Independent Research Project Notes

A Semi-trailer Truck Right-Hook Turn Blind Spot Alert System for Detecting Vulnerable Road Users with Transfer Learning

Charles Tang

Massachusetts Academy of Math and Science at WPI

Research Advisors: Mr. Nicholas Medeiros, Kevin Crowthers, Ph.D.

Table of Contents

Knowledge Gaps

This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved
What are the blindspots of a truck?	Finding an image.	https://amainsider.com/big-trucks-blind-spots-road-safety/	8/19/22
How can bicycles be detected?	Reading a journal article about cyclist detection.	[Article #14]	9/12/22
How risky are collisions between cyclists and trucks?	Reading an article about truck and VRU collisions.	[Article #7] [Article #24]	8/20/22 10/21/22
What types of bicycle infrastructure can make bicycling on the road safer?	Reading an article on protected intersections.	[Article #12]	9/3/22
What kind of injuries do bicyclists sustain after a collision?	Reading a scientific journal about the severity of injuries	[Article #1]	8/18/22
What are the ingredients of plant-based meats?	Reading a scientific journal article about plant-based meats.	[Article #5]	8/19/22
What kind of deep learning models can be used for object detection?	Reading a general article on object detection models.	[Article #14]	8/27/22
How are object detection models evaluated?	Learning about COCO detection metrics.	[Article #11]	8/27/22
What current technologies are available in reducing/eliminating blind spots?	Reading a few patents and papers on current innovations.	[Article #13] [Patent #1] [Patent #3] [Article #20]	9/4/22 9/18/22 9/24/22 9/25/22
How can custom object detection models be trained?	Learning about Object Detection API	https://tensorflow-object-detection-api-tutorial.readthedocs.io/en/2.2.0/	10/2/22
How can custom object detection models be deployed for real-time applications?	Learning about Tensorflow Lite, Exporting Models, and Coral Dev Board.	https://tensorflow-object-detection-api-tutorial.readthedocs.io/en/2.2.0/ https://coral.ai/products/dev-board	10/16/22

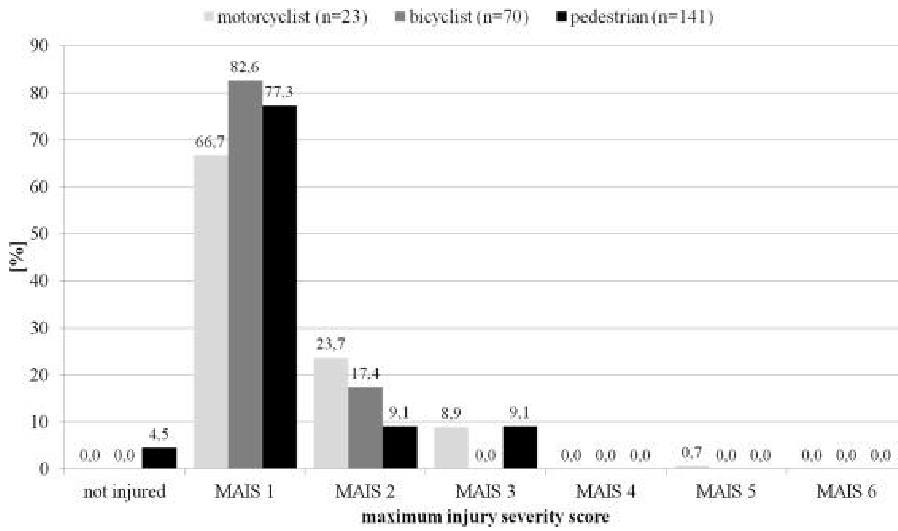
Literature Search Parameters

These searches were performed between 06/22/22 and 12/01/2022.

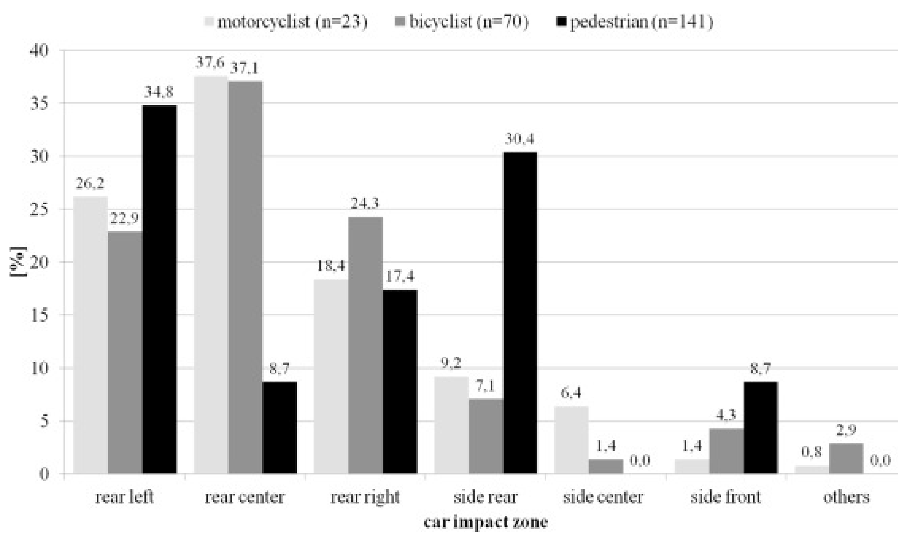
Database/search engine	Keywords	Summary of search
Science Direct	Bike Collisions, Bicycle Safety, Blind Spot, Truck Blind Spot	Found a variety of articles regarding the risk involved in collisions and injuries involved with vehicles and/or bicycles.
Google Search	Bicyclist Safety, Road Usage	Found a variety of government and organization articles regarding safety tips for bicyclists
Google Search	Oral Allergy Syndrome	Found a variety of organizational web articles about oral allergy syndrome.
Google Scholar	Truck and Bicycle Collisions	Found a variety of scientific journal articles regarding truck blindspots and case study injuries sustained by bicyclists.
Google Search	Neural Networks	Found some basic articles about neural networks and some basic guides.
Google Search	Object Detection	Found many general articles and guides to create object detection models for various tasks.
WPI Library Search	Bicycle AND Blind Spot	Found a variety of the safety and risk of vehicle blind spots. Found one article called “Real-time approaching vehicle detection”
Google Scholar	Traffic Safety AND Bikes	Found article “Conflicts between bikes and trucks in urban areas - A survey of Norwegian cyclists”
Engineering Village	Bicycle collision	Found article “CNN-based system to identify bicycle riders and pedestrians: toward minor collision prevention on sidewalks”
Science Direct	Oral allergy syndrome	Found a variety of articles on studying oral allergy syndrome and case studies for treatment.
European Patent Office	Blind spots AND Camera	Found a patent “Apparatus and Methods for Eliminating or Reducing Blind Spots in Vehicle Mirror and Camera Systems”
Google	Object Detection Architectures Papers	Found research articles on R-CNN, Faster R-CNN, SSD and various other object detection architectures.

[Article #1] Injury severity – 8/18/22

Source Title	Injury severity of pedestrians, bicyclists and motorcyclists resulting from crashes with reversing cars
Source citation (APA Format)	Decker, S., Otte, D., Cruz, D. L., Müller, C. W., Omar, M., Krettek, C., & Brand, S. (2016). Injury severity of pedestrians, bicyclists and motorcyclists resulting from crashes with reversing cars. *Accident Analysis & Prevention, 94,* 46–51. https://doi.org/10.1016/j.aap.2016.05.010
Original URL	https://www.sciencedirect.com/science/article/pii/S0001457516301646?via%3Dihub
Source type	Scientific Journal Article
Keywords	Bicyclist injuries, car blindspot collisions, bicycle collisions
Summary of key points + notes (include methodology)	The study investigated over 200 pedestrian or cyclist and reversing car collisions and placed them on an AIS/MAIS. The greatest risk of severe injuries with backing cars is pedestrians. 90% of all reversing car collisions happen during the day, and there is no serious injury in around 90% of collisions with reversing cars as well. Notes: - The study investigated a collision database in Germany with documented AIS injury scores from each collision, crash location, type of vehicle, and estimated impact speed - 81% of reversing car collisions occurred at the rear end of the car - Impact speed and pedestrian collisions are positively correlated to severity of injury - Pedestrians were seriously injured in 10% of situations - MAIS scores were highest with pedestrians - Age has a correlation to higher risk of severe injury - Backup cameras and automatic braking may help prevent collisions - Lower body of most people suffer most injuries
Research Question/Problem/ Need	How severe are injuries caused by cars that back out of places and pedestrians, motorcyclists, and bicyclists?

<table>
<tr>
<td>Important Figures</td>
<td>


This figure describes the injury levels of motorcyclists, bicyclists, and pedestrians related to reversing car collisions. It is found that the majority of incidents have MAIS <3, which means that the injuries were not that severe.



This chart identifies places of the car where a collision occurs with VRUs. It is found that the most frequent places of collision are along the rear edge of the car, as well as the side rear section for pedestrians.
</td>
</tr>
<tr>
<td>VOCAB: (w/definition)</td>
<td>
Injury severity - how severe injuries are and how life threatening they are

AIS - abbreviated injury scale which measures injury severity as a threat to life

MAIS - maximum abbreviated injury scale measures the highest injury severeness on the AIS scale which is diagnosed with the help of medical
</td>
</tr>
</table>

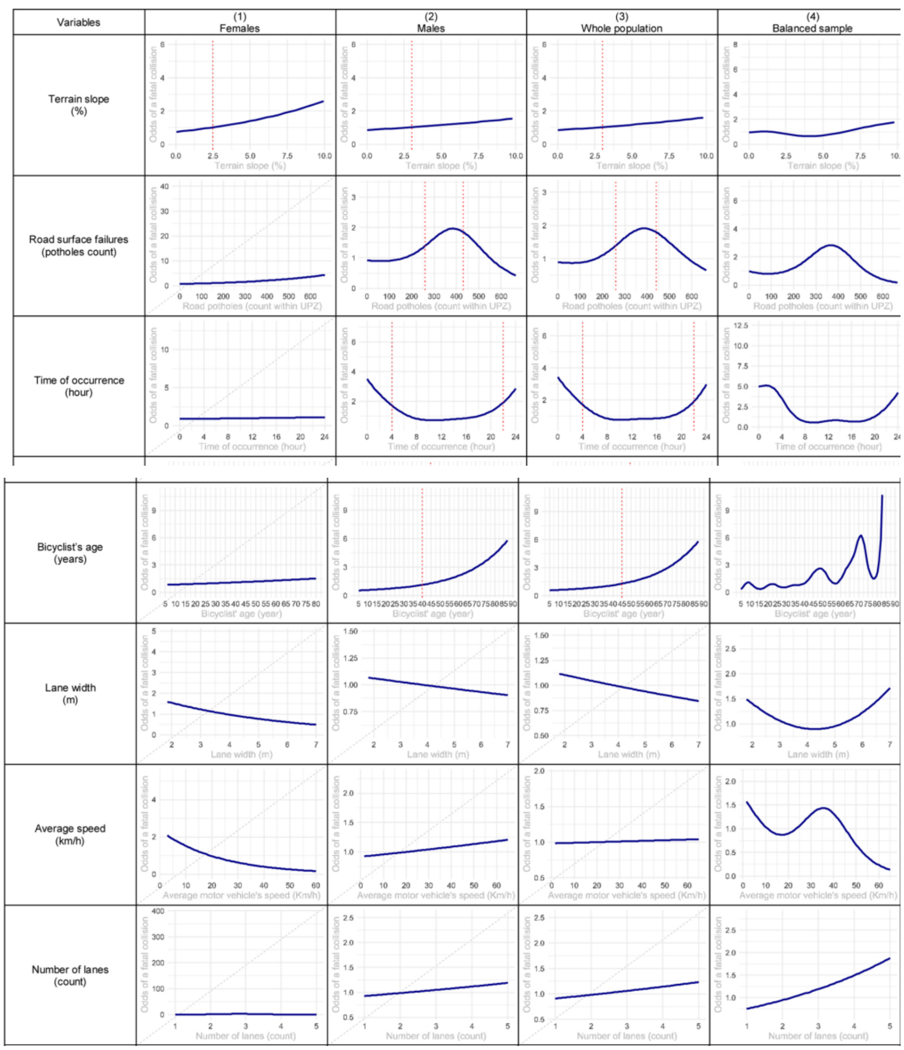
	professionals Impact speed - maximum speed or velocity of vehicle at time of impact Contusion - a bruise
Cited references to follow up on	Attention and expectation problems in bicycle–car collisions: an in-depth study - https://www.sciencedirect.com/science/article/pii/S0001457598000074 Bicyclist Fatalities in New York City: 1996–2005 - Bicyclist Fatalities in New York City: 1996–2005: Traffic Injury Prevention: Vol 10, No 2 (tandfonline.com)
Follow up Questions	1. Could reversing collisions be prevented with speed restrictions on bicyclists and motorcyclists? 2. What protective measures could be placed on pedestrians to prevent high-speed and severe injury collisions? 3. How effective are rear-facing cameras in preventing collisions? 4. What devices are used for automatic braking systems when reversing?

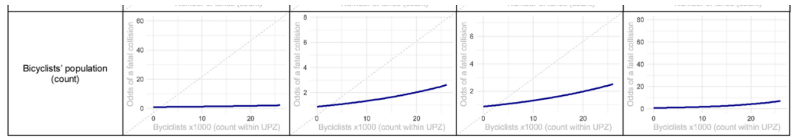
[Article #2] Bicycle safety in Bogotá – 8/18/22

Source Title	Bicycle safety in Bogotá: A seven-year analysis of bicyclists' collisions and fatalities
Source citation (APA Format)	Carvajal, G. A., Sarmiento, O. L., Medaglia, A. L., Cabrales, S., Rodríguez, D. A., Quistberg, D. A., & López, S. (2020). Bicycle safety in Bogotá: A seven-year analysis of bicyclists' collisions and fatalities. *Accident Analysis & Prevention*, *144*, 105596. https://doi.org/10.1016/j.aap.2020.105596
Original URL	Bicycle safety in Bogotá: A seven-year analysis of bicyclists' collisions and fatalities - ScienceDirect
Source type	Scientific Journal Article
Keywords	Bicycle collision, bicyclist injuries and risk, bicycle mortality

Summary of key points + notes (include methodology)	Based on data collected over seven years, the study analyzed each collision's sociodemographic and geospatial data. Variables analyzed included bicyclist characteristics, types of vehicle collisions, and environmental factors. The study concluded that some positive factors associated with collisions are sex, larger vehicles, poor infrastructure, steep terrain, and nighttime.
	
	Notes:
	- Bicycling is good for health, environment, fitness, reduces cancer risk, mental health, etc.
	- Traffic risk is adoption barrier to biking, many people are interested but risks make people avoid it
	- High risk places are along main corridors and intersections
	- Boulevards (wider roads) are significantly safer for bicyclists
	- Types of bike lanes:
	    - Off-street bike lanes (on sidewalks)
	    - Segregated on-road bike lanes
	    - Paint-de;o,oted on-road bike lanes
	    - Shared-use bike lanes
	- Collected data from local traffic collisions and World Resources Institute
	- Georeferenced all collision locations and analyzed the area
	- Collected socioeconomic data as well for the collisions
	- Independent Variables: bicyclist characteristics, types of vehicles, geospatial details
	- Bike advocacy groups have helped collision rates drop by 50%
	- Collisions with larger vehicles were more likely to be fatal
	- Bogota government has expanded bike programs and policies

	- LTS is oppositely correlated to fatal collisions - maybe it attracted more experienced bikers and reduced risk
	- More lanes = riskier for fatal collisions
	- Having dedicated bike lanes and slower moving vehicles would reduce the fatality rates of collision
	- Some future policies:
	    - More bike infrastructure
	    - Law enforcement of speed limits
	    - Gender and equality focused policies
	        - Safe bicycling programs should target females and inexperienced

Research Question/Problem/ Need	How safe are bicyclists from collisions in an area of low to moderate income?
Important Figures	

	 **Fig. 3.** Predictors with nonlinear effects in the baseline and additional GAMM specifications. Estimated contribution to the odds ratio and 95 % confidence region of a fatal bicyclist's collision in Bogotá for the period 2011 to 2017. Vertical dotted lines correspond to thresholds when the odds ratio becomes significantly different from 1. Strikethrough variables were not significant at a 5% significance level. This figure describes the odds of fatal collisions in a variety of scenarios and measures the odds over a variety of risk factors. The most significant factors in fatal collisions are bicyclist age, the number of lanes, and time of occurrence.
VOCAB: (w/definition)	GAMM - generalized additive mixed models (linear model) spatiotemporal - being in both space and time National Longitudinal Mortality Study - database of mortalities from surveys from different demographics *Safety in numbers* - greater exposure = less risk hypothesis Bike lanes - areas on the side of the road for bicyclists to bike on VKmT - vehicle kilometers traveled Spatialtemporal trends - trends relating to space and time Adoption barrier - something that poses an issue to consumers when using a product LTS - levels of traffic stress
Cited references to follow up on	Revisiting the Four Types of Cyclists: Findings from a National Survey - https://journals.sagepub.com/doi/10.3141/2587-11 Geospatial Analysis of Cyclist Injury Trends: An Investigation in Melbourne, Australia - https://www.tandfonline.com/doi/abs/10.1080/15389588.2014.973947 Mixed logit analysis of bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection locations - https://www.sciencedirect.com/science/article/pii/S0001457510002782?via%3Dihub
Follow up Questions	1. If safe biking seemed like a viable policy to promote, would safe driving also help reduce bicycle collisions? 2. How can the cost of creating bike lanes be reduced to promote

	safer biking? 3. What is the reason for the gap in gender mortality rates in bike collisions? 4. How do GANN's work?

[Article #3] Bicycle Safety – 8/19/22

Source Title	Bicycle Safety
Source citation (APA Format)	*Bicycle Safety | Motor Vehicle Safety | CDC Injury Center*. (2022, May 4). https://www.cdc.gov/transportationsafety/bicycle/index.html
Original URL	https://www.cdc.gov/transportationsafety/bicycle/index.html
Source type	General Web Article
Keywords	Bicyclist Safety
Summary of key points + notes (include methodology)	Bicyclists face many risks and the costs of bicycle-related accidents are high. Some risk factors for bicycle accidents are older age groups, adolescents and teens, urban areas, alcohol, and high speeds. Some prevention methods of bicyclist injury or death are helmets, reflective clothing, active lighting infrastructure, and safer roads. Notes: - Ages 55-69 have highest mortality rate for biking - 27% of bicycle collisions occur at intersections - ⅓ of bicycle collisions occur with alcohol influence - Lighting can keep bicyclists safe - 1,000 bicyclists die and 130,000 injured in U.S. every year - Costs > 23 billion dollars in U.S.
Research Question/Problem/ Need	What are some safety risks of bicyclists and what are some ways of preventing them?
Important Figures	
VOCAB: (w/definition)	Fluorescent clothing - clothing with neon colors that glow when in the dark Retro-reflective clothing - clothing with retro reflective panel/tape Active lighting - white lights, rear red lights,
Cited references to follow up on	2019 Traffic Safety Facts - https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813197 2020 Traffic Safety Facts - https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813322
Follow up Questions	1. How effective are helmets at preventing upper body injuries?

	2. What materials are best for making fluorescent or retro-reflective clothing? 3. What improvements could be made to improve roads for bicyclists? 4. On which part of roads are accidents most common?

