6. Intersection 5 does not have any traffic light. So, there is nothing to be updated. The traffic lights (LEDs) at intersection 4 and 7 continue flashing.
7. The car continues its aggressive driving and hits intersection 7. It makes a left turn and exits onto S78 driving eastward towards intersection 8.
8. The detection system detects the aggressive driving instance at intersection 7. It sends intersection 7 coordinates, ID, the exit street name "S78" and detected speed to the alert system.
9. Alert system determines that intersection 8 is the impacted traffic light location and turns on the LED located at that intersection.
10. The car stops once it hits intersection 8.

11. Alert system turns off the flashing for all alerted traffic lights at I4, I7 and I8 after a duration time period.

Note that among the above procedures, Step 3 and Step 8 demonstrates the aggressive driving detections caused by speeding with a straight path and with a left turn, respectively. Step 4 demonstrates the alert system signals multiple traffic light locations because of multiple potential driving paths the car can take on. Last, Step 9 demonstrates the alert system progressively updates the traffic lights to be alerted as the aggressive driving vehicle passes through a different intersection.

We intend to repeat the above procedures multiple times for measuring the accuracy and response time that our system can deliver in a progressive manner.

### *4.1.2 Concurrent Detection and Alert*

For this experiment, we construct concurrent traffic flows with a left turn, and a right turn on a same intersection. As two remote-controlled cars line up in one lane and pass through the intersection with the two types of traffic flows respectively, their driving behaviors are detected and if any of them is aggressive driving, the impacted traffic lights are determined and alerted simultaneously. Figure 17 provides the schematic illustration.

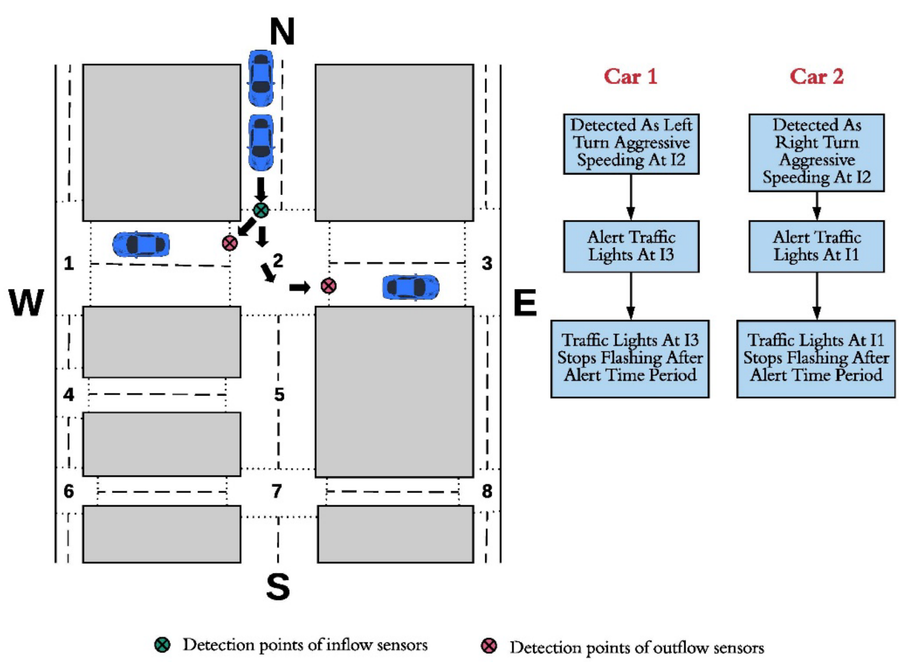


**Figure 17.** The trajectories of a concurrent detection and alert experiment.

Below describes the steps in detail:

1. Two cars line up in sequence starting from the north edge, driving towards the south, and approaching intersection 2.
2. The first car passes through intersection 2 with a left turn and exits onto “S23” street with aggressive speed over the speed limit by 25%.
3. The second car passes through intersection 2 with a right turn and exits onto “S12” street before the first car exists the intersection and with aggressive speed over the speed limit by 20%.

