A Blind Spot Alert Apparatus for Cyclists in Right-Turning Semi-trailer Trucks

Grant Proposal

Charles Tang

Massachusetts Academy of Math and Science

Worcester, MA

Author Note

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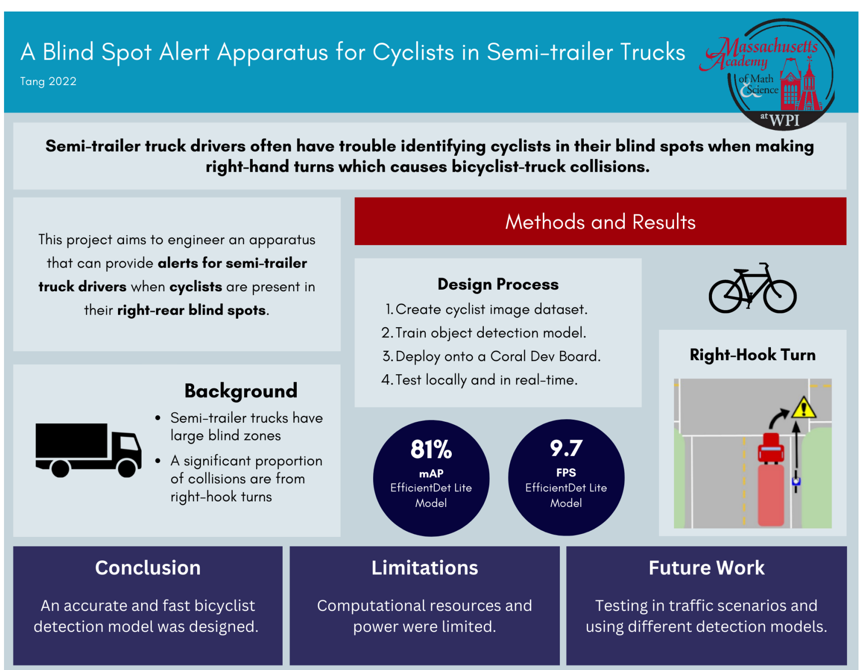
Abstract

In order to reduce the number of truck-cyclist accidents, this study designs a visual-based blind spot warning system for a semi-trailer truck. A large number of cyclist collisions are caused by semi-trailer trucks, more specifically, in right-hook turns. First, the object detection model was created using state-of-the-art lightweight deep learning architectures trained on a cyclist image dataset, which is used to locate and detect cyclists actively. Next, the object detection model was deployed onto a Google Coral Dev Board mini-computer with a camera module and analyzed for accuracy and speed. Lastly, the combined blind spot detection device will be tested in real-time to model traffic scenarios and analyzed further for performance, feasibility, and further work of the apparatus.

Keywords: Bicyclist safety, blind spots, vulnerable road users, object detection, semi-trailer trucks, right-hook turns, cyclist collisions, warning system

Graphical Abstract



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Bicycling is a hobby and sport that many enjoy for its fitness benefits and improvement in mental health. Unfortunately, cyclists often face risks when traveling along a road or path with other motorized vehicles; in the U.S., over 1,000 cyclists die in road accidents, and 130,000 more are injured yearly (Centers for Disease Control and Prevention [CDC], 2022).

Bicyclist Safety and Collisions

Some risk factors that increase the rate of bicyclist collisions include places with fast-moving vehicles, intersections, larger vehicles, poor infrastructure, steep terrain, and poor lighting (Carvajal et al., 2020). Furthermore, over 71% of cyclist incidents happen in urban areas, with 30% of collisions happening at intersections. These cyclist accidents can be attributed to a lack of visual attention, including distraction, which is a leading cause of over 55% of vehicle-cyclist collisions (Jannat et al., 2020).

One type of collision that frequently occurs between cyclists and vehicles is in right-hook turns (Figure 1). Right-hook collisions occur at intersections when right-turning vehicles collide with a cyclist moving straight forwards along the right side of the road. These types of collisions occur when drivers do not detect bicyclists in their oncoming blind spots or when bicyclists do not observe that a driver is going to take a right turn. Some factors that increase the risk of right-hook crashes include the presence of left-turning oncoming traffic, high bicyclist speed and position in a blind spot, and the presence of crossing pedestrians (Jannat et al., 2020).