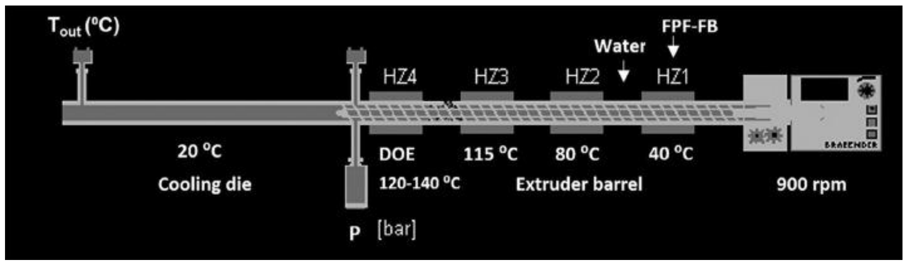
[Article #4] Air Purifiers – 8/19/22

Source Title	Do air purifiers help with allergies?
Source citation (APA Format)	Taylor-Smith, Kerry (2021, September 15). *Do air purifiers help with allergies?* Live Science. https://www.livescience.com/do-air-purifiers-help-with-allergies
Original URL	Do air purifiers help with allergies? | Live Science
Source type	Science Webpage Article
Keywords	Allergies, Air purifiers, pollen allergies,
Summary of key points + notes (include methodology)	This article discusses whether air purifiers can help people with pollen allergies. The article examines a few different types of air purifiers, including medical grade and HEPA filters–which remove most tiny particles–and commercial air purifiers. Although many purifier companies claim to remove allergens and pollen from the air, there is a lack of scientific study on whether they significantly impact allergy symptoms. In addition, the companies who test the purifiers use laboratory conditions that are not representative of everyday living. For cases like asthma and pet allergies, air purifiers may help remove most particles that trigger allergy attacks but will need more study on how to use the purifiers best. This article contributes to my idea of producing better allergy-preventative methods by introducing some knowledge gaps in the field of air purifiers and their effectiveness.
Research Question/Problem/ Need	Do air purifiers help with allergies?
Important Figures	
VOCAB: (w/definition)	HEPA Filters - High Efficiency Particulate Air filters which forces air through fine air mesh to block unwanted air particles Allergens - substance that causes allergic reaction Aeroallergens - allergens found in the air Antihistamines - medication that relieves symptoms of cold, allergies, etc.

	Pollutants - a substance that pollutes the air
Cited references to follow up on	
Follow up Questions	1. What other non-medicinal methods can reduce allergy symptoms? 2. Can masks block aeroallergens and prevent some allergy symptoms? 3. Do Antihistamines work on oral allergy syndrome?

[Article #5] Plant-based meat – 8/19/22

Source Title	Plant-based meat alternatives: Compositional analysis, current development and challenges
Source citation (APA Format)	Ahmad, M., Qureshi, S., Akbar, M. H., Siddiqui, S. A., Gani, A., Mushtaq, M., Hassan, I., & Dhull, S. B. (2022). Plant-based meat alternatives: Compositional analysis, current development and challenges. *Applied Food Research, 2(2)*, 100154. https://doi.org/10.1016/j.afres.2022.100154
Original URL	https://www.sciencedirect.com/science/article/pii/S2772502222001147
Source type	Scientific Journal Article
Keywords	Plant-based meat, alternative meat options
Summary of key points + notes (include methodology)	The article discusses some of the processes, materials, and the outlook of plant-based meats. Plant-based meat alternatives consist of water to make the meat juicy, proteins for the texture and taste, and fats. To retain water for the juiciness of the meat, soy protein or other forms of sticky substances are used. Some of the key properties that are examined in choosing the right proteins are water-holding capabilities, gelling, fat-absorption, solubility, and emulsification abilities. High moisture extrusion forms the meats from the materials, consisting of mixing, melting, cooking, and cooling phases. Factors affecting plant-based meat production are consumer preference, food supply concerns, and production cost. Some future research could be to find ways to decrease the cost of producing plant-based meats and industrialize the process. Notes: - Canola and rapeseed made good proteins for emulsification and foam-forming properties (for when cooked) - Adding oil increases tastiness but over 15% concentration could make the meat slick - Quality of final product is highly dependent on binding agent - Casein, soy protein, wheat gluten, etc. - chicken/beef aroma can be made from soybean-enzyme-hydrolysed proteins - Hydrolysis of vegetable protein or D-xylose or L-cysteine can make a meat like flavor

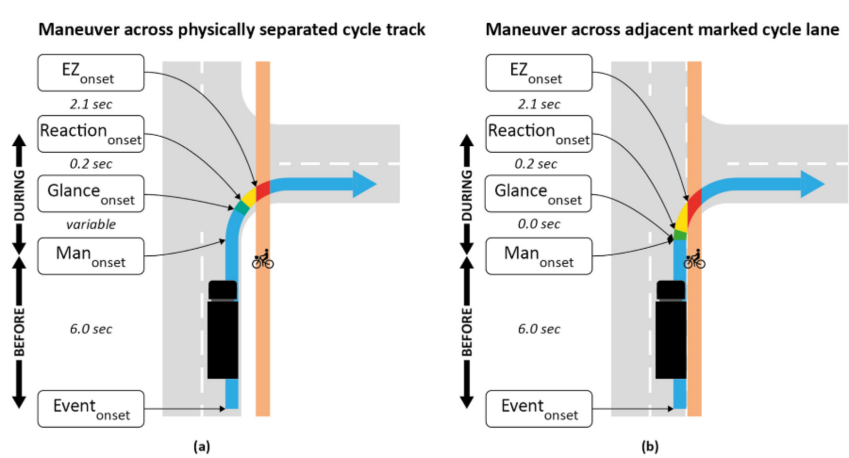
	- Extrusion process has 40% feed moisture and 4 heating zones (see figure) - Can be a pathway to sustainable food supply - Plant-based meat substitutes are 1% of all meat purchases in US - If governments support plant-based meat industry, it may be able to support more change to sustainable food
Research Question/Problem/ Need	What makes plant-based meats similar to normal meats? What are the most important factors in making plant-based meat?
Important Figures	 This figure describes the extrusion process of creating plant-based meats using various extrudes and various sections of heat and nutrient absorption.
VOCAB: (w/definition)	Meat analogues - a non-meat substance that mimics its function TVP - textured vegetable protein made from dehydrated soy product colorectal cancers - cancer in the colon or rectum areas Emulsification - putting one liquid in another and applying hydrogen bonding interactions between bioactive compounds and encapsulating material Peptide sequences - order of amino acid chains Anisotropy - property that allows material to change differently in different directions Isoflavones - a type of skin care compound Binding agents - compounds that bind moisture and fat in meat alternatives D-xylose - sugar isolated from wood L-cysteine - an amino acid Protein desulfation bonding - a characteristic of gluten when the

	protein forms Protein legumes - proteins from beans
Cited references to follow up on	Our daily meat: Justification, moral evaluation and willingness to substitute - https://www.sciencedirect.com/science/article/pii/S0950329319300394?via%3Dihub Opportunities for the Adoption of Health-Based Sustainable Dietary Patterns: A Review on Consumer Research of Meat Substitutes - https://www.mdpi.com/2071-1050/11/15/4028
Follow up Questions	1. How are plant based meats manufactured at a large scale? 2. Are there simpler ways to create plant based meats? 3. What are some alternative binding agents that could improve the function of alternative meats? 4. What proteins can replace soy proteins for those who have an intolerance to gluten?

[Article #6] Driver glance behavior – 8/20/22

Source Title	Caught in the blind spot of a truck: A choice model on driver glance behavior towards cyclists at intersections
Source citation (APA Format)	Jansen, R. J., & Varotto, S. F. (2022). Caught in the blind spot of a truck: A choice model on driver glance behavior towards cyclists at intersections. *Accident Analysis & Prevention, 174*, 106759. https://doi.org/10.1016/j.aap.2022.106759
Original URL	https://www.sciencedirect.com/science/article/pii/S0001457522001956
Source type	Scientific Journal Article
Keywords	Truck blind spot, driver attention, right-turn maneuver, glance behavior, discrete choice model

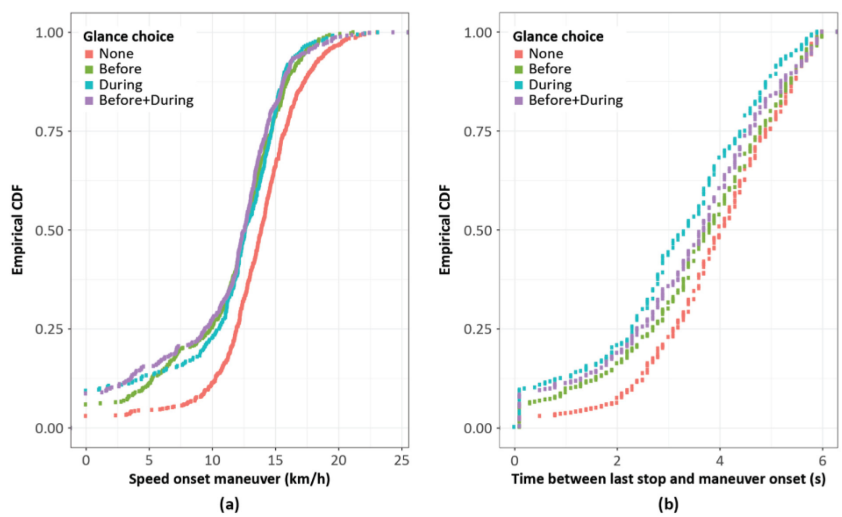
Summary of key points + notes (include methodology)	This article discusses the risks involved with truck drivers and how they neglect to check blindspots before making turns. This can severely increase the risk of collision for bicyclists when trucks make right-hand turns. The study assessed drivers from four Dutch transport companies and represented the standard characteristics of the truck driving population. Cameras were then placed in the truck to accurately track the glances of drivers and their behavior. The statistics showed that about 50% of truck drivers did not make a glance to check blind spots or didn't check at the right time.
	
	Notes:
	- Trucks are the most dangerous collision entities with bicyclists at intersections
	- Blind spots can be covered with blind spot mirrors or cameras
	- ~400 people are killed in Europe due to blind spot crashes each year
	- Truck drivers are instructed to check their blind spots when making a right turn – at least once before and at least once during the maneuver
	- Reasons bicyclist is not seen
	    - Driver may not have looked in the direction of the bicyclist/mirrors
	    - May not have seen bicyclist in mirrors
	    - Blind spot mirrors were checked but not at right timing

	- The bigger the bike lane/further away from road the better the visibility - Driving instruction manuals for trucks are not clear enough for the order to check blind spot mirrors - Drivers need at least 0.2s to determine a hazard - Phase before maneuver = 6s before start - Phase during maneuver = until last moment driver has chance to cast glance on blind spot mirror (figure) - 90% of trucks stopped before maneuver - Average time waiting for maneuver was 2.3s - 29% of events had no glance - 51% of events had glance where it was not applicable to the maneuver – 49% only looked before and not during - Drivers glanced more with marked lanes and advanced stopping lanes – worse infrastructure showed less glances - Drivers were less likely to glance if doing an NDRT - Having vehicles in front (lead vehicles) made it less likely to cast a glance - When bike lanes are separated from the main road, visibility of them is near impossible because they are outside the view of blindspot mirrors - When pedestrians were in front of a truck, attention was drawn to the pedestrian and it was less likely to notice the cyclist coming from the blind spot
Research Question/Problem/ Need	What is the glance behavior of truck drivers before and during right-turning maneuvers at intersections?
Important Figures	 This figure describes the steps in the turning process of a truck when a bicycle is in an adjacent bike lane. Each part of the process has a risk

factor for collision with the bicyclist.

Table 1
Distribution of glance choices as a function of whether a glance during the maneuver was applicable (i.e., starting ultimately 2.3 s prior to the maneuver onset). N.A. = glance choice not applicable.

	Glance during maneuver applicable		Glance during maneuver not applicable	
Glance choice	*N*	%	*N*	%
None	409	29.28	256	50.59
Before	186	13.31	250	49.41
During	341	24.41	N.A.	N.A.
Before + During	461	33.00	N.A.	N.A.
Total	1397	100.00	506	100.00



This figure identifies glance behavior of truck drivers which shows the correlations between speed and time with glance behavior.

VOCAB: (w/definition)

VRU - vulnerable road users (cyclists, pedestrians, motorcyclists)

DAS - data acquisition system

Logit Model - a statistical model to predict probability of an event happening

Likelihood ratio test - a statistical test used to compare the goodness of fit of two models based on the ratio of their likelihoods

Correlation matrix - table showing correlation coefficients between two things

NDRT - non-driving related tasks

Cited references to follow up on	Endangerment of Pedestrians and Bicyclists at Intersections by Right Turning Trucks
Follow up Questions	1. Are blind spot auditory systems able to detect bicyclists? 2. Are blind spot mirrors able to check the full blindspot? 3. How effective are cameras at checking blindspots? 4. What system could be implemented to directly alert drivers of VRUs on the right-hand side? (especially those cycling through during a green light)

[Article #7] Blind Zone of a Truck – 8/20/22

Source Title	Exploring the Influencing Factors and Formation of the Blind Zone of a Semitrailer Truck in a Right-Turn Collision
Source citation (APA Format)	Wang, Q., Sun, J., Wang, N., Wang, Y., Song, Y., & Li, X. (2022). Exploring the Influencing Factors and Formation of the Blind Zone of a Semitrailer Truck in a Right-Turn Collision. *Sustainability, 14(16)*, 9805. https://doi.org/10.3390/su14169805
Original URL	https://www.mdpi.com/2071-1050/14/16/9805
Source type	Scientific Journal Article
Keywords	Traffic safety, blind zone, semitrailer truck, collision accident, bicyclist injuries, PC-Crash

Summary of key points + notes (include methodology)	This study analyzes the formation of a blind spot when semitrailer trucks make right-turns and the risk it poses to cyclists on an adjacent lane. Some factors tested on the PC-Crash software that influence blind spots are turning speed, turning radius, and the influence of different wheel positions on accidents. Lastly, accident simulations showed that the wheel positions and the location of the collision greatly influence the severity of the cyclist injuries.
	
	Notes:
	- Blind zones are the critical area for serious accidents and deaths
	- 45% of all fatal crashes between bikes and trucks are because of blind zones
	- 30% of truck accidents are when trucks turn right and collide with a VRU
	- Blind zone of rearview mirror is increased in a right-turn and blocks view due to trailer body
	- If a VRU is inside the inner wheel difference blind zone, they can be crushed - 70% of accidents and 90% fatality rates
	- High turning speed makes more overlap between bike lanes and blind zones
	    - 60% of bike lane is taken over by semitrailer trucks when they right turn
	- Low turning speed allows VRU to have time to save themselves
	- Recommend right-turn speeds to be < 20 kmh
	- Front area of truck has more collisions + more severe
	    - More easily for the body to be crushed in front positions

<table>
<tr>
<td></td>
<td>

- Collision process
    - Stage 1: VRU collides with truck
    - Stage 2: Rider falls to ground
    - Stage 3: Rider crushed by wheels
- Stage 3 is more dangerous and make injuries severe/fatal
- Double blind zone causes risk to increase / visibility to fall (see figure)
- Infrared, radar, ultrasonic, cameras can be used to identify VRUs in blindspot

</td>
</tr>
<tr>
<td>Research Question/Problem/ Need</td>
<td>How are blind-spot zones formed on right turning trucks and what is the severity of accidents caused from collisions with non-motor vehicles?</td>
</tr>
<tr>
<td>Important Figures</td>
<td>

Figure 2. Blind zone test for the inner wheel difference.

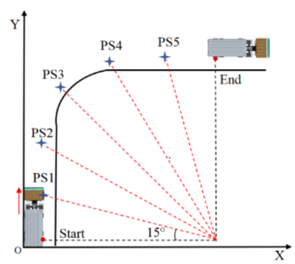


Figure 3. Blind zone test for the rearview mirror.

This figure describes the 5 major points of blind zones developed by a truck when it makes a right-turn.

right-turn collisions could be further studied.

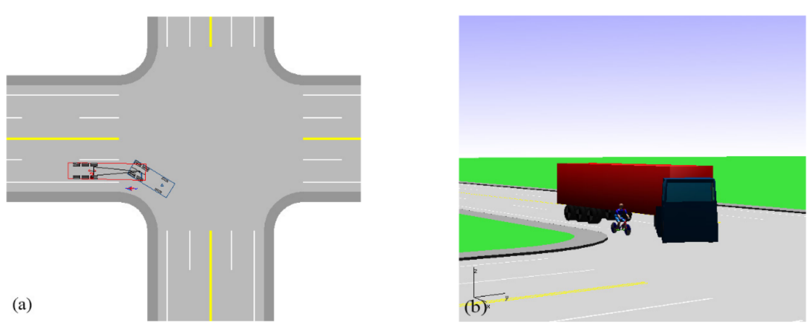
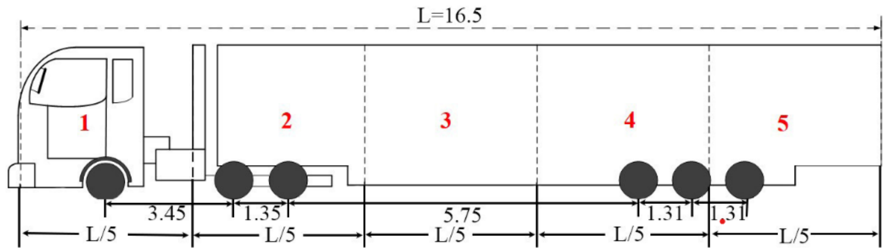


Figure 5. Right-turn collision scenario model: **(a)** 2D view of the collision scene; **(b)** 3D view of the collision scene.

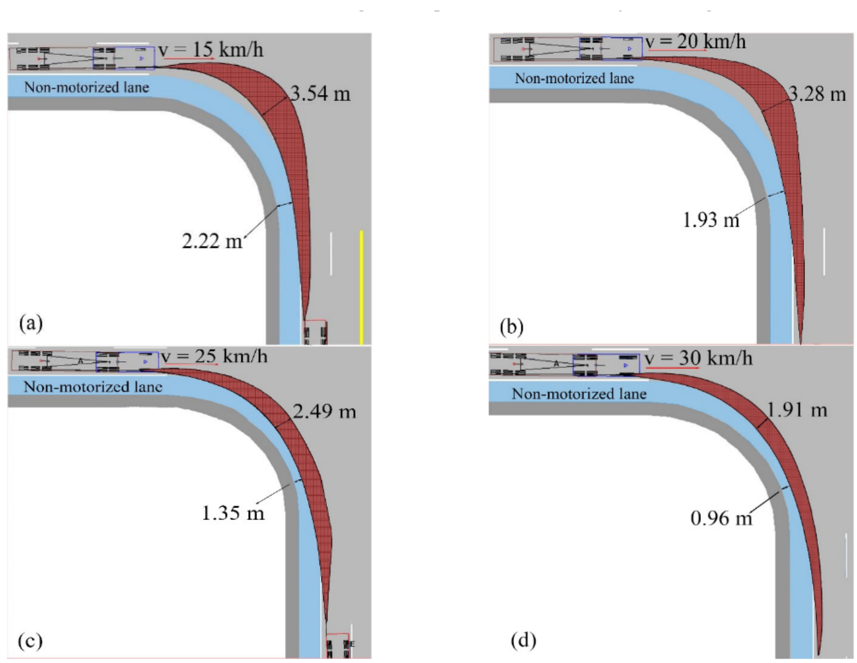
This figure describes the view of a scenario in 2D and 3D where a truck

</td>
</tr>
</table>

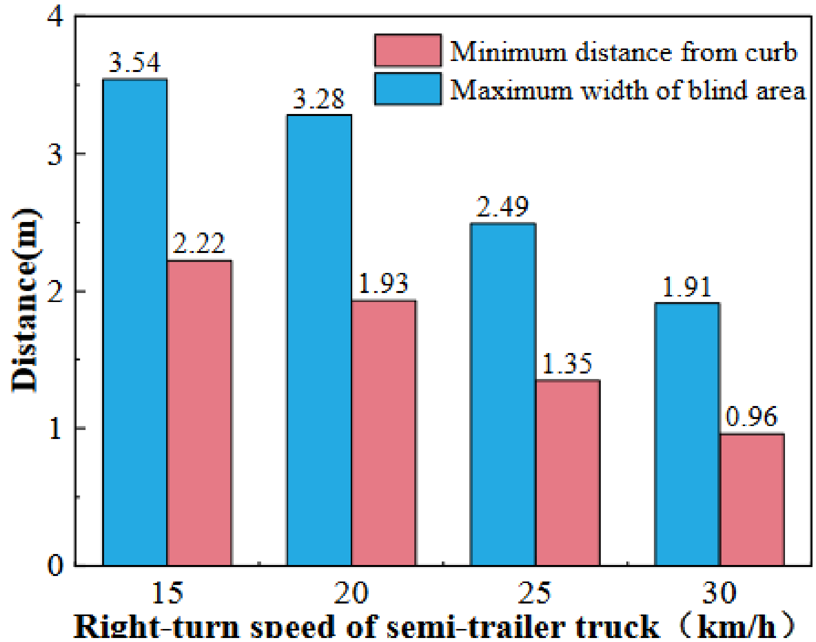
has a collision with a cyclist when making a right-hand turn.