4. The detection system detects the first car's aggressive driving behavior at intersection 2. It sends intersection 2 coordinates, ID, the exit street name "S23" and detected speed to the alert system.
5. The alert system determines intersection 3 is the impacted traffic light location and flashes the LED located at intersection 3.
6. The detection system detects the second car's aggressive driving behavior at intersection 2. It sends intersection 2 coordinates, ID, the exit street name "S12" and detected speed to the alert system.
7. The alert system determines intersection 1 is the impacted traffic light location and flashes the LED located at intersection 1.
8. The first car stops at intersection 3. The second car stops at intersection 1.
9. Alert system turns off the flashing for all alerted traffic lights at I3 and I1 after a duration time period.

Note that among the above procedures, Steps 4, 6 and steps 5, 7 occur concurrently.

We intend to repeat the above procedures multiple times for measuring the accuracy and response time that our system can deliver in a concurrent manner.

### *4.1.3 Aggressive Red-Light Violation*

To test red light violation, we used two push-pin buttons, red and green, to toggle the traffic light color settings at intersection 2. Whenever a button was pressed, the light at intersection 2 will turn that button's color. At the beginning of each trial, the red button is pressed, turning the light at intersection 2 red. Then we waited for 5 seconds, and afterward had one car driving straight through intersection 2. The detection system is expected to detect the aggressive red-light violation at intersection 2.

## 4.2 Experimental Variables

During various experiments that we conducted, we kept the setup, the markup values used in aggressive driving modeling and speed limits at all the intersections unchanged. The independent variables are the car's speed, trajectory, and red light setting. The dependent variables are driving behavior and any alerted traffic lights.

## 4.3 Experiment Data

The goal of our experiment measurements is to verify the accuracy and response time of our detection and alert systems.

We measure the detection accuracy by observing how often our detection system correctly detects expected aggressive driving instances, and the alert accuracy by observing how often our alert system correctly signals the impacted nearby traffic lights as expected. The detection response time is the extended time the system needs to determine any aggressive driving instance after a vehicle passes through an intersection, while the alert response time is the total time starting from an aggressive driving instance being detected to all the impacted traffic lights being determined and alerted. To measure these, we outputted speed values, detected driving behaviors, alerted intersection IDs, and various timestamps in the Arduino IDE's serial monitor and transferred them onto Google sheet for further analysis.

| Trial No. | Traffic Type | Average Speed OR Time Lapse After Red Light On | Expected Driving Behavior | Detected Driving Behavior |
|---|---|---|---|---|
| 1 | Straight-line | 1.6 MPH | Aggressive speeding | Aggressive speeding |

| | | | | |
|---|---|---|---|---|
| 2 | Straight-line | 1.1 MPH | Normal | Normal |
| 3 | Left-turn | 1.5 MPH | Aggressive speeding | Aggressive speeding |
| 4 | Right-turn | 1.3 MPH | Aggressive speeding | Aggressive speeding |
| 5 | Left-turn | 1.2 MPH | Normal | Normal |
| 6 | Right-turn | 0.9 MPH | Normal | Normal |
| 7 | Straight-line | 8 seconds | Aggressive red light | Aggressive red light |
| 8 | Straight-line | 3 seconds | Normal | Normal |

Intersection speed limit = 1.0 MPH, Straight-line speed markup = 30%, Left-turn speed markup = 25%, Right-turn speed markup = 20%, Red light markup time period = 5 seconds

**Table 1.** The accuracy data for detection system.

| Trial No | Experimental Type | Aggressive Driving Detection Intersection | Expected Alerted Intersections | Actual Alerted Intersections |
|---|---|---|---|---|
| 1, 2 | Progressive alert | #2 | #4 and #7 | #4 and #7 |
| 1, 2 | Progressive alert | #7 | #8 | #8 |
| 3, 4 | Concurrent alert left turn | #2 | #3 | #3 |
| 3, 4 | Concurrent alert right turn | #2 | #1 | #1 |

**Table 2.** The accuracy data for alert system.

Table 1 shows the detection accuracy measurement based on the 8 trials conducted on Intersection #2. Table 2 shows the alert accuracy measurement based on the 4 trials with 2 for each above-described experiment type. Both of these tables show that we obtained 100% accuracy in detection and alert results.