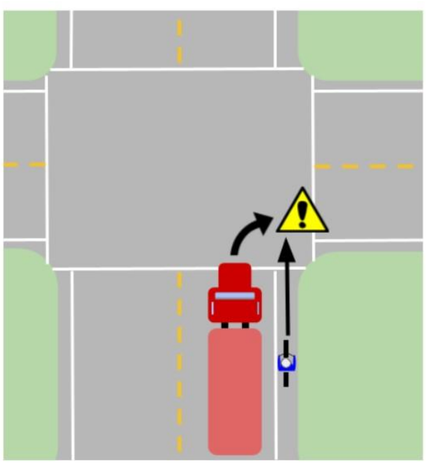

Figure 1: *Semi-trailer truck right-hook turn scenario.*

Note. This scenario has a high risk of a right-hook crash, which can cause severe cyclist injuries.

Blind Spots of Semi-Trailer Trucks

Semi-trailer trucks have large blind spot zones on the vehicle's left, right, front, and rear. The right-hand blind spot poses the most danger to vulnerable road users (VRUs) – cyclists, pedestrians, moped riders, and motorcyclists – especially when making right turns. Blind spots are a leading cause of cyclist-truck incidents—they account for 45% of all collisions between bicycles and trucks (Wang et al., 2022). Additionally, semi-trailer trucks are disproportionately involved in more severe cyclist collisions compared to other vehicles (Richter & Sachs, 2017). When a semi-trailer truck makes a right turn, the blind spot from the right rearview mirror increases as the view is blocked by the trailer's body. This makes turns especially dangerous because VRUs in this blind spot zone cannot be detected and face a high risk of collision and fatality (Wang et al., 2022).

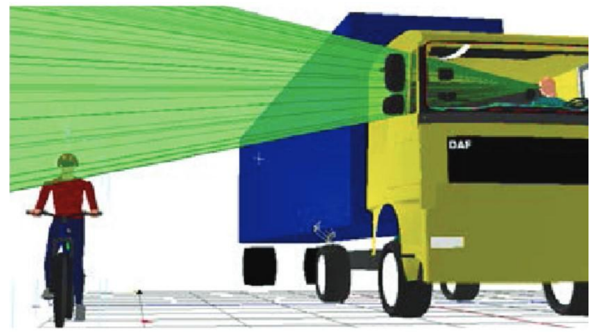

Figure 2: *Limited visibility of cyclists from a semi-trailer truck driver.*

Note. From "The development of a truck concept to allow improved direct vision of vulnerable road users by drivers" by S. Summerskill and R. Marshall, 2015, *Procedia Manufacturing*, 3, 3717-3724. CC BY-NC-ND.

In the European Union, as a safety measure, semi-trailer truck drivers are instructed to check their blind spots before and during a right turn to check for VRUs. However, a study investigating the glance behavior of truck drivers during right-hand turns shows that drivers only correctly check their blind spot mirrors about 50% of the time, which results in a higher risk of collision between trucks and VRUs (Jansen & Varotto, 2022).

The recent growth in interest in cycling places a more significant need on infrastructures and addressing safety concerns to make cycling more inclusive for all (Dill & McNeil, 2016). Furthermore, the general opinion on bicycling in urban areas shows that most people are concerned about the safety of cycling. A survey covering the top 50 metropolitan areas found that 51% of people are interested in cycling but concerned about the risks of cycling without improved safety systems (Dill & McNeil, 2016). This shows a significant need for widespread safety systems to make cycling more appealing to all.

Object Detection

Object detection is when algorithms can locate and classify objects in an input image or video. Object detection algorithms predict bounding boxes to find the location of each object. Recent novel object detection algorithms use deep learning and convolutional neural networks (CNNs). See Appendix B for further information on object detection algorithms.

Section II: Specific Aims

Engineering Need

Bicyclists face numerous risks when traveling along urban roads and intersections. Semi-trailer truck drivers often have trouble identifying cyclists in their blind spots when making right-hand turns which can cause bicyclist-truck collisions. The overall aim of this project is to engineer a device that can detect cyclists in a truck's right-rear blind spot and provide alerts for semi-trailer truck drivers. The final product of this project is to be developed using Tensorflow, a machine learning library, and trained on collected bicyclist data, which will be analyzed and tested to satisfy the specific aims discussed below.