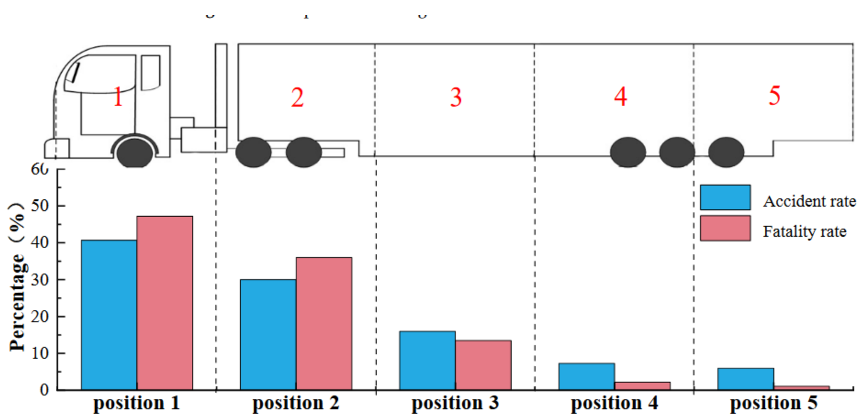
This figure describes the 5 zones of a truck where a collision can happen.



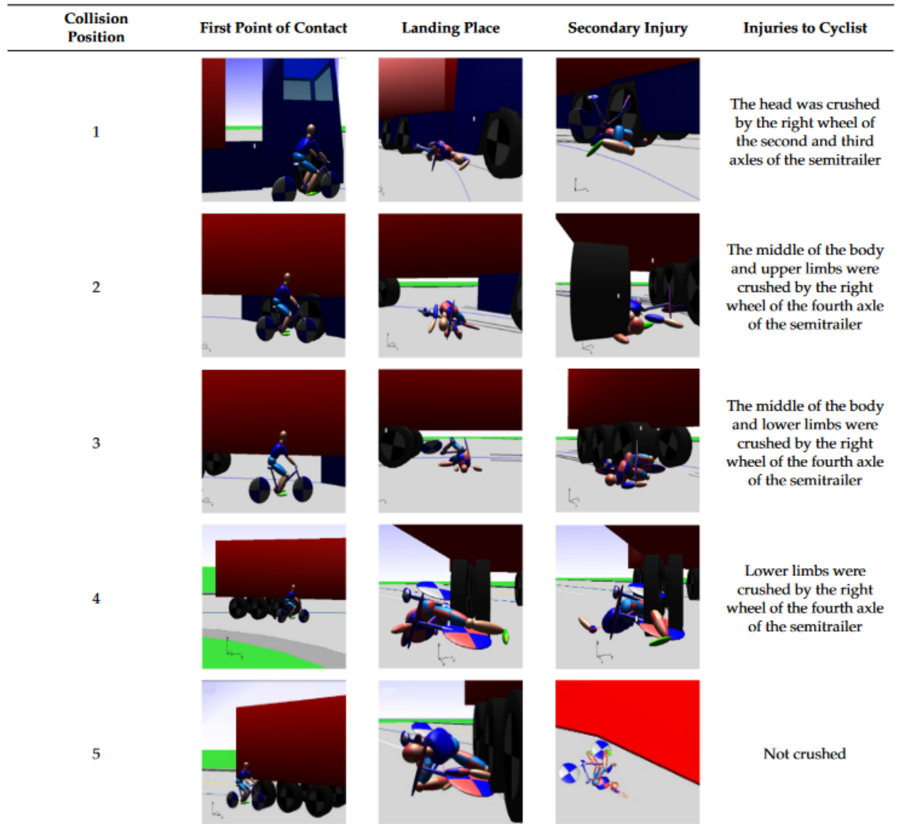
This figure shows the overlap of the truck path and the cyclist path when making a right-hand turn while varying the speed and thus the turn radius.



This figure quantifies the previous figure by describing the blind zones and distance from curb changing as speed of the turning maneuver changes.

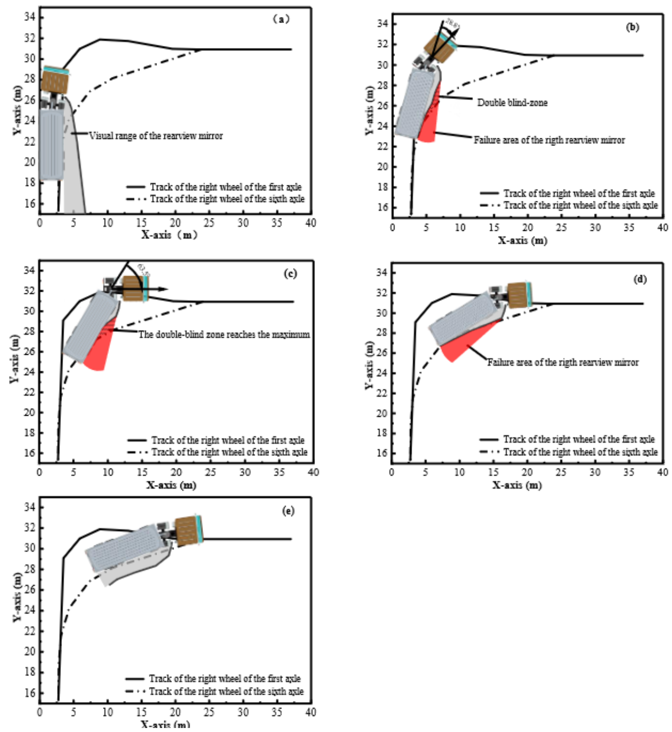


This figure shows the accident rate and fatality rates of each collision section of the truck. The places most prone to accidents and fatalities are near the front of the truck.



Collision Position	First Point of Contact	Landing Place	Secondary Injury	Injuries to Cyclist
1				The head was crushed by the right wheel of the second and third axles of the semitrailer
2				The middle of the body and upper limbs were crushed by the right wheel of the fourth axle of the semitrailer
3				The middle of the body and lower limbs were crushed by the right wheel of the fourth axle of the semitrailer
4				Lower limbs were crushed by the right wheel of the fourth axle of the semitrailer
5				Not crushed

This figure visualizes and compares some of the scenarios where cyclists collide with trucks and what happens to the cyclist when they collide in each section of the truck.

	 This figure describes the double-blind-zone that occurs when trucks make a right-hand turn where the mirror does have visibility and the truck trailer blocks visibility as well.
VOCAB: (w/definition)	Blind Zone - blind spot or area which driver cannot see with mirrors or peripheral vision Inner wheel difference - radius difference between front and rear wheels when a semitrailer truck turns right Inner wheel difference blind zone - area swept by the inner wheel difference Double blind zone - when the inner wheel difference blind zone and the rear right view mirror blind zone produces a degree of overlap during a right turn
Cited references to follow up on	Accidents between freight vehicles and bicycles, with a focus on urban areas - https://www.sciencedirect.com/science/article/pii/S2352146517307810?via%3Dihub
Follow up Questions	1. Can cameras be used to detect VRUs in adjacent lanes? 2. What are some safety measures VRUs can adhere to in order to reduce the risk of collision? 3. How can drivers be reminded to reduce their turning speed as a

	safety precaution? 4. Do double trailer trucks have a greater inside wheel difference blind zone and greater risk of collision? 5. How can a red-light or stop before an intersection change the blind zones of right-turning trucks?

[Article #8] Four Types of Cyclists – 8/21/22

Source Title	Revisiting the Four Types of Cyclists: Findings from a National Survey
Source citation (APA Format)	Dill, J., & McNeil, N. (2016). Revisiting the Four Types of Cyclists: Findings from a National Survey. *Transportation Research Record, 2587(1)*, 90–99. https://doi.org/10.3141/2587-11
Original URL	https://journals.sagepub.com/doi/10.3141/2587-11
Source type	Scientific Journal Article
Keywords	Bicycles, cyclists

Summary of key points + notes (include methodology)	This study examines classifications of cyclists based on their personality and attitudes toward bicycling. A survey examined results from 3,000 adults in the 50 largest U.S. metropolitan areas.
	
	Notes:
	- A Portland-based study categorized people in four types below
	- This study compares the results of the portland study to a nationwide averages
	- 3000 adults in the 50 largest metropolitan areas were surveyed
	- Study had 3 parts: comfort level of bicycling, interest in bicycling, and recent behavior in bicycling
	- Some barriers to bicycling were needing to travel longer distances, little bike infrastructure, traffic, and not having a bike
	- Bicyclists are labeled as
	    - Strong and fearless - 7%
	        - Do not need bike infrastructure to ride well
	    - Enthused and confident - 5%
	        - Comfortable on streets but prefer bike infrastructure
	    - Interested but concerned - 51%
	        - Want to ride bike but needs bike infrastructure
	    - No way no how - 37%
	        - Will not ride a bike no matter what on streets
	- Surveyed adults in 50 largest areas
	- Survey was created by authors and National Association of Realtors
	- Questions used were similar to previous study with Portland to reflect changes from Portland to National study

	- Was conducted over phone and the web in 2015
	- Survey was matched to the national demographic of gender, age, race, education, ideology, political interest, and region
	- Study slightly overrepresented lower income, women, and skewed slightly older
	- People who are physically unable to ride a bike are no way no how
	- Portland survey used more questions, which may cause differences in results
	- Interested but concerned less likely to bike for transportation and rode the least
	- 50% of people who hadn't ridden a bike in the past 30 days do not own a bike
	    - Lower income people less likely to own a bike
	    - Affordability needs to be improved with bikes
	- Women are more likely to be in the no way no how
	- Millennials were likely to be interested but concerned
	- Oldest generation most likely to be no way no how
	- Interested but concerned group most concerned about traffic safety – bike infrastructure should be improved
	- 58% of people with children were interested but concerned, 49% of people without children were interested but concerned
	- College graduates were most likely to be interested but concerned
	- 64% believe biking brings benefit to the environment
	- Attitudes toward biking does not correlate with comfort level of biking
	- No way no how group had less access to pedestrian/bike infrastructure and did not like them as much either
	- Differences were not very significant between groups
	- Many interested but concerned group did not like to drive
	    - This group biked for recreational purposes rather than transportation
	- Safety of traffic posed a fear to a lot of people
	- Bikesharing systems could help encourage biking more

Research Question/Problem/ Need	What is the attitude of the majority of people towards biking and what affects their willingness to bike?

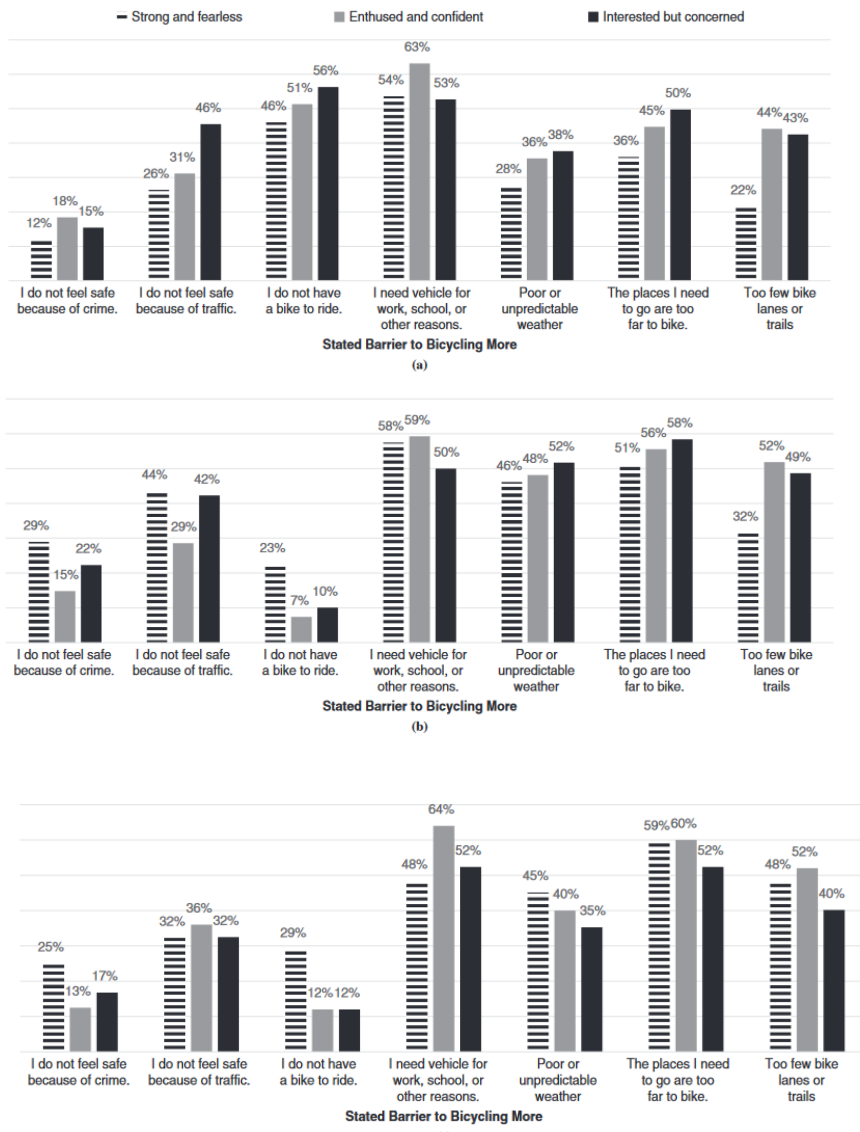
Important Figures

TABLE 2 Summary of Categorization Method

Level of Comfort	Interest in Riding More	Cyclist Type
Very comfortable on nonresidential street without bike lanes	Any response	Strong and fearless
Very comfortable on nonresidential street with bike lanes	Any response	Enthused and confident
Less than very comfortable on nonresidential street with or without bike lanes	Strongly agree, somewhat agree, somewhat disagree, I don't know	Interested but concerned
	Strongly disagree	No way, no how[a]
Very uncomfortable on path or trail separate from the street	Any response	No way, no how[a]
Physically unable to ride a bicycle or don't know how to ride a bicycle	Any response	No way, no how[a]

[a]A total of 80 respondents who were originally classified as no way, no how, but who had ridden a bicycle in the past 30 days, were moved to the interested but concerned group.

This table displays the various categories of responses, comfort levels, and types of cyclists.



This figure compares the types of cyclists and their answers to barriers that prevent them from biking more.

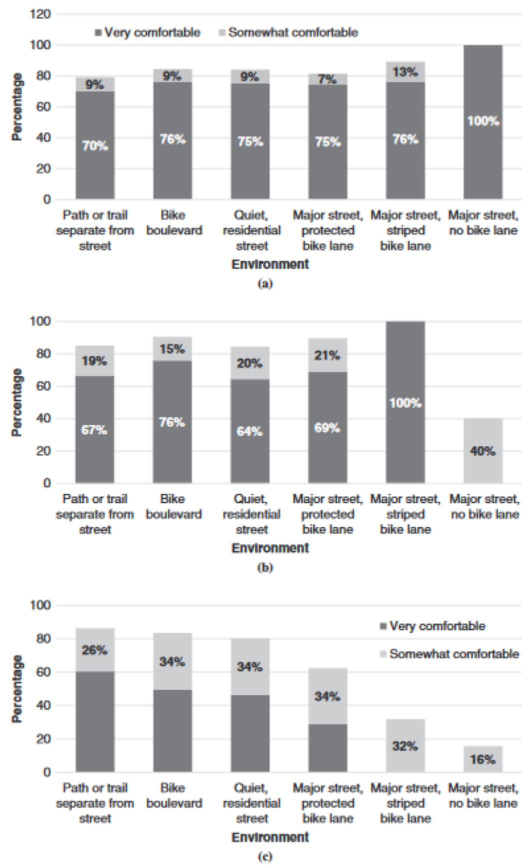
<table>
<tr>
<td></td>
<td>


FIGURE 2 Comfort level bicycling by environment and cyclist type: (a) strong and fearless, (b) enthused and confident, and (c) interested but concerned (figures at 100% result from method used to define types).

This figure visualizes the main comfort levels of bikers on each set of infrastructure across all types of bikers.
</td>
</tr>
<tr>
<td>VOCAB: (w/definition)</td>
<td>Typology - study of classification

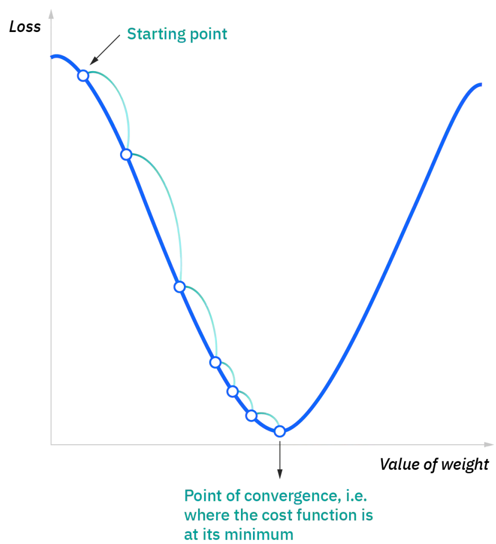
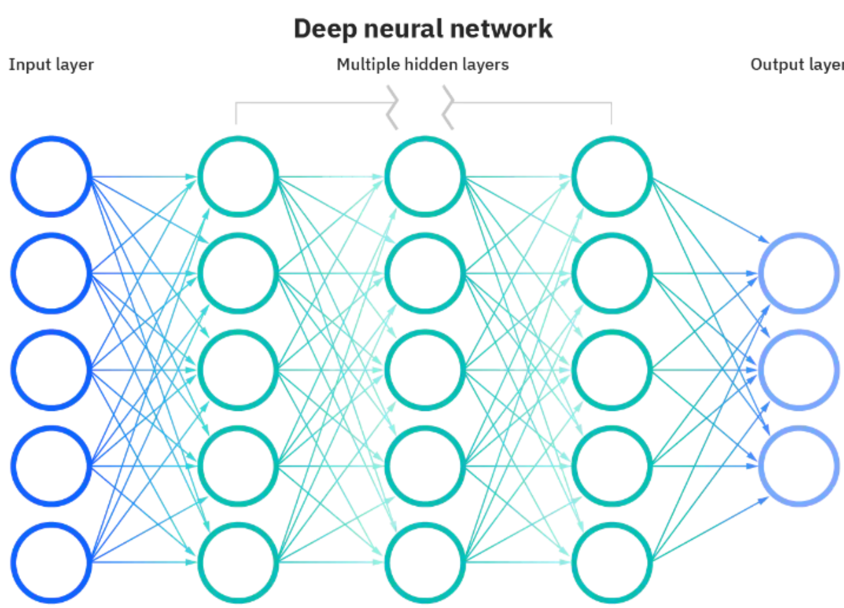
BIkesharing system - a system where people borrow and return bikes are different places</td>
</tr>
<tr>
<td>Cited references to follow up on</td>
<td>How Can Psychological Theory Help Cities Increase Walking and Bicycling? - https://www.tandfonline.com/doi/abs/10.1080/01944363.2014.934651?journalCode=rjpa20</td>
</tr>
<tr>
<td>Follow up Questions</td>
<td>
1. How can we mitigate safety concerns that bicyclists or non-bicyclists have about biking?
2. Can bike lanes extend the maximum distance people are willing to travel via bicycling?
3. How can public transportation be improved to accommodate more bicyclists?
</td>
</tr>
</table>

	4. Do bike sharing systems include helmets to improve user safety?

[Article #9] What are Neural Networks – 8/23/22

Source Title	What are Neural Networks?
Source citation (APA Format)	What are Neural Networks? | IBM. (n.d.). Retrieved August 22, 2022, from https://www.ibm.com/cloud/learn/neural-networks
Original URL	https://www.ibm.com/cloud/learn/neural-networks
Source type	General Web Article
Keywords	Neural Networks, Deep Learning, AI, Machine Learning

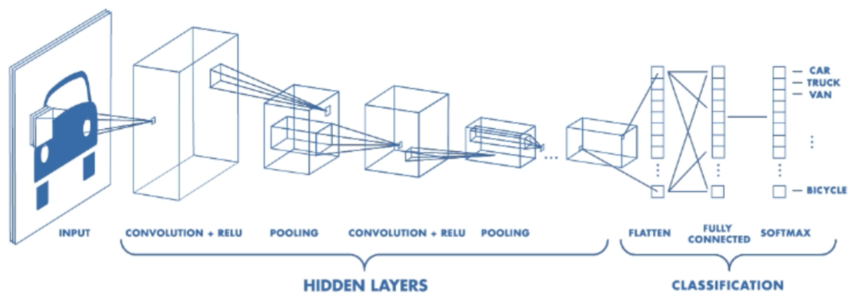
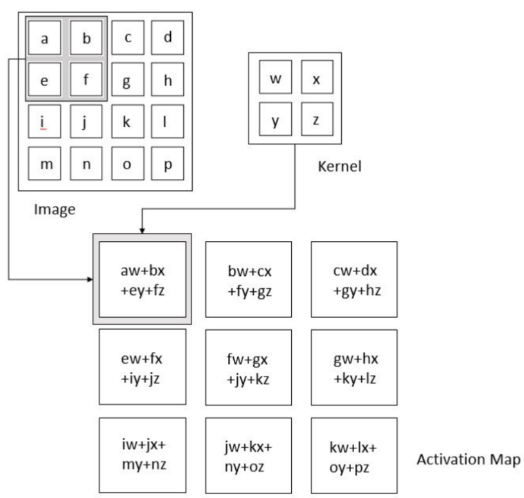
Summary of key points + notes (include methodology)	Neural networks use training data to learn a task and improve accuracy over time. For example, they can perform tasks like image recognition, speech recognition, and other AI tasks. Some parts of a neural network include nodes and layers, and some processes include forward propagation, back propagation, and gradient descent.
	