For response time measurements, we conducted 6 trials with 3 for each experiment type. Note that for either experiment type, each trial will yield 2 sets of detection response time and alert response time. So, the 6 trials generate 12 sets of data points. Figure 18 and Figure 19 show the detection and alert response times over all trials respectively. The response times are fairly consistent. The average detection response time is 159 milliseconds and the average alert response time is 100 milliseconds. We consider both as real-time responses.

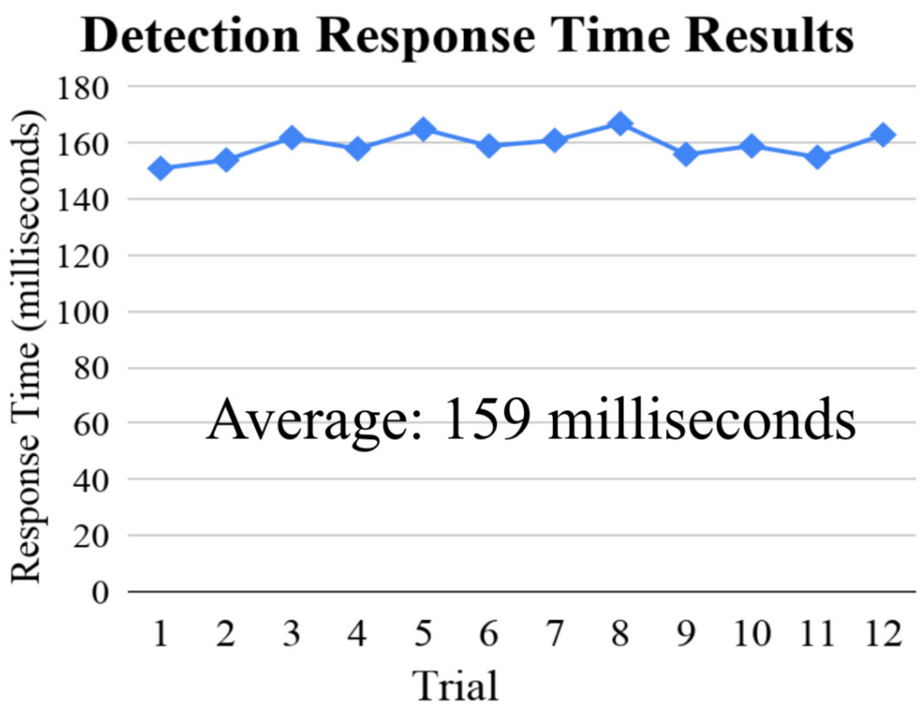


**Figure 18.** Detection response time data.

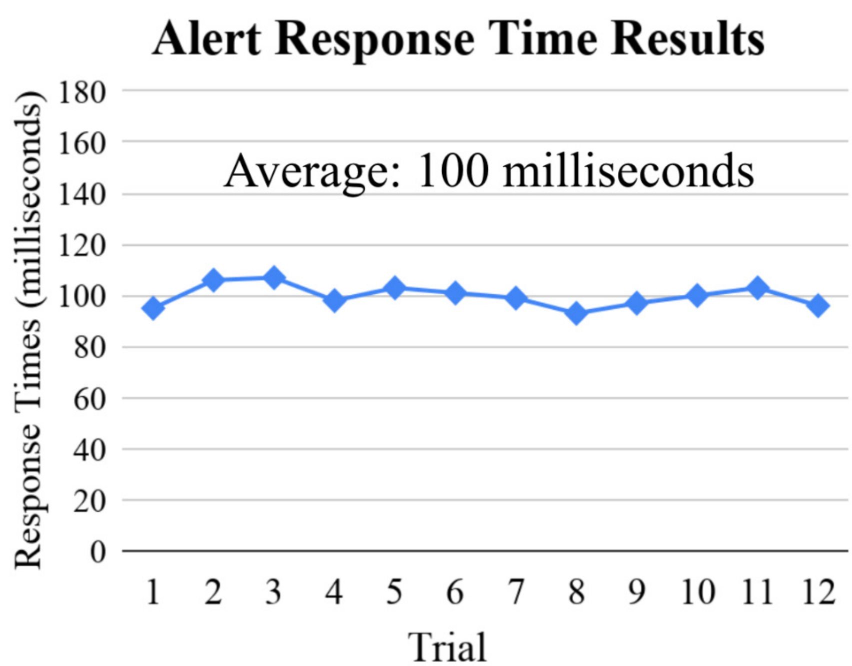


**Figure 19.** Alert response time data.

## 5. Experimental Challenges

We encountered three notable challenges while we conducted our experiments.