Specific Aims

The primary concern of this project is to design technology to prevent collisions and injuries that occur when drivers cannot see bicyclists. In order to do this, we set three main benchmarks. (1) The first goal of this study is to develop a system that can actively detect cyclists with greater than eighty percent accuracy in a semi-trailer truck's blind spot. (2) The second objective of this safety system is to create warnings for cyclists in a truck's right-rear blind spot within a two-second interval to reduce the risk of truck-cyclist collision. The speed of the blind spot system is critical in preventing collisions so that drivers can react quickly and appropriately to potential collisions. (3) The final specific aim for this design is that it should be portable and installable on most semi-trailer trucks. Current blind spot safety systems are not easily deployable and have high-cost barriers that prevent widespread usage.

Section III: Project Goals and Methodology

Relevance

Bicyclist safety is crucial in maintaining safe urban environments. This study develops a system to prevent cyclist collisions and potential fatalities or injuries. Additionally, this study contributes a unique implementation of real-time object detection and testing strategies related to driver assistance systems.

Innovation and Competitor Analysis

Various bicyclist detection or blind spot assistance systems for drivers and vehicles have been proposed. One such design involves a modification to the design of a semi-trailer truck cab by reducing the overall height and adding window apertures to improve the driver's blind spots (Summerskill & Marshall, 2015). However, this design lacks portability and raises questions about the costs of implementing such a design. Another design that attempts to solve the blind spot issue involves a mechanism that changes the angle of the rearview mirrors when making turns or lane changes (Clegg, 2012). These mirror systems do not provide an active warning system that can alert drivers of cyclists in their blind spots, and drivers may ignore their blind spots when making maneuvers. One literature discusses a deep-learning solution to the cyclist detection problem involving LiDAR scans and a convolutional neural network, which reached

80% mAP (Saleh et al., 2017). While LiDAR systems for cyclist detection prove to be an accurate solution, implementing LiDAR systems on modern vehicles is very costly and difficult, with prices ranging from $1,000 to tens of thousands of dollars.

The proposed visual bicyclist detection device would be able to mitigate these pitfalls. This design will provide accurate bicycle detection, be low-cost, and be easily integrable into current technologies, which will be one of the first of its kind.

Methodology

Functional System Requirements

This blind spot apparatus will align with the Automotive Safety Index Level (ASIL) B subcategory in the ISO 26262 automotive safety standards to (a) have a safety development lifecycle, (b) evaluate the risk of the system, and (c) validate the various modules of the system. Category ASIL-A represents the lowest risk of hazardous situations and ASIL-D represents the highest risk. Safety systems are required to undergo fault testing and code coverage, which are discussed in further subsections.

Design Process

This cyclist detection system uses innovative technologies to achieve state-of-the-art performance. The first step in designing a cyclist detection system using deep learning techniques is to determine or create a dataset with bounding box annotations for cyclists. One such dataset that proves adequate for this task is the CIMAT cyclist orientations dataset (Garcia-Venegas et al., 2021). Using the Tensorflow, the dataset would be trained on a SSD MobileNet or EfficientDet model. The model would then be deployed onto the Google Coral Dev Board with a Coral Camera or a webcam, and a 3D printed attachment would be designed for usability on a semi-trailer truck mirror. Figure 3 illustrates an outline of the final design.

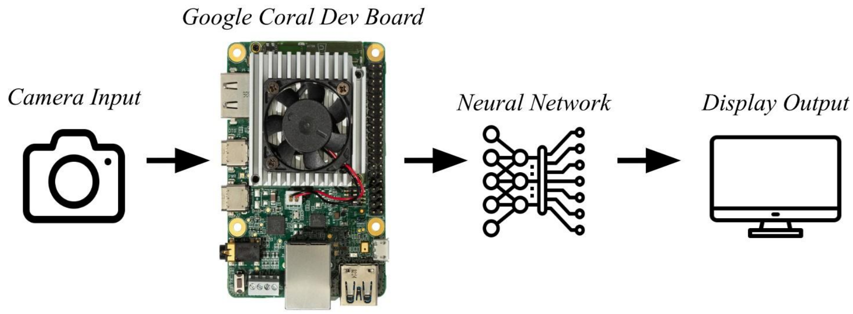

Figure 3: *Overview of design of cyclist detection apparatus for blind spots of semi-trailer truck*

Note. This apparatus is to be attached to a semi-trailer truck right-hand mirror.