	Notes:
	- A type of machine learning
	- Structure is similar to a human brain
	- If the output of any node is over a threshold, it is activated and sends information to the next layer
	- Uses training data to learn and improve accuracy
	- Can classify data once trained
	- Speech recognition and image recognition can be done with NN’s
	- Each node has a weight and a bias, WX + B
	- Then passed through activation function
	- Then becomes input to the next layer node
	- Notation
	    - i - index of sample
	    - Y-hat - predicted output
	    - Y - actual value
	    - M - number of samples
	- Error from prediction to actual outcome is calculated with a cost function
	- Train model with backpropagation and calculate error and adjust parameters accordingly
	- Convolutional neural networks are used for image recognition
	- Recurrent neural networks use temporal data for future outcomes

Research Question/Problem/ Need	What are Neural Networks?
Important Figures	 This graph is an example of gradient descent and how the process can converge at its minimum.  This figure describes a deep neural network with many hidden layers, an input layer, an output layer, and many interconnected neurons.
VOCAB: (w/definition)	ANN - Artificial Neural Networks have nodes, layers, with input layers, hidden layers, and output layers

	Activation Function - if output meets a threshold, it fires the node Cost Function - 1 / 2m * sum_1^m(y_hat - y)^2 , is the cost between prediction and actual value Gradient Descent - process where function optimizes its task Back Propagation - process that updates function with error and adjustments from output to input
Cited references to follow up on	Backpropogation applied to handwritten zip codes - http://yann.lecun.com/exdb/publis/pdf/lecun-89e.pdf
Follow up Questions	1. How are images passed through neural networks? 2. How can neural networks be used to do facial recognition? 3. How can neural networks do object detection? 4. How can neural networks do voice recognition? 5. How can neural networks do translation tasks? 6. What are some common activation functions? 7. How does gradient descent work?

[Article #10] CNNs – 8/25/22

Source Title	Convolutional Neural Networks, Explained
Source citation (APA Format)	Mishra, M. (2020, September 2). *Convolutional Neural Networks, Explained.* Medium. https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939
Original URL	https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939
Source type	General Web Article
Keywords	Convolutional Neural Networks, Neural Networks, image recognition
Summary of key points + notes (include methodology)	Convolutional neural networks (CNN's) are neural networks that are composed of convolutional, pooling, and fully connected layers. These networks are able to input images and perform some function on them, such as classification. In addition, they can perform object detection, semantic segmentation, and image captioning. Notes: ● - Each image is a grid of values for pixel values ● Layers are arranged to detect patterns from simple to advanced as they progress ● When A dot Kernel, Wout = (Win - Spatial Size + 2 * Padding) / 2 + 1 ● Pooling shrinks the size of the matrix to reduce computation size ● Fully connected layer help compute representation of output from input ● Activation functions: ReLU, TanH, Sigmoid perform non-linearity functions and are often put right after convolution layers ● Basic convolutional neural network: a. Input b. Convolution c. Pooling d. Convolution e. Pooling f. FC Layer g. Output

	● CNN architectures are available for object detection ● CNN's can write subscripts/captioning for videos
Research Question/Problem/ Need	How do Convolutional Neural Networks work and what can they do?
Important Figures	 This diagram shows the process an image goes through when passed through a CNN. The image goes through convolutional and pooling layers, then through FC layers and finally a classification layer.  This figure shows how convolutions work when a kernel is applied to each section of data and features are extracted.
VOCAB: (w/definition)	Convolution layer - a dot product between the input matrix and a kernel matrix and the kernel window slides through the matrix Stride - sliding size of kernel window Activation map - 2D part of the image that is formed when kernel is applied on part of an image Padding - extra values put around the matrix to prevent size of matrix

	to shrink when kernel is applied Pooling - Applies function to a window of nearby inputs MaxPooling - finds the maximum of each sliding window and outputs it in that part of the matrix Fully Connected Layer - normal layer filled with neurons Sigmoid - $\sigma(\kappa) = 1/(1+e^{-\kappa})$ where values are between 0 and 1 ReLU - $f(x) = \max(x, 0)$ Tanh - activation function similar to sigmoid but between -1 and 1 Semantic Segmentation - breaks apart image to assign each area to an object
Cited references to follow up on	Faster R-CNN: Towards Real-Time Object - Detection with Region Proposal Networks - https://arxiv.org/pdf/1506.01497.pdf Semantic Image Segmentation via Deep Parsing Network - https://arxiv.org/pdf/1509.02634.pdf
Follow up Questions	1. How many convolution layers is optimal? 2. How many pooling layers is optimal? 3. What kind of information are extracted by convolution layers? 4. How can objects be recognized inside specific regions? 5. How many difference objects can be detected in semantic segmentation? 6. How accurate are current object detection models?

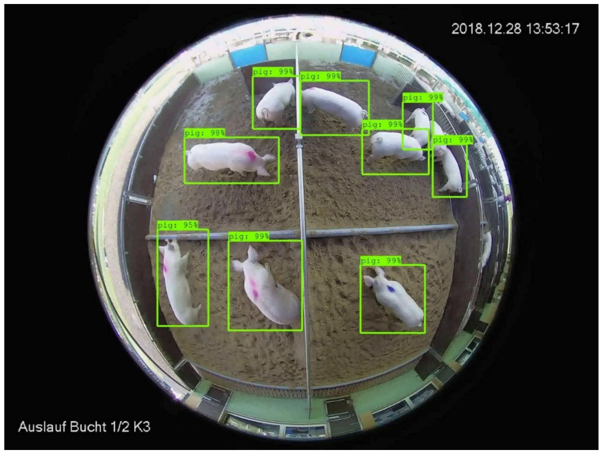
[Article #11] Object Detection Guide – 8/27/22

Source Title	Object Detection in 2022: The Definitive Guide
Source citation (APA Format)	Boesch, G. (2022, May 9). *Object Detection in 2022: The Definitive Guide.* Viso.Ai. https://viso.ai/deep-learning/object-detection/
Original URL	https://viso.ai/deep-learning/object-detection/
Source type	General Web Article
Keywords	Object Detection, Deep Learning, Object Detection Algorithms

Summary of key points + notes (include methodology)	Object detection can solve a variety of tasks such as identifying people, captioning images, tracking objects, autonomous driving, and more. Object detection deep learning models can be categorized into two types: two-stage detectors and one-stage detectors. In addition, these detectors each have their own set of benefits and performances on standardized benchmarks.
	
	Notes:
	- Object detection is a large field in AI and can detect objects in visual images or videos
	- Object detection can detect people from different views, and it can count the number of people in an image
	- Applications include healthcare monitoring, autonomous driving, video surveillance, robot vision, etc
	- Image processing does not use deep learning but uses various manual techniques to perform tasks on images
	- Deep LEarning uses past history of images and training to perform a task well
	- A common benchmark is the MS COCO
	- YOLO
	    - A single-stage detector and is much faster than two-stage detectors
	    - Good for small object classifications but worse for larger objects
	    - ImageAI can train custom YOLO models without much programming
	    - YOLO scores different regions in the image based on whether it thinks an object appears there
	    - Detections are identified as positive areas

	- YOLOv3 has a 57.9% mAP on COCO and uses overlapping areas when training
	- YOLOv4 improves more features such as geoimaging, implement self-adversarial training, and more
	- SSD
	    - A one-stage detector
	    - Has much higher accuracies and better for smaller images
	    - It outputs bounding boxes as different aspect ratios and scales for each object detected
	    - It then scores each object in each box and adjusts the boxes to better fit the detected object
	    - It is easy to train
	- RNN
	    - Two-stage detector
	    - Much slower but has higher accuracies
	    - First selects regions of an image - anchor boxes
	    - Labels the bounding boxes and categories within each one
	    - Then use CNN to extract detections or features
	    - RNN’s are computationally heavy
	    - Fast/Faster-RCNN help improve speed by reducing the number of iterations run through the image
	- SqueezeDet
	    - Object detector built for autonomous driving
	    - Is extremely fast]Uses convolution layers as intermediate and output layers
	    - Can find bounding boxes and identify objects
	- MobileNet
	    - Based on SSD and is for smaller applications
	    - Was implemented using Caffe deep learning framework
	    - Outputs a vector for each object with bounding box coordinates within
	- YOLOR
	    - New object detector
	    - Uses implicit and explicit knowledge and improves accuracy and greatly improves speed
	    - It is currently the fastest object detector

Research Question/Problem/ Need	What is object detection and how does object detection work using neural networks?

Important Figures	 This figure displays the output of object detection models with bounding boxes and classifications of recognized objects in the image or video.
VOCAB: (w/definition)	Person detection - object detection that is designed to detect people in videos or images YOLO - a deep learning object detection algorithm Image Processing - a tool for processing images without historical data for training COCO - a microsoft dataset that is a benchmark for object detection models MAP - (Mean Average Precision) a metric that evaluates object detection models SSD - (single-shot detector) a deep learning algorithm that uses a deep learning network to predict bounding boxes in object detection SqueezeDet - a single-shot detector algorithm that is used for object detection in cars MobileNet - a single-shot detection network for object detection
Cited references to follow up on	https://viso.ai/deep-learning/yolor/ https://viso.ai/deep-learning/object-tracking/
Follow up Questions	1. How is MAP calculated? 2. Could MobileNet be integrated with the YOLOR algorithm? 3. What are some alternatives to the MS COCO benchmark? 4. What is explicit and implicit knowledge in the YOLOR

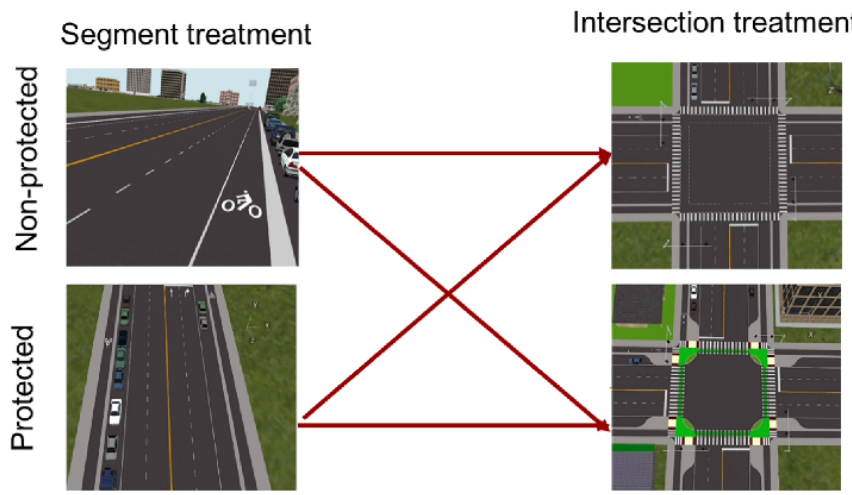
	algorithm? 5. How does YOLO compare to SSD?

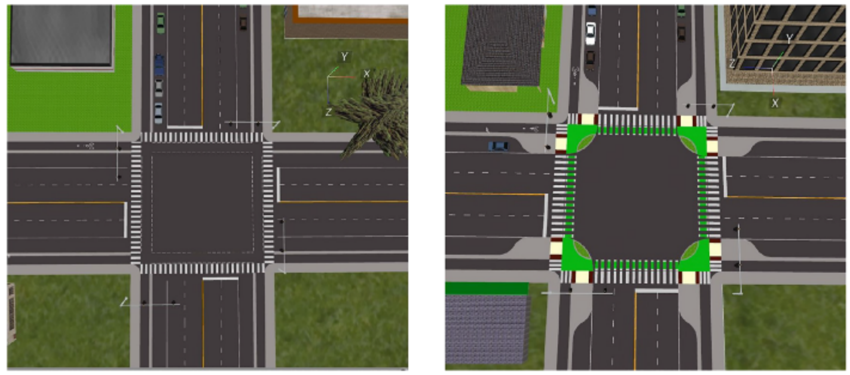
[Article #12] Protected intersections – 9/3/22

Source Title	The role of protected intersections in improving bicycle safety and driver right-turning behavior
Source citation (APA Format)	Deliali, K., Christofa, E., & Knodler Jr, M. (2021). The role of protected intersections in improving bicycle safety and driver right-turning behavior. *Accident Analysis & Prevention, 159*, 106295. https://doi.org/10.1016/j.aap.2021.106295
Original URL	https://linkinghub.elsevier.com/retrieve/pii/S0001457521003262
Source type	Scientific Journal Article
Keywords	Protected bike lane, protected intersection, bicycle safety, right-hook crash, driving simulator, eye-tracking device

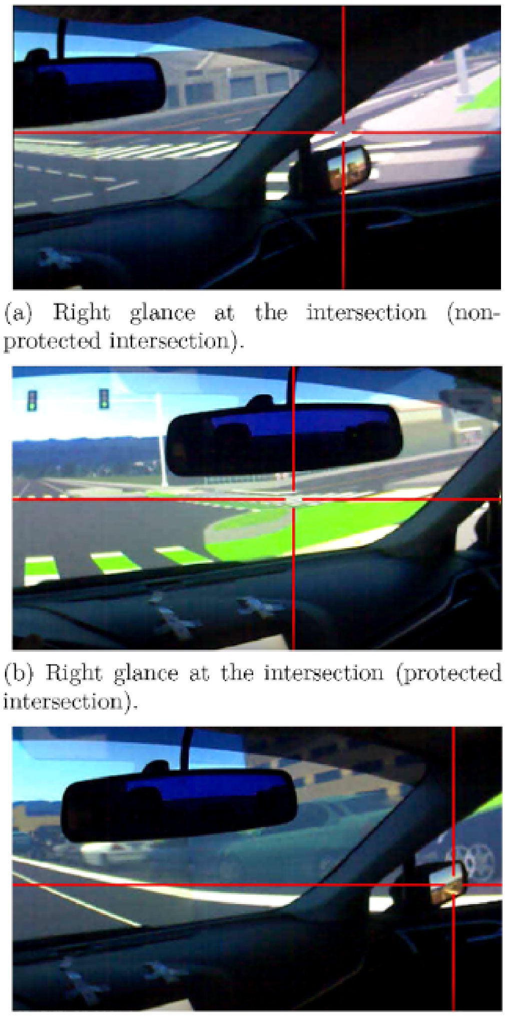
Summary of key points + notes (include methodology)	Protected bike lanes are designed to protect bikers from oncoming traffic. This study analyzed driver behavior from a driving simulator experiment. The results showed that drivers make less frequent glances to protected bike lanes when driving alongside them, but glance more to the right before a right-hand turn.
	
	- ⅓ of crashes between bicyclists and vehicles are at intersections
	- 43% of bicyclist deaths are at intersections
	- Right-hook crashes are very common
	- Drivers may forget, not see, or not process bicyclists when making turns
	- Bicycle infrastructure is designed to give more space to bicyclists and feel safer to bicyclists
	- Added distance between road and protected bike infrastructure may prevent drivers from detecting cyclists
	    - Parking lanes on right side of road can block drivers view to detect bicyclists
	        - This may increase risk of collision?
	- Dutch intersections helps prevent right-hook collisions by adding space between cyclists and cars
	    - Cars make wider angle turns
	    - Have more space to see bicyclists
	    - Will meet the bike lane in the turn in front of them, which prevents collision if brakes are applied

- Gaps in previous research: Have not researched the impact of protected bike lanes at intersections, have not studied driver behavior when driving next to a protected bike lane
- Driving simulator was used to research – similar functionalities with real car
    - Can accelerate, brake, turn, screens, projectors, mirrors, dash, sound environments
- Eye-tracking device used to track glances of participating drivers
- Tested four scenarios:
    - Straight segment with protected bike lane leading to non-protected intersection
    - Straight segment with protected bike lane leading to protected intersection
    - Straight segment with normal bike lane leading to non-protected intersection
    - Straight segment with normal bike lane leading to protected intersection
- Each scenario was tested with and without bikers present
- Normal bike lanes was between a parking lane and traffic lane
- Protected bike lane was between parking lane and sidewalk
- Three variables for glances tracked
    - Right glance at non protected intersection
    - Right glance at protected intersection
    - RIght glance at right-side mirror
- 32 participants recruited
    - Each participant had a 3-4 min practice drive to familiarize with the environment
- Bias was introduced in the dataset because the majority of people did not glance right in the intersection
- Used a synthetic data generation technique to generate data to reach significant statistical power
- All participants glanced at the cyclists when present in normal bike lanes
- Participants glanced at cyclists in protected bike lanes 76% of the time
- Presence of bicyclist was strongest factor in determining if a driver glanced right at an intersection
- Protected intersections had more right glances
- Models for driving speed behavior reported insignificant results
- Presence of bicyclist slightly decreased average speed - Cohen's D value of 0.183

Research Question/Problem/ Need	How is the behavior of drivers and the safety of bicyclists impacted by protected bike lanes at intersections?
Important Figures	 (a) Protected bike lane with a fixed, raised barrier (b) Protected bike lane with parking buffer (c) Raised protected bike lane **Fig. 1.** Different configurations of protected bike lanes (PBL); these bicycle treatments are also known as separated bike lanes or cycle tracks. This diagram compares the three types of protected bike lanes. Each bike lane has a different set of barriers or buffers and designs that all attempt to make cycling safer.  **Fig. 3.** Bicycle infrastructure treatment combinations. This diagram compares a 2D and 3D view of protected and non-protected intersections and bike infrastructure.

	 (a) Non-protected (or conventional) intersection (b) Protected intersection (Source: Deliali et al. (2020)) **Fig. 4.** Simulated conventional and protected intersections. This figure compares protected and non-protected intersections for bicyclists.