1. Initially the infrared sensors frequently suffer false detection after we tuned their detection distances. It turns out some sensors' detector orientations were slightly disturbed as the experiments being conducted. We resolved the issue by using electrical tape to wrap each sensor around its post and making them firmly pointing vertically downwards.
2. We need to use RC cars in our testing. These RC car's turning angles were too wide for our setup size. We ended up building copper guiding rails to direct RC car's turning trajectory, proving to be very effective.
3. Lastly, we hit a mysterious coding issue where our program mistakenly thought a same sensor detects something repeatedly. It turns out Arduino's clock speed is fast enough to complete a previous detection's handling before that passing object moves out of the sensor's sight. We fixed this by adjusting our code such that once an object is detected, it waits until the object disappears from the sensor detection.

## 6. Conclusion

We presented the idea and design of leveraging existing traffic light infrastructure to detect aggressive driving that poses imminent accident threats, and then alert nearby drivers to reduce or avoid the collateral damage potentially caused by those accidents. We prototyped the design on an Arduino board and applied it to an experimental setup that consists of streets and intersections with traffic lights and infrared sensors. Furthermore, we conducted experiments showing 100% accuracy in detection and alert results, along with the average response time for detection and alert being at a real-time level.

## 7. Future Work

We think there can be future improvements in the following areas:

Resolve current detection system limitations

- Explore other speed sensors like Doppler sensor that capture speed with a single point detection.
- Add vehicle identification and tracking capability such as leveraging a license plate capturing camera.

Expand more alert targets

- Alert nearby drivers' smartphones based on the intersection location of a detected aggressive driving instance and using the smartphone's GPS capability.
- Notify a detected aggressive driving instance to a nearby police station for prompt intervention by law enforcement.

## 8. Acknowledgements

We would like to thank Corey Brown, our middle school principal, for lending a hand with the project when needed as well as Patti Carothers for making our research project as successful as it is. All authors had similar contributions in the research and paper writing. For reference, all of our code and videos that we used to verify the detection and alert system can be found here.

## 9. References

1. Ballot, James P. "Archived Tables." III, www.iii.org/table-archive/21313

2. Guan Haike, Kasahara Ryosuki, Yano Tomoaki, "Traffic Light Recognition and Dangerous Driving Events Detection from Surveillance Video of Vehicle Camera." Ingenta Connect, Society for Imaging Science and Technology, 29 Jan. 2017, www.ingentaconnect.com/content/ist/ei/2017/00002017/00000004/art00002

3. "Aggressive Driving Behaviour (Background Paper)" UNECE, 11 May 2004, www.unece.org/trans/roadsafe/rs4aggr.html

4. Chawla, Deepika. Semantic Scholar, International Journal for Research in Applied Science and Engineering Technology, 2017, www.semanticscholar.org/paper/A-Novel-Approach-to-Detect-and-Identify-the-Driving-Chawla/e5a9c1c6e4af2e51b4c23a1d3f28842edd50da39

5. Kumtepe, O., Akar, G.B. & Yuncu, E. Driver aggressiveness detection via multisensory data fusion. J Image Video Proc. 2016, 5 (2016). https://doi.org/10.1186/s13640-016-0106-9

6. Moukafih, Youness. "Aggressive Driving Detection Using Deep Learning-Based Time Series Classification" Aggressive Driving Detection Using Deep Learning-Based Time Series Classification - IEEE Conference Publication, Institute of Electrical and Electronics Engineers, 29 July 2019, https://ieeexplore.ieee.org/document/8778416

7. Cheung, Ernest. "Classifying Driver Behaviors for Autonomous Vehicle Navigation." Gamma, 2018, https://gamma.cs.unc.edu/TDBM/Ernest_IROS_W_2018.pdf