Preliminary Work

Specific Aim #1.

The first and primary aim of this project is to develop a system that will actively and accurately detect cyclists through a camera. The designed system will be at least eighty percent accurate and cover the right-rear blind spot of a semi-trailer truck. As per this study, two sufficiently accurate, as determined by the accuracy testing procedures prototype object detection models have been trained. These model architectures were chosen because they offer state-of-the-art lightweight mobile capabilities for object detection.

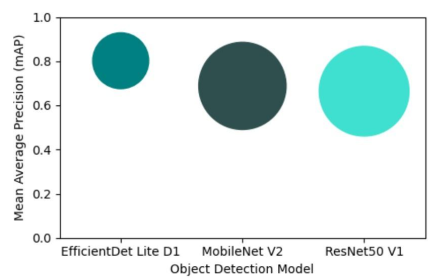

Figure 4: *Performance of prototype cyclist detection models*

Note. The bubble size represents the file size of the final trained model.

The first model consists of an SSD MobileNet V2 object detection model that was fine-tuned on the CIMAT cyclist orientations (8 classes) dataset. The MobileNet architecture is lightweight and portable, which makes it suitable for real-time detection in automotive safety systems (Sandler et al., 2018). The second model consists of an EfficientDet Lite model trained using the Tensorflow Lite API (Tan et al., 2020). To further improve cyclist detection speed in mobile environments, an Edge Tensor Processing Unit (TPU) was used (Seshadri et al., 2022). Additionally, to improve accuracy, the CIMAT bicyclist orientations dataset was also reconfigured and used as a single-class detection dataset. The results of all trained models are listed in Table 1 and shown in Figure 4.

Table 1.
Results for Prototype Object Detection Models

Object Detection Model	Number of Classes	Froze initial layers?	mAP	mAP (IoU:50)	Model Size (MB)
MobileNet V2	**8**	**No**	**0.688**	**0.838**	**16.5**
EfficientDet Lite D1	**1**	**Yes**	**0.802**	**0.977**	**7.6**
EfficientDet Lite D2	1	Yes	0.777	0.971	9.7
ResNet50 V1	8	No	0.664	0.823	17.0
EfficientDet Lite D1	8	Yes	0.459	0.564	7.4

Note. The bolded rows were chosen as the best performing prototype models.

Specific Aim #2.

The second aim of the blind spot alert apparatus is to provide timely detections within an interval of two seconds. Using the Google Coral Dev Board, the latency and frames per second (FPS) of each object detection model will be analyzed. The latency will be measured as the total time between inputting an image from the camera module and displaying a prediction on the LCD screen. Figure 5 shows the frames per second for the EfficientDet Lite model trained for single-class cyclist detection.

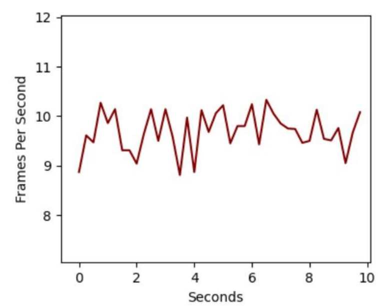

Figure 5: *Frames per second of EfficientDet Lite single-class cyclist detection.*

Note. The average frames per second is 9.7. The average inference time per frame was 103.3 milliseconds.

Specific Aim #3.

The final objective of this project is to design a device that can be portable and installable onto most existing semi-trailer truck cabs. The design of the device is to be lightweight and have a 3D-printed connector piece that will allow the camera module to be attached to the right rear-view mirror of the truck. The camera module would be wired to the Coral Dev Board and LCD display, which will be accessible from within a truck cab.

Testing Procedure

Object Detection Model Accuracy Testing.