Accident Analysis and Prevention 159 (2021) 106295



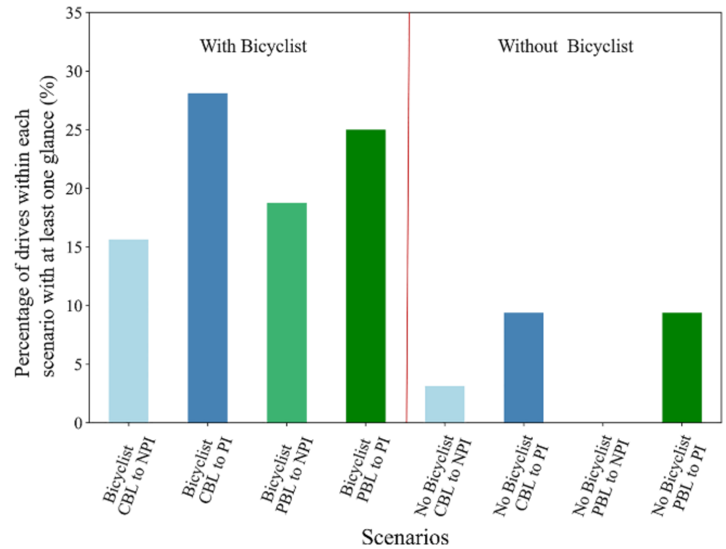
(a) Right glance at the intersection (non-protected intersection).

(b) Right glance at the intersection (protected intersection).

(c) Right glance at the intersection through the right side mirror.

Fig. 8. Areas of interest for right glances.

This diagram identifies the locations of right-hand glances of drivers when they look at their mirrors, intersections, and more.



Percentage of drives within each scenario that participants glanced right at the intersection at least once (Zone 1 or 2).

This chart compares the percentage of test drivers that glanced in each scenario from a conventional or protected bike lane to a conventional or protected intersection.

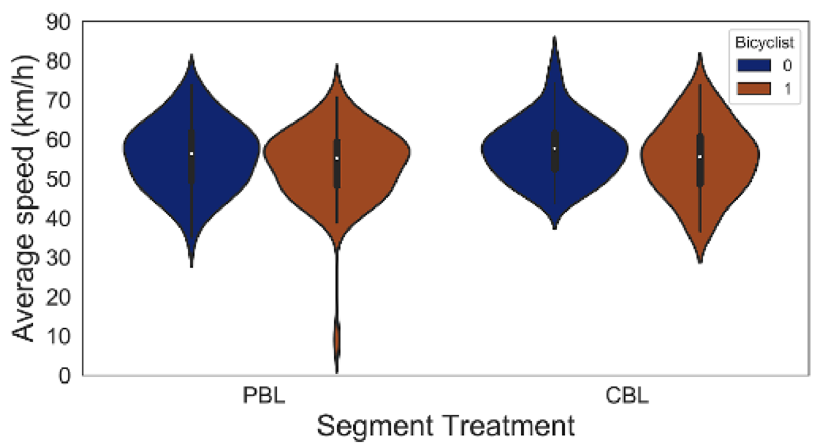
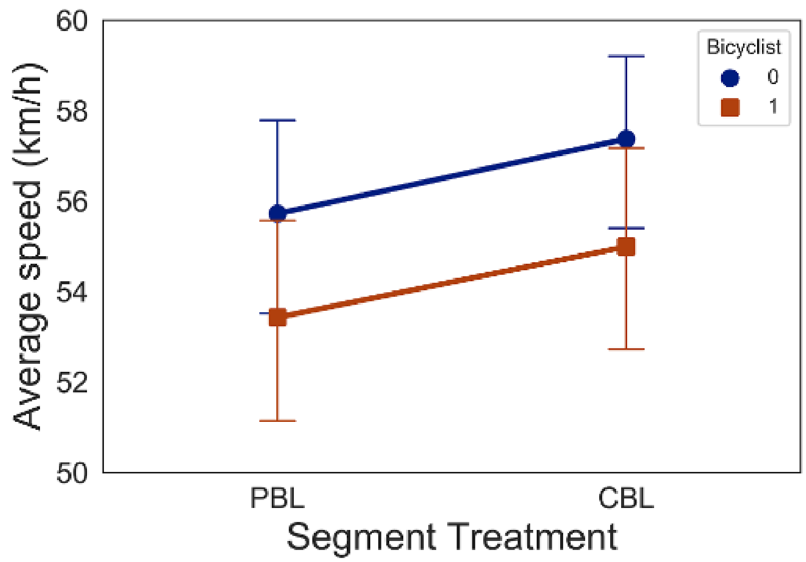


Fig. 10. Speed violin plots for segment AB (Blue: no bicyclist is present; Brown: a bicyclist is present). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

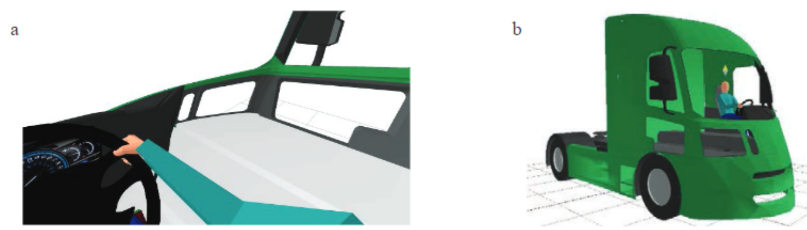
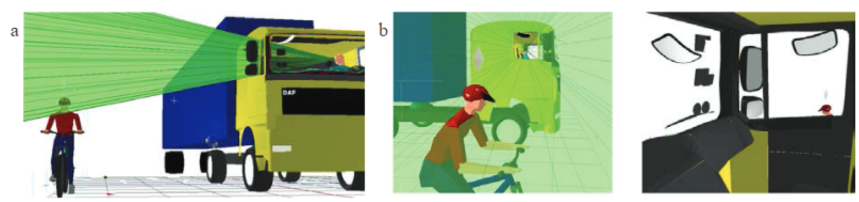
This figure is a violin plot of each segment that measures the average speed of drivers when there are bikes and in what type of infrastructure.

	 **Fig. 11.** Interaction between bicycle infrastructure treatment at the segment and bicyclist presence. These line segments in a chart compare the average speeds in conventional versus protected segments with and without bicyclists in the lanes.
VOCAB: (w/definition)	Right-hook turn - when a car turns right in front of a bicyclist biking forwards Protected bike lane - bike lanes physically separated from pedestrian sidewalks and vehicle traffic Multimodal operation - different ways of transportation from place to place Bicycle treatments - infrastructure designed to support bicycle transportation Dutch intersection - a protected intersection with cyclist and vehicle lanes designed with better visibility by the cyclists and drivers Statistical Power - a measure of study efficacy to determine chance of getting a true result/effect Cohen's D Value - a standard deviation that compares between two groups
Cited references to follow up on	Attentional requirements on cyclists and drivers in urban intersections - https://www.sciencedirect.com/science/article/pii/S1369847819303

	961 Modeling the impact of traffic conditions and bicycle facilities on cyclists' on-road stress levels - https://www.sciencedirect.com/science/article/pii/S1369847817305466 Visual Attention Failures during Turns at Intersections: An On-road Study - https://hfast.mie.utoronto.ca/wp-content/uploads/Kaya_Ayas_Ponnambalam_Donmez_CARSP_2018_April26.pdf
Follow up Questions	1. How would driver behavior and glances change if the traffic signal showed a red light, forcing the driver to stop first? 2. Would a longer or more complicated driving scenario with a GPS screen change glance behavior? 3. Would a larger participant population address the bias for the majority who did not glance to their right in the intersection when bicycles were not present? 4. Do vehicle blind spots affect the visibility of bicyclists when glancing through right-hand mirrors?

[Article #13] Truck Concept – 9/4/22

Source Title	The Development of a Truck Concept to Allow Improved Direct Vision of Vulnerable Road Users by Drivers
Source citation (APA Format)	Summerskill, S., & Marshall, R. (2015). The Development of a Truck Concept to Allow Improved Direct Vision of Vulnerable Road Users by Drivers. *Procedia Manufacturing, 3,* 3717–3724. https://doi.org/10.1016/j.promfg.2015.07.803
Original URL	https://www.sciencedirect.com/science/article/pii/S2351978915008045
Source type	Scientific Conference Article
Keywords	Trucks, Blind Spot, Vulnerable Road Users
Summary of key points + notes (include methodology)	This study examines the impact changing the design of a truck for aerodynamic purposes would have on the blind spots of a truck. By using a digital modeling system, this study developed a concept model of a truck and analyzed the view drivers would have on Vulnerable Road Users. The results showed that vision from the truck cab was slightly improved and it could help drivers identify VRUs better. Notes: - Growth in cycling in London has more concerns about bicyclist safety - Heavy Goods Vehicle are much more associated with cyclist collisions and accidents - European Parliament discussed increasing HGV length and improve safety in the cab design - Previous study funded by UK Transport and Environment group created a design - This study evaluates the design with SAMMIE CAD Digital Human Modeling system - Driver position to determine eye perspective was determined by previous studies and data - Investigated safety in cab design and windows - Investigated direct vision to identify VRUs - Adding extra windows below windscreen was feasible - Cab design was lower to the ground - Deprove off-road capabilities but increase direct vision of VRUs

	- Study analyzed pedestrians in front of the truck, VRUs at the two front corners of the truck, and alongside the right of the truck - Blind spot is measured by the distance away from the vehicle that the objects are hidden - Lower design and added windows near the bottom of the truck greatly improve visibility to all nearby pedestrians and VRUs - Current standards in truck design do not exist and should be the topic of further research
Research Question/Problem/ Need	How does a concept truck cab designed to improve aerodynamics and pedestrian safety impact the visibility of VRUs to truck drivers?
Important Figures	 Fig. 3. (a) View through the driver's eye showing the additional window apertures (b) FKA concept iteration 2.  Fig. 4. (a) The projection from the drivers eyes through the windows. (b) the intersection of the cyclists head and shoulders with the projection. (c) the view through the driver's eyes of the cyclist's head. This figure provides a basic visual of the view from the driver's eye in the new cab concept and an exterior design view. This figure also described the visibility of VRUs in a normal cab from inside and the visibility range outside.

3.1. Forward visibility of pedestrians

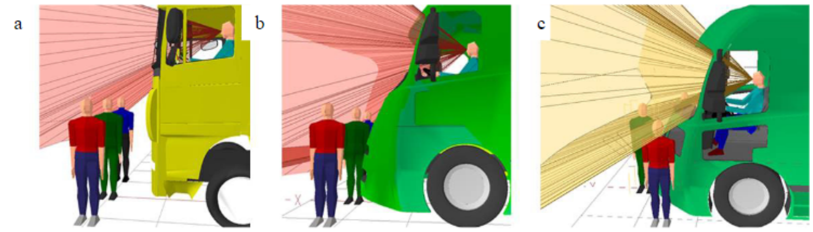


Fig. 5. (a) Pedestrian visibility for the DAF XF baseline vehicle (b) Pedestrian visibility for the FKA concept (c) Pedestrian visibility for the FKA concept iteration 2.

Table 1. The results for the forward visibility of pedestrians.

Visual object	Distance from the vehicle front DAF XF	Distance from the vehicle front FKA concept	Distance from the vehicle front FKA Concept iteration 2
Blue human	690mm	530mm	Visible
Green human	575mm	Visible	Visible
Red human	647mm	486mm	Visible

This figure identifies the minimum distance between pedestrians and the truck cab to be visible and highlights the significant improvements in this new truck cab design.

3.2. Forward visibility of cyclists

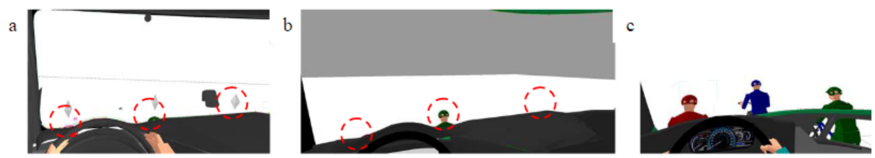


Fig. 6. (a) Driver's eye view of cyclist visibility for the DAF XF baseline vehicle (b) FKA concept (c) FKA concept iteration 2.

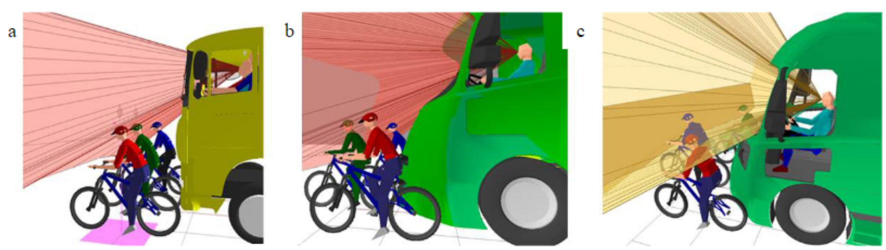


Fig. 7. (a) Cyclist visibility to the front of the DAF XF baseline vehicle (b) FKA concept (c) FKA concept iteration 2.

This figure compares what a normal truck cab view from the inside would look like with VRUs very close to the front. In the redesigned cab, the VRUs are much more visible and clear.

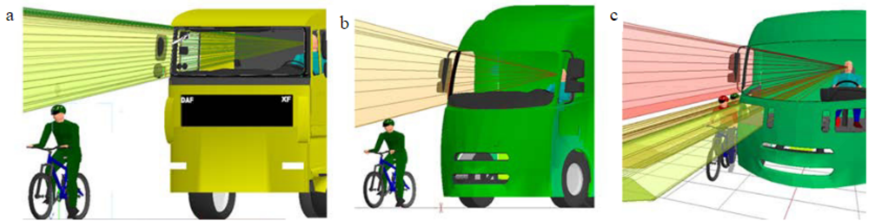


Fig. 8. (a) Cyclist visibility to the passenger side of the DAF XF baseline vehicle (b) FKA concept (c) FKA concept iteration 2

Table 3. The results for the passenger's side visibility of cyclists.

Visual object	Distance from the vehicle side DAF XF	Distance from the vehicle side FKA concept	Distance from the vehicle side FKA Concept iteration 2
Passenger side cyclist	1903mm	1458mm	Visible

This figure shows the differences in the visibility of cyclists on the passenger side of the truck cab. The new truck cab design significantly improves visibility of cyclists and allows them to be visible through the window apertures.

Fig. 9. (a) Cyclist visibility to the driver's side of the DAF XF baseline vehicle (b) FKA concept (c) FKA concept iteration 2.

Table 4. The results for the driver's side visibility of cyclists.

Visual object	Distance from the vehicle side DAF XF	Distance from the vehicle side FKA concept	Distance from the vehicle side FKA Concept iteration 2
Driver's side cyclist front	36mm	Visible	Visible
Driver's side cyclist rear	106mm	Visible	Visible

This figure shows the visibility of cyclists on the driver side of the truck. With the added window apertures, cyclists are much more visible even when extremely close to the cab.

VOCAB: (w/definition)

Heavy Goods Vehicle - a vehicle with a total weight over 12 tons

Direct vision - field of vision from the drivers eye point that can be seen without the aid of indirect vision devices such as mirrors or cameras

Eyellipses - statistical representation of driver eye locations

Indirect vision - field of vision from the driver that can be seen using indirect vision devices such as mirrors or cameras

Cited references to follow up on	Development of a new eyellipse and seating accommodation model for trucks and buses - https://rosap.ntl.bts.gov/view/dot/20426
Follow up Questions	1. Is the possible injury severity of cyclists being run over and crushed decreased with the lower design? 2. Can the extra window apertures pose a risk for glass shard exposure when front collisions occur? 3. How does the lower design affect right-rear and left-rear blindspots when detecting VRUs? 4. Would drivers recognize the presence of VRUs in peripheral vision when in the lower window apertures?

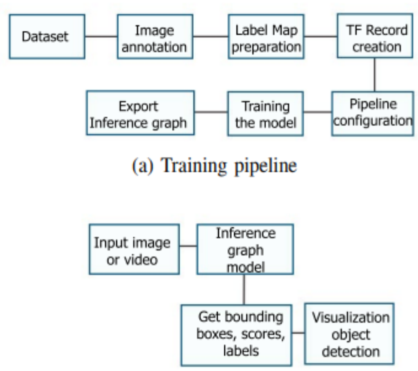
[Article #14] VRU Detection – 9/10/22

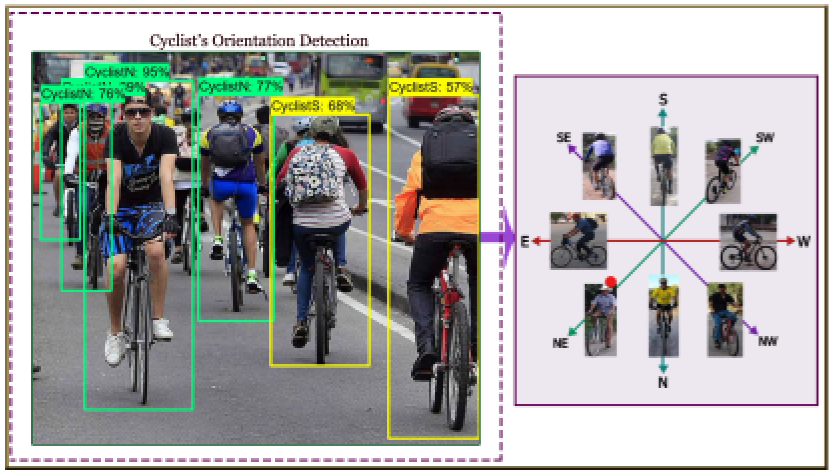
Source Title	On the safety of vulnerable road users by cyclist orientation detection using Deep Learning
Source citation (APA Format)	Garcia-Venegas, M., Mercado-Ravell, D. A., & Carballo-Monsivais, C. A. (2021). On the safety of vulnerable road users by cyclist orientation detection using Deep Learning. *Machine Vision and Applications, 32(5)*, 109. https://doi.org/10.1007/s00138-021-01231-4
Original URL	https://arxiv.org/pdf/2004.11909.pdf
Source type	Scientific Journal Article
Keywords	VRUs, Bicyclies, Deep Learning, Object Detection

Summary of key points + notes (include methodology)	This study aims to detect the orientation of cyclists. They used various deep learning, transfer learning, and object detection models to detect bicycles and created a dataset to train the models. The results show that all of the deep learning methods tested showed strong performance.
	