Object detection models are often tested on a set of metrics (COCO Object Detection) that measure an average of the precisions—the percentage of detections that are correct out of all detections made—and recall—the percentage of detections that were made out of all ground-truth detections—of the model. This metric is called Mean Average Precision (mAP), and it is calculated over various Intersection Over Union (IoU) levels (Lin et al., 2015). Trained object detection models will be tested on the validation dataset, which comprises 20% of the original CIMAT cyclist orientations dataset.

Code Coverage Testing.

The design of a safety-critical system requires conducting tests on most parts of the code. Numerous unit tests will be conducted to validate code, and module tests will be conducted to validate the integration of the camera and object detection modules. Furthermore, the finished apparatus will be tested thoroughly in a variety of real-time scenarios.

Real-Time Testing.

The real-time testing environment will include a dummy, a bicycle, a fixed mount for the blind spot apparatus, and the blind spot apparatus. The dummy will be placed on a bicycle to model a cyclist, and the bicycle will be run down a track or guided by a rope. The blind spot apparatus will be fixed to a tripod mount or a semi-trailer truck side mirror. The device will be tested qualitatively for its effectiveness in detecting cyclists from the viewpoint of a truck cab and feasibility for industry usage.

Section IV: Resources and Facilities

Current Equipment

Current equipment that has either already been obtained or is available for use is the Google Coral Dev Board, the aluminum case, a camera module, and a bicycle for real-time testing. Furthermore, basic computational resources are available for object detection training use.

Potential Obstacles

One potential roadblock that may occur is difficulty in finding computational resources available to train an object detection model. A potential solution to this roadblock would be to inquire about computational resources at the WPI Academic and Computing Center or purchase hosted GPU services. Another potential roadblock that may occur is finding a semi-trailer truck or a large vehicle to test real-time bicyclist detections. This roadblock can be overcome by modeling semi-trailer truck cabs with a tripod to simulate the height of the mirror in real-time testing.

Section V: Ethical Considerations

This study will not involve human participants or animal subjects. Potential safety concerns would include handling electrical components and wiring. Addressing this concern would include wearing gloves when handling electrical components and being aware of hardware and electrical components to prevent them from overheating or building up too much static electricity. Another safety concern includes field testing and having large vehicles in the presence of cyclists. To mitigate these concerns, vehicles would be instructed to move slowly to prevent any accidents, or model testing environments will be developed to prevent the concern of human safety.

Section VI: Budget

Table 2.

Proposed Budget for this Project.

Items	Quantity	Total	Percent of Total
Google Coral Dev Board (1 Gb RAM)	x1	$140.00	38%
Google Coral Dev Board Aluminum Case	x1	$25.00	7%
Google Coral Camera	x1	$30.00	8%
LCD Screen + Case	x1	$125.00	32%
Computational Resources	–	$30.00	8%
Other Hardware Materials	–	$25.00	7%
Total	–	$375.00	–

Note. These costs are estimated and may deviate from actual expenses.

Section VII: Timeline

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Section VIII: Appendices

Appendix A. Grant Agency Information

This proposal is to be submitted to the National Science Foundation (NSF) Computer and Information Science and Engineering Robust Intelligence (RI) program. The RI program offers grant awards to PIs who research the field of machine learning, computer vision, and artificial intelligence. Awards are granted to those who make contributions and develop systems that advance society using the above methods.

Appendix B. Object Detection

The majority of object detection architectures have a feature extractor and a meta-architecture. First, images pass through feature extractors–such as the VGG, MobileNet, Inception, and ResNet–which extract features through a convolutional neural network. Then, the features are passed through a meta-architecture such as an Region-Based Convolutional Neural Network (R-CNN) or Single-Shot Detector (SSD) model. R-CNNs first locate the general regions an object may be and then output the object's bounding boxes and classifications (Girshick et al., 2014). On the other hand, Single-Shot Detector (SSD) models consist of a single step to predict bounding boxes and classifications (Liu et al., 2016). SSD models are smaller in size and generally have faster computational speed but lower accuracy on smaller objects than R-CNN models (Huang et al., 2017).

Object detection models are often trained using transfer learning, which uses a pre-trained model on a large dataset and fine-tunes it to specialize in a specific task. One such dataset that is commonly used for transfer learning is the Microsoft COCO Dataset, which contains over 200,000 labeled images and 80 object categories (Lin et al., 2015).

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