	Notes:
	- Although systems for supporting drivers are becoming better, number of accidents and deaths increase
	- Road/traffic deaths are the tenth cause of death
	- Some issues to detecting cyclists are:
	    - Various orientations
	    - Aspect ratios/appearance
	    - Lack of labeled datasets with poor background
	- Older methods used HOG feature extraction and SVM classification
	- Newer methods with deep learning, CNNs, RCNNs, etc may be more effective
	- CNN's may be able to learn higher level features
	- Region based networks are more accurate, classification based algorithms are much faster
	- It is important to determine the movement of the cyclists, not only detect them
	- Cyclists always move in a forward direction – measuring their orientation is important
	- This study created a new dataset "Detect-Bike"
	    - 11,000 images, 20299 bikes

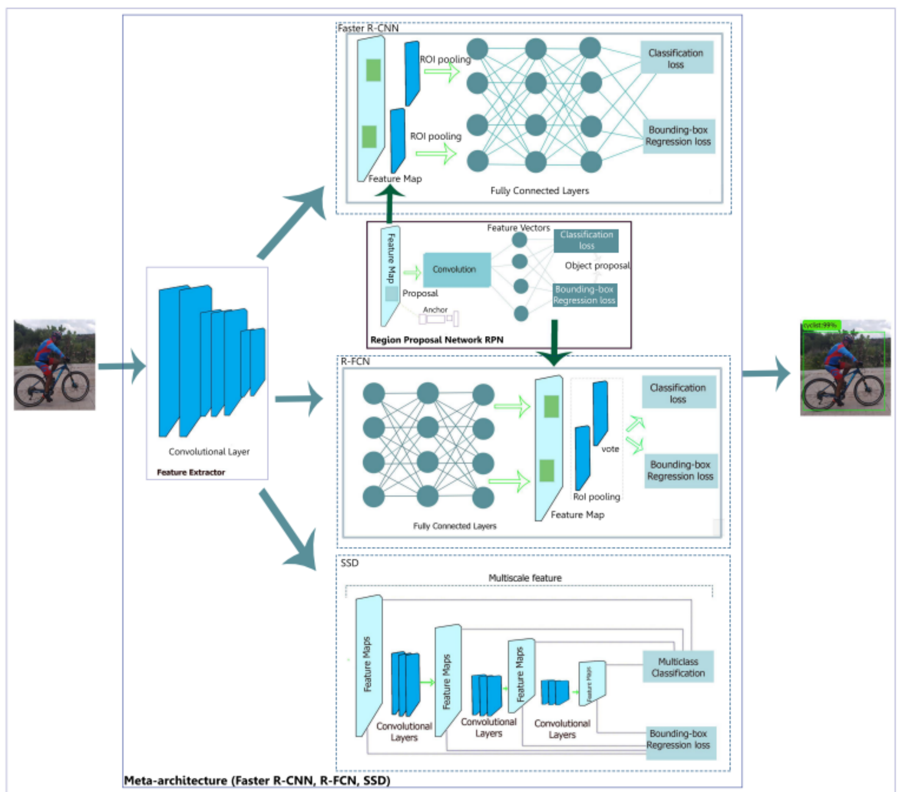
	- Uses an SSD. RCNN, Faster RCNN, RFCN, MobileNet, InceptionV2, ResNet, InceptionResNet feature extractors
	- Uses transfer learning and tensorflow object detection
	- Experimental Results
	    - Best for cyclist detection
	        - Faster-RCNN + Inception V2 = High Accuracy
	        - SSD + Inception V2 = Faster
	    - Cyclist Orientation
	        - Faster RCNN + ResNet50 = High Accuracy
	        - Faster-RCNN + Inception V2 = Balanced
	        - SSD + Inception V2 = Faster
	- Goal: Prevent possible collisions by analyzing orientation with object detection
	- Former methods used many decision trees and image processing techniques which became computationally heavy
	- KITTI Dataset is a good benchmark for cyclist detection
	    - Does not have enough cyclist data
	- New Dataset accounts for more cyclists and annotations
	    - Two datasets, one for bounding box, one for bounding box + orientation
	- Study finds trade off between accuracy and speed
	- Method of building models:
	    - Dataset
	    - Image ANnotation
	    - Label Map Preparation
	    - TF Record Creation
	    - Pipeline Config
	    - Train Model
	    - Export Inference Graph
	- Testing models:
	    - Input image/video
	    - Inference graph
	    - Get bounding boxes, labels, etc
	    - Visualization
	- Detect-Bikev1 has 12,000 bicyclists for single class detection
	- Detect-Bikev2 has 20,000 cyclists for multi-class detection
	- RCNN based networks use Region Proposal Networks to identify ROIs and then make predictions
	- SSD based networks skip the RPN step and use one deep learning neural network
	    - Reduces time significantly but also reduces accuracy
	    - Useful for real-time application

- How Images are processed
  - 1. Convolutional Layer / Feature Extractor
    - MobileNet, Inception, ResNet, InceptionResNet
    - Available in TF Object Detection API
  - 2. Passed into a meta-architecture
    - Faster R-CNN, RFCN, SSD
  - 3. Output
- Average Precision, FPS is recorded to determine tradeoff
- Use COCO detection metrics + Open Image V2 detection metrics
- 80% training, 20% testing
- Used pycocotools package to help
- Most detectors had acceptable performance
- SSD + MobileNetV2 could not detect farther away cyclists
- Recall *r* used as a metric, which measures true positives, false negatives – r = TP / (TP + FP)
- Precision/recall curve - AP = 1/11 sum_0, 0.1, … 1 (Pinterp(R))
  - Pinterp is an interpolation function that takes max precision at each recall
- Used IoU as a metric as well
- AP can be averaged over IoU between 0,5 and 0.95
- Classification loss is defined as log loss of the probability distribution of the class
- Localization loss is error of bounding box predictor
- All models are trained with Detect-Bikev1 and v2
- All models evaluated with AP large, medium, small
  - Performance based on size of cyclists
  - RCNN and RFCN were better for medium/small bikes than SSD
  - Faster RCNN + InceptionResNetV2 was most accurate with greatest APm and APs
    - 30 times slower than SSD + MobileNetV2
  - Faster R CNN + ResNet101 better for APL
  - AP threshold was set to 0.5 for IoU
- Faster-RCNN + InceptionV2 had good time response and strong feature extractors
- SSD much faster time response – has problems identifying smaller cyclists however, good results on large-size cyclists
  - Good for real-time where faraway cyclists can be neglected
  - SSD + InceptionV2 is very good
- Having fast detections is important for tracking objects in real time

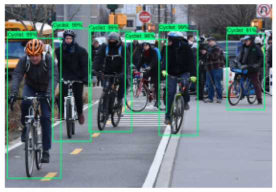
	- DetectBikev2 dataset is not perfectly balanced – most examples are of larger cyclists - Larger examples are more important for collision prevention though - Deeper networks need more training to work better - All models with Faster RCNN worked well for cyclist orientation detection - SSD meta-architecture works well for larger instances but cannot differentiate direction within +- 45 deg that well - SSD + InceptionV2 is good for fast orientation detection and has good trade-off between speed and accuracy - Future research would be to implement and test techniques on vehicles for detecting cyclist movement - Future research could determine cyclist hand signals
Research Question/Problem/ Need	What deep learning methods are feasible and perform well in detecting VRUs and their orientation?
Important Figures	 (a) Training pipeline (b) Inference pipeline This flow chart describes the process to train and run the model. The data first becomes annotated and labeled, then is passed to train in Tensorflow. This model was then tested with various images and videos and predicted bounding boxes. This was then visualized with image processing.



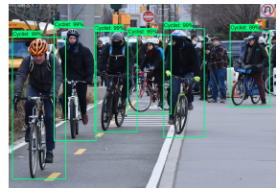
This figure shows how cyclists are classified with bounding boxes and 8 different orientation positions.



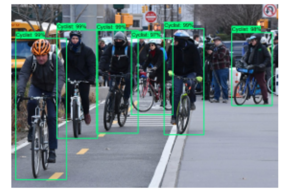
This figure describes the object detection model with a feature extractor and a meta-architecture that the convolutional output goes through.



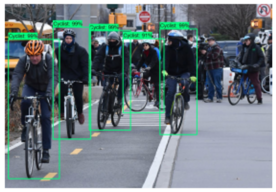
(a) FasterRCNN-ResNet101



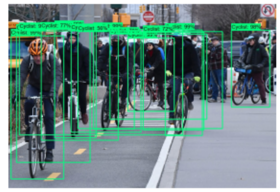
(b) FasterRCNN-InceptionV2



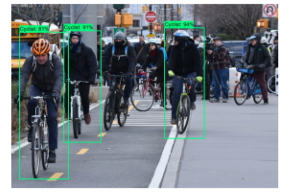
(c) FasterRCNN-ResNet50



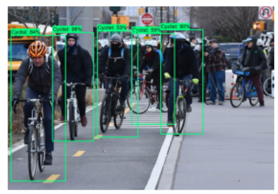
(d) FasterRCNN-InceptionResNetV2



(e) RFCN-ResNet101

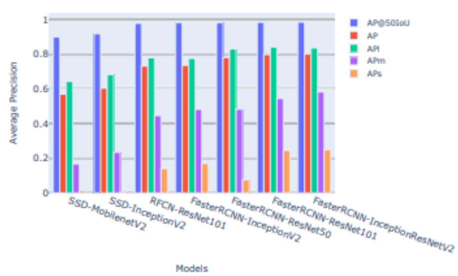


(f) SSD-MobilenetV2



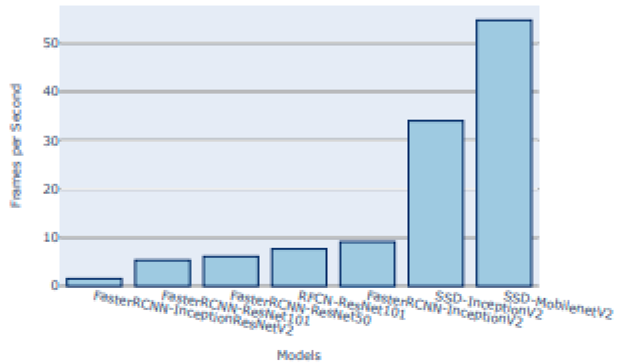
(g) SSD-InceptionV2

This figure shows a visual difference between the efficacy of various architectures and how many cyclists are detected with bounding boxes labeled.



(a) Average Precision by size.

This chart shows the various AP (average precision) metric ratings of each meta-architecture based on IoU, small cyclists, medium cyclists, and large cyclists.

	 This chart compares the FPS (frames per second) of the various meta-architectures. This measures the speed with FPS.
VOCAB: (w/definition)	Transfer Learning - using a machine learning model from one problem and applies the model to another problem Intelligent Transportation Systems (ITS) - new methods for traffic management and safety Advanced Driver Assistance Systems (ADAS) - systems that protect and support drivers HOG-SVM - Histogram of Gradients Oriented feature extractor + Support Vector Machine classification which performs very well for pedestrian detection (not deep learning TsinghuaDaimler Cyclist Benchmark Dataset (TDCB) - a dataset used as a benchmark for cyclist detection Monocular Images - images taken using a small monocular/telescopic device Region of Interest (ROI) - the region that is identified/proposed with a region proposal network that has a high object score Intersection Over Union (IOU) - metric to detect overlap between predicted bounding box with Bp as predicted box and Bgt as ground box = area(intersect(Bp, Bgt))/area(union(Bp, Bgt))
Cited references to follow up on	Thermal-Based Pedestrian Detection Using Faster R-CNN and Region Decomposition Branch - https://ieeexplore.ieee.org/document/8986298 Speed/accuracy trade-offs for modern convolutional object detectors - https://arxiv.org/abs/1611.10012v3

	Cyclist detection in LIDAR scans using faster R-CNN and synthetic depth images - https://ieeexplore.ieee.org/document/8317599
Follow up Questions	1. How can semantic segmentation be implemented and what is the efficiency compared to bounding box predictions? 2. How can 3D bounding box annotations be generated for 2D images? 3. How are TF records trained in the model? How are the object detection models implemented? 4. Where can the dataset DetectBike v1/v2 be found? 5. Were preloaded weights from pre-training on the COCO dataset, OpenImages, or ImageNet?

[Article #15] OAS – 9/12/22

Source Title	Oral allergy syndrome (OAS)
Source citation (APA Format)	Oral Allergy Syndrome Symptoms, Diagnosis & Treatment | AAAAI. (n.d.). Retrieved September 12, 2022, from https://www.aaaai.org/tools-for-the-public/conditions-library/allergies/oral-allergy-syndrome-(oas)
Original URL	https://www.aaaai.org/tools-for-the-public/conditions-library/allergies/oral-allergy-syndrome-(oas)
Source type	General Web Article
Keywords	Oral Allergy Syndrome, Allergies, Birch Tree Pollen,

Summary of key points + notes (include methodology)	Oral allergy syndrome is an allergy that is caused by various pollen and can trigger allergic reactions when people come in contact with various foods. There are no definitive tests for OAS, but avoiding raw foods can prevent reactions.
	
	Notes:
	- 50-75% of adults allergic to birch tree pollen have OAS
	- Proteins in fruits/vegetables are very similar to this pollen
	    - Confuses immune system and cause allergic reactions
	- Allergic reaction when raw fruits/vegetables come in contact with mouth
	- Symptoms:
	    - Itchiness
	    - Swelling
	    - Anaphylaxis
	    - Trouble breathing
	    - Hives
	- Is a mild allergy
	- Table below shows relationship between pollen allergy and types of food that may cause an allergic reaction
	- There is no specific test for OAS
	    - Blood test/skin tests usually work

Research Question/Problem/ Need	What is oral allergy syndrome?

Important Figures

Oral allergy syndrome – pollens and cross-reacting foods

Season	Spring	Summer	Late Summer-Fall	Fall
Pollen implicated in the oral cross-reactivity reactions with foods	Birch	Timothy and orchard grass	Ragweed	Mugwort
Fruit				
Pitted fruit				
Apple	X			
Apricot	X			
Cherry	X			
Peach	X	X		
Pear	X			
Plum	X			
Melons				
Cantaloupe			X	
Honeydew			X	
Watermelon		X	X	
Other				
Banana			X	
Kiwi	X			
Orange		X		
Tomato		X		
Vegetables				
Bell pepper				X
Broccoli				X
Cabbage				X
Carrot	X			
Cauliflower				X
Celery	X			
Chard				X
Cucumber			X	
Garlic				X
Onion				X
Parsley	X			X
White potato		X	X	
Zucchini			X	
Spices				
Aniseed				X
Caraway				X
Coriander				X
Fennel				X
Black pepper				X
Legumes*				
Peanut	X			
Soybean	X			
Nuts*				
Almond	X			
Hazelnut	X			

*Mouth or throat itching from peanut, soybean, almonds and hazelnuts may also be an initial manifestation of a more serious food allergy with the potential for anaphylaxis. See an allergist / immunologist if such symptoms are noted.

This table shows the various foods that cause allergic reactions when they cross-react with antibodies in people that have allergies to these pollen.

VOCAB: (w/definition)

Oral Allergy Syndrome (OAS) / Pollen Fruit Syndrome (PFS)- a food allergy caused by eating specific types of foods with oral symptoms

Anaphylaxis - a serious reaction caused by allergies that is life-threatening

Cited references to follow up on

Hay Fever / Rhinitis - https://www.aaaai.org/Conditions-Treatments/Allergies/Hay-Fever-Rhinitis

Follow up Questions

1. What proteins are most similar with these pollen?
2. How can a body learn to differentiate between the pollen and proteins?

	3. What are some currently researched tests for OAS? 4. What factors affect whether or not someone with birch tree pollen allergy will develop OAS?

[Article #16] OAS Review (9/13/22)

Source Title	Oral allergy syndrome: a clinical, diagnostic, and therapeutic challenge
Source citation (APA Format)	Webber, C. M., & England, R. W. (2010). Oral allergy syndrome: A clinical, diagnostic, and therapeutic challenge. *Annals of Allergy, Asthma & Immunology, 104(2)*, 101–108. https://doi.org/10.1016/j.anai.2009.11.007
Original URL	https://www.sciencedirect.com/science/article/pii/S1081120609000088
Source type	Scientific Literature Review
Keywords	Oral Allergy Syndrome, Immunology, Allergies, Food Allergy

Summary of key points + notes (include methodology)	This literature review provides a review of the scientific literature about oral allergy syndrome. This review evaluates articles about clinical trials, pathophysiology, diagnostic investigations, and treatments for OAS. This article concludes that OAS is very challenging to study because of the many complications that must be understood for treatment or diagnosis.
	
	Notes:
	- Funded by GlaxoSmithKline - pharmaceutical company
	- OAS occurs with aeroallergens with oral symptoms
	- Symptoms may progress to down to the digestive system in 8.7% of patients
	- Anaphylaxis in 1.7% of patients
	- Cross-reactive proteins cause OAS
	    - PR-10 – is heat-changeable
	    - Profilin – semi heat-changeable
	    - Lipid transfer protein – not very heat changeable
	- Fresh food skin prick test has best results for diagnostic
	- Treatment is avoiding allergic foods and Epi-pen
	- Mixed results in immunotherapy
	
	- OAS identified in research in 1942
	- Very common with hay fever/allergic rhinitis
	- Study in 1982 determined that 70% of people allergic to birch pollen had OAS
	- 20% of people allergic to grass had OAS
	- Estimations: 5% of children, 8% of adults have OAS that have pollen allergies
	- OAS definition is not very clear
	    - Early studies described as a food allergy with oral

	symptoms caused by exposure to specific food allergens
	- Later characterized by IgE food sensitivity
	- Early studies observed some people had oral symptoms only and others had digestive symptoms later (vomit, nausea, etc)
	- More research is needed about symptoms outside oral area and risk factors for OAS
	- Initial studies on antigens and OAS correlated allergens with plant pollens
	- Identified IgE epitopes are similar to pollen antigens
	  - Pollen allergens cause OAS
	- OAS is caused by IgE cross-reactivity between aeroallergens and plant proteins
	- The proteins found in plants are hard to extract
	  - Most common antigens causing OAS are pathogen response proteins
	- IgE antibody v.s. PR protein reacts → OAS
	- Most common PR protein for OAS → PR-10 family
	- Birch tree allergens are part of the PR-10 family
	  - Is an aeroallergen
	  - Reacts to proteins found in apples, cherries, apricots, pears, carrots, celery, potato, hazelnut
	- PR-10 proteins are unstable when heated or digested
	  - Proteins are hard to extract since they are destroyed when digested
	- PR-5 family have cross-reactivity with mountain cedar pollen
	- Prolifins lead to OAS even without birch allergy
	- Involved in many different OAS allergies and some types are heat-stable and are not that easily altered
	- LTP is also an allergen that causes OAS
	  - Can cause OAS and anaphylaxis because they are heat-stable and proteolysis-stable
	  - LTP transfer lipids from liposomes to mitochondria and help defend plants from fungus and bacteria
	  - Are in the PR-14 family
	- Anaphylaxis differences are based on heat-labile proteins
	  - LTP are more likely to cause anaphylaxis than PR-10 or Profilins
	- Diagnostic of OAS is hard because there are many different antigens and each has a different laibility
	- DBPCFC did not seem to reflect true/full results of OAS – but this is an area of controversy
	- OAS has unique symptoms and various studies have conflicting results with testing with DBPCFC
	- Some studies compare sensitivity and specificity of diagnostics with history of client
	- Reliability of skin prick tests are questioned
	- OAS antigens/PR-10 proteins are not maintained well when

processed so skin testing is not effective
- FFSPT is better/more sensitive than commercial skin prick testing
- FFSPT can also detect LTP antigen and PR-10 antigen reactions
- Testing for specific IgE proteins can diagnose OAS
- Treatment of OAS includes avoiding the foods, education, and epinephrine injections
- Diagnoses have errors and better recommendations should be researched
- Immunotherapy has been researched and results are mixed
- Many studies show increase in tolerance after more exposure
- However, tolerance did not stay for many months
- SLIT may improve some various symptoms and reduce sensitivity

Research Question/Problem/Need

How does OAS work and how can it be treated with a variety of past and current research?

Important Figures

Table 1. Common OAS Triggers and Related Allergens and Source

Food	Allergen and source							
	Trees			Grass nonspecific	Weeds			No pollen
	Birch	Cedar	Ficus		Mugwort	Ragweed	Goosefoot	
Aniseed					Unknown[17a]			
Apple	PR-10[12]	PR-5[13b]						LTP[13]
Apricot	PR-10[12]							LTP[12]
Asparagus								LTP[25]
Banana						Profilin[17]	Profilin[17]	
Bell pepper		PR-5[13b]						
Broccoli					Unknown[17a]			
Cantaloupe					Unknown[17a]	Unknown[17a]		
Caraway seed					Unknown[17a]			
Carrot	PR-10[12]			Profilin[12]	Profilin[17]			
Cauliflower					Unknown[17a]			
Celery	PR-10[12]			Profilin[12]	Profilin[12]			
Chamomile					Unknown[17a]			
Cherry	PR-10[12]	PR-5[13b]						LTP[12]
Chicory	PR-10[25]							
Coriander					Unknown[17a]			
Fennel					Unknown[17a]			
Fig	Unknown[24a]		Unknown[25a]	Unknown[25a]				
Garlic							Profilin[17]	
Hazelnut	PR-10[13]							LTP[25]
Honeydew						Unknown[17a]		
Jackfruit	PR-10[25]							
Kiwi fruit		PR-5[13]						
Leek					Unknown[17a]			
Lettuce								LTP[25]
Lychee								Profilin[19]
Maize								LTP[13b]
Mango					Unknown[17a]			
Melon						Profilin[17]	Profilin[17]	
Mustard					Profilin[17]			
Onion					Unknown[17a]			
Paprika		PR-5[13b]			Unknown[17a]			
Parsley	PR-10[12]				Unknown[17a]			
Peach	PR-10[13]				Profilin[17]		Profilin[17]	LTP[12]
Peanut	PR-10[25]							
Pear	PR-10[12]							
Potato	PR-10[12]							
Plum	PR-10[12]							
Soybean								LTP[12]
Tomato		PR-5[13]						
Watermelon						Unknown[17a]		
Zucchini						Profilin[17]		

Abbreviations: LTP, lipid transfer protein; OAS, oral allergy syndrome; PR, pathogen response.
[a] Although a clinical relationship has been described, the exact protein class is not established.
[b] In vitro sequence homology between pollen and fruit; no reported in vivo reactions.

This table shows the knowledge gaps and known proteins that cross-react and cause OAS.

VOCAB: (w/definition)

Pathophysiology - study of disordered physical processes associated

	with some disease Aeroallergen - allergens that are dispersed through the air Oral-pharyngeal symptoms - symptoms in the mouth and pharynx areas Cross-reactive protein - a protein in one substance that is similar to pollen in another substance Heat-labile - susceptible to alteration or destruction under heat Sublingual Immunotherapy (SLIT) - treating allergies by giving the person small amounts of the substance that they are allergic to Skin-prick testing (SPT) - using skin pricks to identify allergens Allergic rhinitis - hay fever, a disorder caused by allergens such as dust, pollen, hair, etc Angioedema - condition of swelling under the skin due to allergic reaction IgE - antibodies associated with allergies Atopic eczema - inflammation of skin that causes itches or rashes Atopic allergy - people with an increased level of IgE antibodies Pollinosis - hay fever/allergic rhinitis Immunoelectrophoresis technique - tests that measure immunoglobulins in the blood Antigen - something that causes an immunological response in the body Immunoglobulins - glycoprotein molecules/antigens found in plasma of blood Immunoblot inhibition assays - using blots to test if antigens can recognize target proteins Epitope - part of an antigen that is recognized by the immune system Pathogen response (PR) proteins - proteins produced in plants in case of pathogen attack Betula verrucosa (Bet v) - birch tree allergy in the PR-10 family of PR

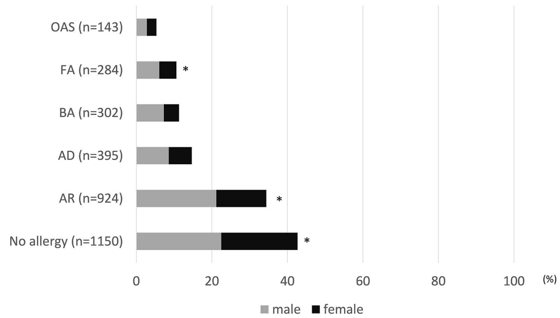
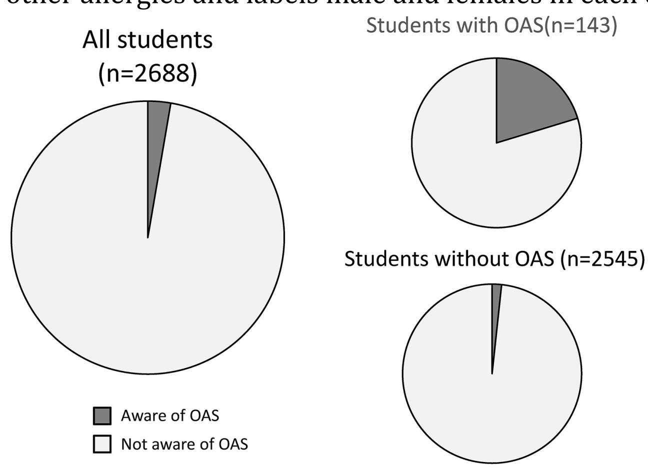
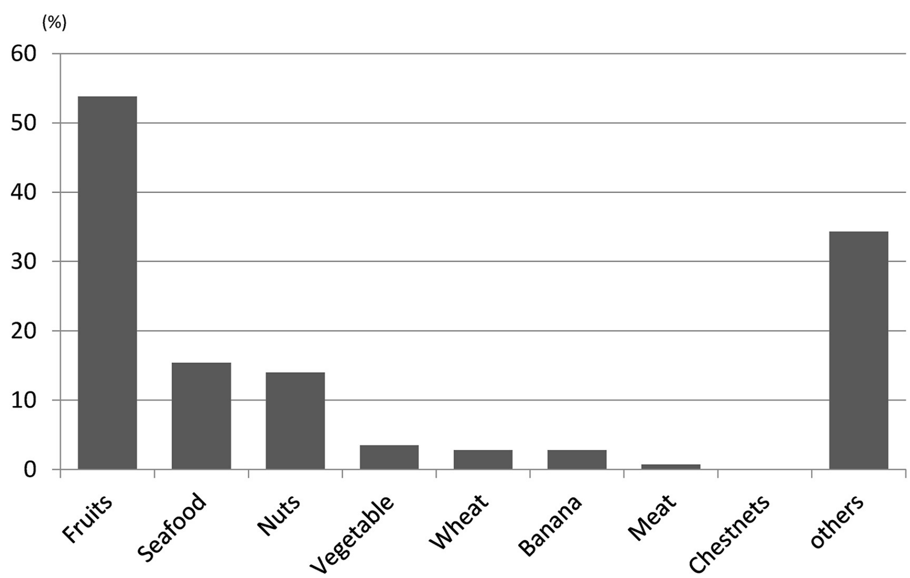
	proteins Prolifins - monomeric actin-binding proteins and help with membrane-cytoskeleton function Systemic symptom - symptoms that affect larger parts of the body Lipid transfer protein (LTP) - protein family that are found in plants and can cause transfer protein syndrome allergy Proteolysis - break down of proteins into amino acids/smaller chains Liable - easy to alter/change Double-blinded, placebo-controlled food challenge (DBPCFC) - a standard for diagnosing food allergies and OAS Fresh fruit skin prick test (FFSPT) - skin prick tests using components of fresh fruits or vegetables Radioallergosorbent Test (RAST) - lab test that determines IgE levels if there is an allergic reaction Immunocap Test - an allergy test that measures specific IgE antibodies over many allergy components Basophil Activation Test - IgE activated white blood cells (basophils) produce lipids which can be tested for
Cited references to follow up on	Successful sublingual immunotherapy with birch pollen has limited effects on concomitant food allergy to apple and the immune response to the Bet v 1 homolog Mal d 1 - https://www.sciencedirect.com/science/article/pii/S0091674906023554 Comparison of results of skin prick tests (with fresh foods and commercial food extracts) and RAST in 100 patients with oral allergy syndrome - https://www.sciencedirect.com/science/article/abs/pii/0091674989900833
Follow up Questions	1. In studies regarding SLIT and its effect on patients, did a more tolerant allergy result in higher or lower IgE antibody levels? 2. Can scent from an OAS-triggering allergen trigger an allergic reaction? 3. Is fainting or light-headedness and OAS-symptom when

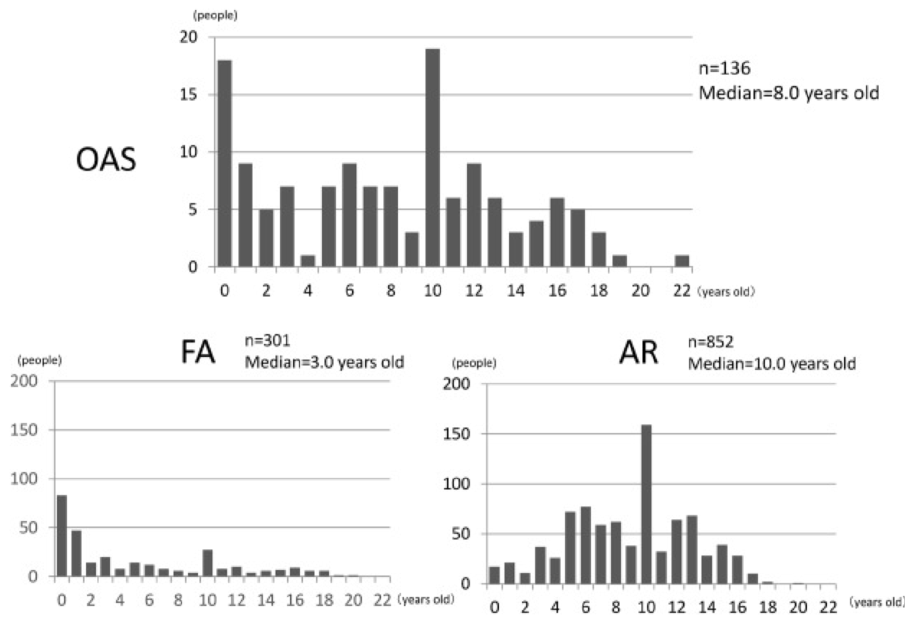
	triggered by scent? 4. What enzymes can break down members of the PR-10 families

[Article #17] OAS Survey – 9/16/22

Source Title	Factors associated with the development of oral allergy syndrome: A retrospective questionnaire survey of Japanese university students
Source citation (APA Format)	Matsumoto, M., Takenaka, M., Aoyagi, K., Tomita, Y., Arima, K., Yamauchi-Takihara, K., & Murota, H. (2021). Factors associated with the development of oral allergy syndrome: A retrospective questionnaire survey of Japanese university students. *Allergology International, 70(4)*, 458–462. https://doi.org/10.1016/j.alit.2021.02.003
Original URL	https://www.sciencedirect.com/science/article/pii/S1323893021000150
Source type	Scientific Journal Article
Keywords	Awareness of OAS, Oral Allergy Syndrome, Risk Factors, Cross-sectional study
Summary of key points + notes (include methodology)	This study investigates the prevalence in OAS in a group of Japanese university students. The study consists of a questionnaire survey to 2688 first-year students which described the awareness of OAS and other allergic diseases. The results showed that few students were aware of the term OAS and there were correlations of OAS with other allergic diseases. Notes: - OAS is IgE0mediated food allergy - Leads to oral-pharyngeal mucosal symptoms immediately after consumption - Most allergens for OAS are easily broken down by digestive system - Symptoms are localized - People can avoid OAS by avoidance or cooking the food - A survey including healthy and allergic people has not been conducted before - Investigates onset age and risk factor - Study involved first-year Japanese students at Osaka University - Questionnaire/survey with a marksheet sent and collected later - 3339/3343 of the responses were analyzed, the rest had insufficient data or outside of age group - Ages 30+ were excluded to keep age more a control variable/reduce impact of age lifestyle - Survey asked about age, gender, illnesses, onset age of allergic diseases (allergic rhinitis, OAS, bronchial asthma, atopic

<table>
<tr><td></td><td>
dermatitis), awareness of OAS, family history of OAS, hand eczema
- Statistical Package for Social Sciences was used to study survey responses
- Differences in gender were accounted for using chi-square test
- OAS + other allergic disease relationship used logistic regression and calculated coefficients
- The mean age of students was 18.4 y.o.
- 10% of people had food allergies
- 34% had allergic rhinitis
- 14/6% had atopic dermatitis
- 11.2% had bronchial asthma
- 5.3% of people had characteristics of OAS
- 2.7% of all people were aware of OAS
- 20% of people with symptoms of OAS were aware of OAS
    - OAS is a relatively new term and awareness is low in general population
- Fruits were most major cause of OAS (50%)
- There were significant correlations between OAS, AD, AR, and BA
- Onset age of OAS was mostly between 0-10 y.o. or later with the development of another FA or AR
- Gender did not affect onset age of OAS
- Onset age of OAS caused by fruits was much older than other food causes
- Females were more likely to be affected by OAS than males – but results differ across studies – not significant however
- 65% of people with OAS also had AR
- 10% of people with AR had OAS
- Seafood allergy OAS is likely in people with AD or hand eczema – number of people were too low to study statistics of hand eczema
- Previous study showed OAS most commonly developed between 10-30 y.o.
- Another study showed that AR developed most commonly under 10 y.o.
    - Two previous studies suggest OAS develops after AR?
    - This study shows that AR and OAS develop at the same time
- The onset of puberty and development of AR may be correlated – both are peak at 10 y.o.
- Bias in survey because it only included Osaka students
- Answers from students may not be accurate since they are based on previous memory
</td></tr>
<tr><td>Research Question/Problem/</td><td>What is the prevalence of OAS in the general population of healthy people and what are the onset ages and risk factors for OAS?</td></tr>
</table>

Need	
Important Figures	 This figure describes the population of the sample size with OAS or other allergies and labels male and females in each category.  This figure shows the awareness of the OAS in the sample population with and without OAS.  This figure shows the foods that cause OAS and the percentage of OAS caused by this type of food.

	 This figure shows the number of people with each type of allergy and the age of onset of these allergies.
VOCAB: (w/definition)	Oral mucosa - a mucous membrane that lines the inside of the mouth Bronchial asthma - a lung disorder where airways are narrowed, constricted, or inflamed Atopic dermatitis - condition that causes inflamed/itchy skin from contact with an allergen Hand Eczema - a type of eczema/skin allergy that only affects the hand
Cited references to follow up on	Risk factors for oral allergy syndrome in patients with seasonal allergic rhinitis - www.medicinaoral.com/pubmed/medoralv16_i3_p312.pdf Oral Allergy Syndrome - https://www.sciencedirect.com/science/article/pii/S1323893015307322
Follow up Questions	1. Can the correlation between the type of pollen causing the OAS and the food causing the OAS be studied? 2. How has the number of AR patients changed over the past 20 years? 3. What causes the spike in the onset of OAS in males since birth? 4. Does the onset age of OAS differ with allergies that are not related to fruits such as seafood?

[Patent #1] Mirror Apparatus – 9/18/22

Source Title	Apparatus and Methods for Eliminating or Reducing Blind Spots in Vehicle Mirror and Camera Systems
Source citation (APA Format)	Clegg, T. (2012). *Apparatus and Methods for Eliminating or Reducing Blind Spots in Vehicle Mirror and Camera Systems* (Patent No. US2012022749 (A1)). https://worldwide.espacenet.com/publicationDetails/biblio?FT=D&date=20120126&DB=EPODOC&locale=&CC=US&NR=2012022749A1&KC=A1&ND=1
Original URL	https://worldwide.espacenet.com/publicationDetails/biblio?CC=US&NR=2012022749A1&KC=A1&FT=D&ND=1&date=20120126&DB=EPODOC&locale=
Source type	Patent Application (Abandoned)
Keywords	Mirror systems, blilnd spots, camera systems, vehicles, mirror adjustments

Summary of key points + notes (include methodology)	This patent describes methods to eliminate or reduce blind spots on all vehicles. The methods included an adjustment of the mirror or camera on the vehicle with an ability to return to the original position.
	
	Notes:
	- TLDR: Pre-set mirror positions activated by switches or turn signals similar to pre-set chair positions
	- Mirror systems are used by drivers to see areas around vehicle without turning head/body
	- Three mirrors is the normal for drivers
	- One mirror is outside driver window, one outside passenger window, one in the center of the windshield
	- Most cars have ability to adjust angles of mirrors from within
	- Modern cars have back-up cameras
	    - Camera is usually on license plate
	    - Camera view is shown on display
	- Blind-spots are a difficulty when on-ramp to an expressway
	    - Find break in traffic while using non-helpful side mirror
	    - Mirror has blind-spot at the point of the merger
	    - If driver cannot see, they might physically look back and lose attention in the front → rear-end crash
	    - Need to improve mirror design
	- Goal: reduce rear-end on-ramp collisions by 65-70%
	- Apparatus adjusts at least one of the mirrors or cameras when driving

<table>
<tr>
<td></td>
<td>

One signal activation source connected to a motor
First activation moves mirror or camera to improve blind spot view
Optional return to original position
Eliminates blind spot for a short period of time

Lane change would make an activation signal to move mirror(s) to a preselected position

Turn signal would activate
Turning off turn signal would make mirror return

Switches could be available to driver to initiate changes
Canceling signal or turning off switch would move mirror back to original position
Activation signal should cause adjustment to mirror/camera to new position with a pause
Lane-change movement would be quick
Apparatus can have many preset positions which can be enabled on command

Parking
Viewing curb

Change in mirror positions would be between 5 to 20 relative to driver

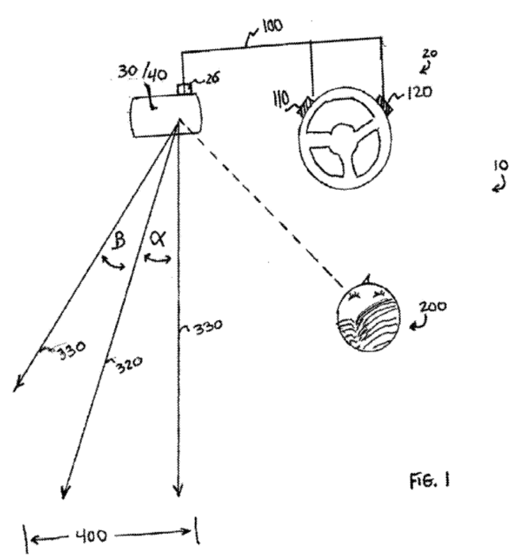
</td>
</tr>
<tr>
<td>Research Question/Problem/ Need</td>
<td>How can vehicle mirrors or cameras be adjusted to eliminate or reduce blind spots?</td>
</tr>
<tr>
<td>Important Figures</td>
<td>


FIG. 1

This figure describes the apparatus that reduces blind-spots in a car by measuring the angles of the mirror and the space that the mirror covers. The change in sight would be described from the angle alpha to beta to describe a lane-change to the space 400. After the return signal is sent, the mirror changes back to the original alpha state.
</td>
</tr>
</table>

VOCAB: (w/definition)	On-ramp - the part of the road that merges onto a freeway Sight angle - the angle of visibility from a certain place
Cited references to follow up on	Vehicle Detection and Alert System with Blind Spot Elimination Function - https://worldwide.espacenet.com/publicationDetails/biblio?DB=EPODOC&II=9&ND=2&adjacent=true&FT=D&date=20090305&CC=US&NR=2009059403A1&KC=A1 Vehicle blind spot mirror - https://worldwide.espacenet.com/publicationDetails/biblio?DB=EPODOC&II=2&ND=2&adjacent=true&FT=D&date=20010227&CC=US&NR=6193380B1&KC=B1 AUTOMATIC REARVIEW MIRROR ADJUSTMENT SYSTEM FOR VEHICLE - https://worldwide.espacenet.com/publicationDetails/biblio?DB=EPODOC&II=10&ND=2&adjacent=true&FT=D&date=20100121&CC=US&NR=2010017071A1&KC=A1
Follow up Questions	1. How can the signal activator differentiate between merging or lane changing left-turn signals and regular left-turns? 2. How can a signal activator dynamically adjust the mirrors along the curve of an on-ramp to best support the driver and eliminate blind-spots? 3. How is the rear-view mirror adjusted to view blind spots? 4. How can back-up cameras be adjusted because they are grounded to one-place? 5. Could a camera be attached to the mirror to eliminate blind spots on an on-ramp as well?

[Article #18] LiDAR Cyclist Detection – 9/19/22

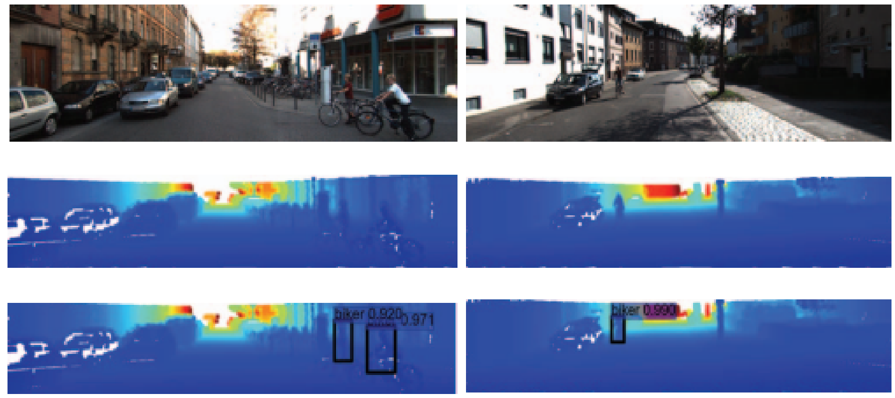
Source Title	Cyclist detection in LIDAR scans using faster R-CNN and synthetic depth images
Source citation (APA Format)	Saleh, K., Hossny, M., Hossny, A., & Nahavandi, S. (2017). Cyclist detection in LIDAR scans using faster R-CNN and synthetic depth images. *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 1–6. https://doi.org/10.1109/ITSC.2017.8317599
Original URL	https://ieeexplore.ieee.org/document/8317599
Source type	Scientific Conference Paper
Keywords	Cyclist detection, LIDAR, Faster-RCNN, Synthetic Depth Images, Object detection, KITTI dataset

Summary of key points + notes (include methodology)	This study aims to detect cyclists using deep learning methods. This study develops a method to generate synthetic LIDAR cyclist data and train a Faster RCNN model with it. The results show that this new model performs better than HOG-SVM and show that the method of synthetic data is viable.
	
	Notes:
	- Detection of VRUs are mostly sensor-based or vision-based
	- Vision-based systems are deemed superior because sensors are too sensitive to surroundings
	- Not much learnable data for cyclists/datasets
	    - Solution is to generate synthetic data
	- Appearance/viewpoint of cyclist can affect accuracy of detection a lot
	- 3D lidars can obtain the shape of objects no matter the direction
	- This study uses Faster RCNN
	    - Trained on synthetic depth images that are labeled with bounding boxes
	- Originally HOG feature extractors, decision forest trees, and SVM classifiers were used to detect cyclists and orientations
	    - These techniques used limited data and feature extraction and classification process are separated
	- This study trains an end-to-end CNN
	- CNNs are good for visual-related deep learning
	- CNNs are composed of convolutions, pooling, FCs, and ReLu → which can be trained with gradient descent
	- Faster RCNNs
	    - Two modules: Region proposal (generate RoIs), CNN

	(smaller feature maps + FCs + softmax/regression)
	- Original RCNNs had a slow process of proposing regions
	- Faster RCNN has a fully convolutional RPN
	- Generated annotated depth data with cyclists in various traffic scenarios
	- Generated depth data rather than raw images because most vehicles rely on LIDAR sensors rather than RGB cameras
	- First created two different 3D models of traffic in cities
	- Each traffic model had cyclist models and 4 virtual LIDARS following them
	- The four virtual cameras generate depth images with cyclists in the scene from different viewpoints
	- Generated 10,000 annotated synthetic depth images
	- 8,000 images for training data, 2000 images for testing data
	- Synthetic generated depth images have low contrast→increased entropy of each image by colorizing each image before training
	- Faster RCNN could be end-to-end trained and has strong past accuracy and performance in real-time
	- Loss of each example = Loss of RPN + Loss of RCNN
	- Uses classification log loss for RPN and regression loss for bounding boxes of RCNN
	- 10E-3 learning rate, 50K iterations, momentum of 0.9, weight decay of 5x10E-4
	- Performances on synthetic testing dataset (AP %)
	    - HOG-SVM - 73.6
	    - Faster RCNN (3 convolutional layer) - 66.8
	    - Faster RCNN (VGG1024 - 5 conv layer) - 80.3
	    - Faster RCNN (VGG16 - 13 conv layer) - 89.7
	- Qualitative results show that VGG16 Faster RCNN generalized well to 3D LIDAR scans from KITTI dataset which were more complex and used different LIDAR sensors

Research Question/Problem/ Need	How can cyclists be detected with LIDAR data?

Important Figures



This figure is an example of a 3D LIDAR scan on a street. The top images are RGB original images. The middle images are projected LIDAR scans in 2D. The bottom images have bounding box predictions on cyclists.

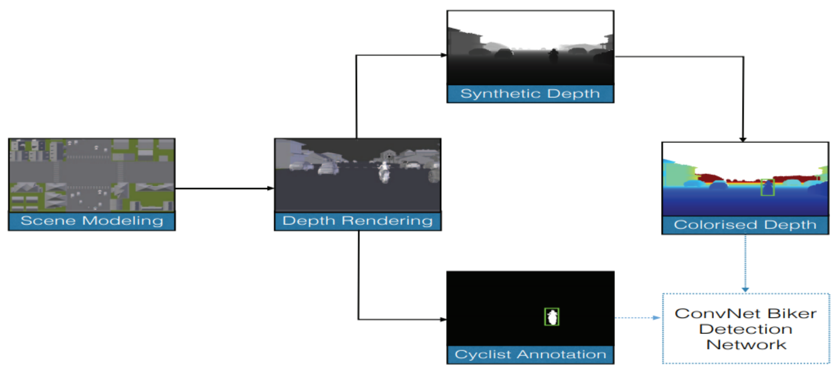
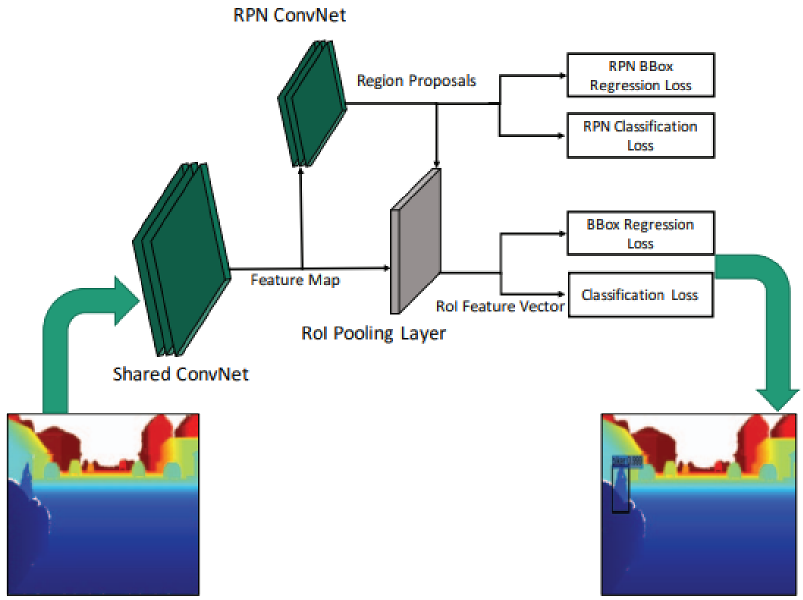


Fig. 2. Data generation and preparation pipeline. Scenes with urban traffic environment objects are firstly constructed inside Blensor. After two rendering phases, both synthetic depth images and its ground truth cyclist annotated instances are generated. Synthetic depth images are then pre-processed by shifting into (0,255) range and colorized by applying colour jet mapping. Both colorized depth images with its corresponding annotation of cyclist instances are fed to the ConvNet cyclist detection network for training.

This diagram displays the steps taken to the training process of the object detection network. LIDAR scans are first rendered and annotated and then colorized to show depth. Then the 2D images are trained using a CNN.

	 This figure shows the process an image goes through to prejudice bounding boxes. The LIDAR image is passed through a CNN to produce a feature map and is then passed through a region-proposal network to generate proposals for regions. This is then passed through pooling layers to generate a ROI feature vector to predict the cyclist position.
VOCAB: (w/definition)	LIDAR - a detection system that uses radar technologies with lasers Feature maps - the input and output for each convolutional layer Region Proposal Network (RPN) - the part of a neural network that generates regions of interest Entropy - measure of uncertainness and randomness
Cited references to follow up on	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks - https://ieeexplore.ieee.org/abstract/document/7485869 Fast Cyclist Detection by Cascaded Detector and Geometric Constraint - https://ieeexplore.ieee.org/document/7313303 Bicyclist detection in large scale naturalistic driving video - https://ieeexplore.ieee.org/abstract/document/6957928
Follow up Questions	1. What is the cost of implementing a LIDAR system with an object detection model on a real-time application? 2. What is the difference in prediction time between HOG-SVM and Faster RCNN?

	3. Where can this synthetic dataset be found? 4. Would the model train to higher accuracies if it used an Adam optimization algorithm instead of SGD? 5. How would a Faster RCNN perform against SSD models? 6. What is the testing accuracy of the Faster RCNN model on depth-images from the KITTI dataset?

[Article #19] Right-Hook Crash Effects – 9/22/22

<table>
<tr><td>Source Title</td><td>Right-Hook Crash Scenario: Effects of Environmental Factors on Driver’s Visual Attention and Crash Risk</td></tr>
<tr><td>Source citation (APA Format)</td><td>Jannat, M., Tapiro, H., Monsere, C., & Hurwitz, D. S. (2020). Right-Hook Crash Scenario: Effects of Environmental Factors on Driver’s Visual Attention and Crash Risk. Journal of Transportation Engineering, Part A: Systems, 146(5), 04020026. https://doi.org/10.1061/JTEPBS.0000342</td></tr>
<tr><td>Original URL</td><td>https://ascelibrary.org/doi/10.1061/JTEPBS.0000342</td></tr>
<tr><td>Source type</td><td>Scientific Journal Article</td></tr>
<tr><td>Keywords</td><td>Bicycle–motor vehicle crash, Right-hook crash, Bicyclist, Road safety, Driving simulator, Driver behavior</td></tr>
<tr><td>Summary of key points + notes (include methodology)</td><td>This study investigates the causes of right-hook crashes at signalized intersections. This study uses simulated road scenarios with right-turn maneuvers to identify the changes in the driver’s visual attention. The results show that left-turning oncoming traffic, heightened bicyclists speed and blind spot position, and the presence of pedestrians all increase the risk of a right-hook crash.

Notes:
TLDR: Bicyclist approaching from behind the driver in a blind spot poses the greatest risk–the driver may not see the bicyclist approach the intersection
Most bicycle vehicle crashes occur at intersections in urban areas
Can occur as a result of traffic control and lane geometries
This study investigates RH crashes after a stopped signalized intersection with no dedicated right-turn lane
Both car and bicyclists are moving in the scenarios
RH crash scenario
Bicyclist overtakes slow moving car and vehicle turns into the bicyclist
Vehicle overtakes bicyclist and makes turn and bicyclist collides into turning vehicle
NHTSA
840 fatal bicyclist accidents in 2016 - 2.2% of transportation fatalities
71% of fatal bicycle crashes happened in urban areas
30% at intersections</td></tr>
</table>

	- Lack of visual attention is most common accepted cause for vehicle crashes - NHTSA - 55.7% of intersection crashes occur because of lack of attention, distraction, inadequate viewage - Inadequate surveillance was leading reason for intersection crashes - scan location to safely complete a maneuver

- Drivers often fail to detect bicyclist coming from right-side because they are focused on cars coming from left
    - Improper allocation of driver's visual attention
    - Bicycle coming from behind is very difficult to detect
- This study analyzes the specifics of driver visual attention and identify scenarios that are dangerous
- 67 participants from Corvallis, OR → resulted in 51 participants because 16 participants had motion sickness
    - Mean age 30, 30 males, 21 females, at least 1 year license, $20 compensation
- OSU (Oregon State University) Driving Simulator
    - 2009 Ford Fusion cab
    - Motion sensors
    - Surround sound
    - Displays/Projectors for environment and mirrors
    - Accurate representation for real driving environment
- The study tracked the eye movement and used infrared lights and pupil position to show where the person is looking at
- If a person looks at something for 100ms it is tracked as a pause/glance
- Collected 20 videos each 25s from each participant of approaching intersections
- Each video was annotated with eye-movement data with ASL Results Plus software and drew area of interest polygons in intervals of frames
    - Dataset had all glances as areas of interest with fixation and duration of each fixation
- 21 right-turning scenarios tested in urban scenarios
- Each scenario had 3 traffic lanes and a bicycle lane in both directions
- No specific right and left turning lanes were used
- Speed limit of 35mph
- Varied incoming traffic, crossing pedestrians, and bicycle position and speed
- Bicycles were visible in the mirrors when approaching intersection
- Procedure
    - Participants were surveyed on demographics prior to the driving simulation

	- Practiced on simulator for 3-5 min
	- Were allowed to adjust mirrors, seat, wheel
	- Instructed to follow driving laws and practices
	- Each participant had a head-mounted eye tracker
	- Each simulation took 20-30min to complete
	- Average total fixation duration measured time of visual attention of each AOI
	- IVs:
	  - Presence of bicyclist
	    - No bicyclist
	    - Bicyclist approaching from behind driver
	    - Bicyclist in front of driver
	  - Cyclist speed
	    - 12mph
	    - 16mph
	  - Presence of oncoming left-turning traffic
	    - No vehicles
	    - 3 oncoming vehicles
	  - Presence of pedestrians
	    - No pedestrian
	    - One pedestrian on crosswalk
	- (Portland Oregon study) Speed of cyclist overtaking right-turning vehicle is a risk factor for RH crashes
	- Drivers mostly could not detect crashes with cyclists because attention was drawn elsewhere
	- Right-hook crashes more possible if bicyclist is approaching from behind
	  - 87% of scenarios drivers fixated on bicyclist when it is in front
	  - 44% of scenarios drivers fixated on bicyclist when it approached from behind
	- Drivers fixated more time on slower bicyclists
	- Faster approaching bikes are more likely to be in a RH crash
	- More pavement markings or signs could help prevent RH crashes
	- Curving bicycle lane/separating it coud help/protected intersections
	- Traffic signal intervals could be modified as well to allow bikes to go at different times

Research Question/Problem/ Need	What are the most significant causes to right-hook crashes and why do they occur from a vehicle driver perspective?

Important Figures

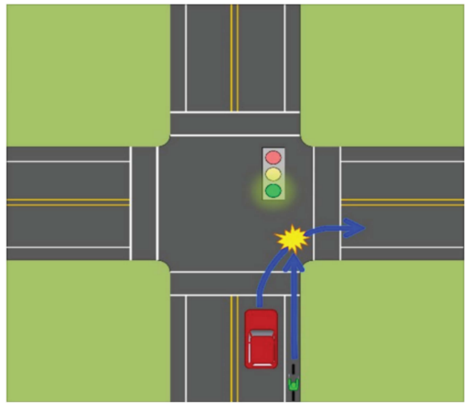
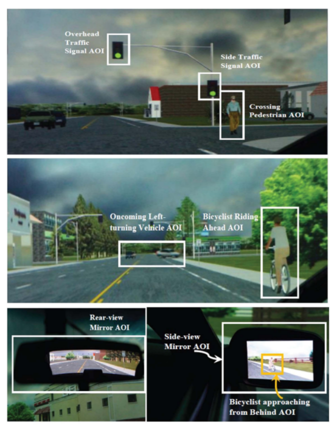


Fig. 1. Schematic description of a right-hook crash.

This figure describes a right-hook crash between a vehicle and a cyclist.



g. 7. Examples of different AOIs drivers fixated on during the experiment. (Image by Mafruhatul Jannat.)

This figure shows a variety of different scenarios tested with pedestrians, other cars, cyclists, and turns.

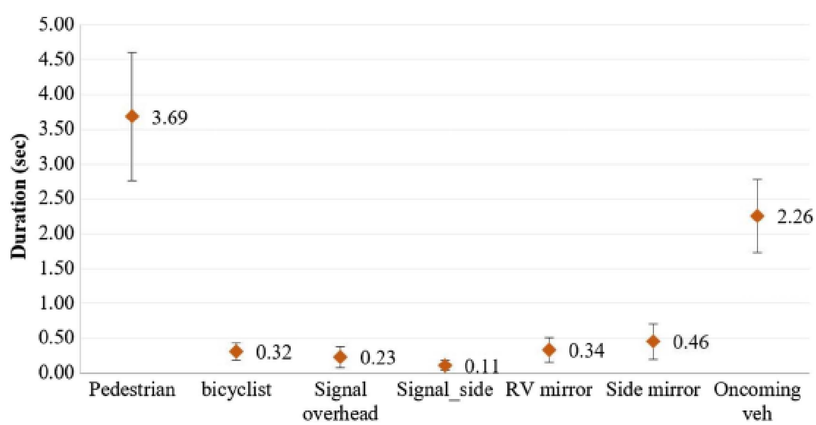


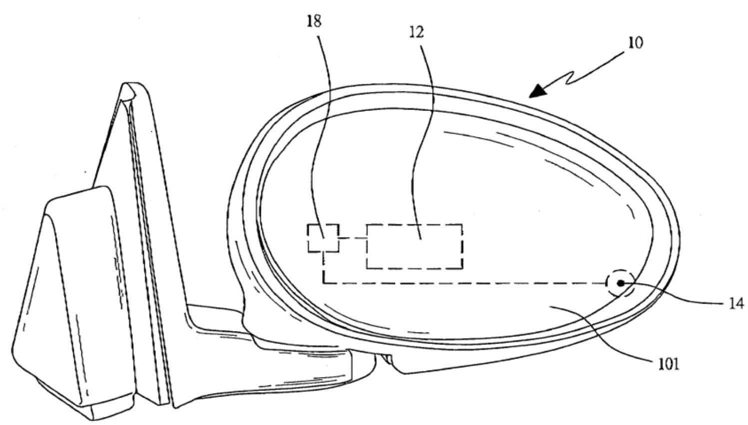
Fig. 9. ATFD with 95% CIs for one of the most visually complex scenario (bicyclist approaching from behind at 7.15 m/s, three vehicles, one conflicting pedestrian).

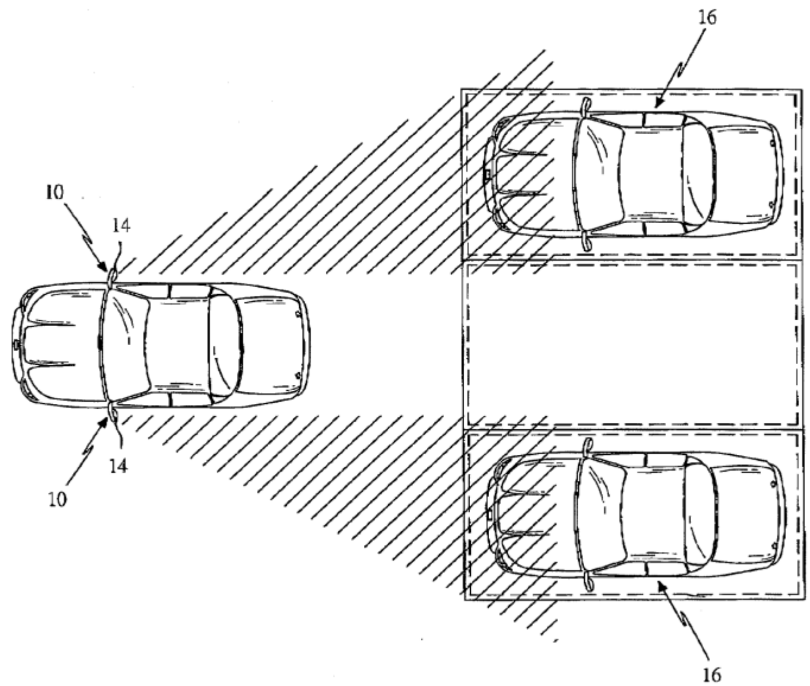
	In complex driving scenarios, drivers were most likely to be fixed on oncoming vehicles or pedestrians at an intersection and did not spend as much time glancing at bicyclists or other factors.
VOCAB: (w/definition)	Right-hook crash - a type of bicycle-motor vehicle crash that occurs between a right-turning vehicle and a through-moving bicycle at an intersection Average total fixation duration (ATFD) - the average duration of a fixation of the eye on an area of interest AOI - area of interest determined by eye fixations ANOVA - analysis of variance to see if there are statistically significant distinctions between two results
Cited references to follow up on	Evaluation of bike boxes at signalized intersections - https://www.sciencedirect.com/science/article/abs/pii/S0001457510003246?via%3Dihub Sign location, sign recognition, and driver expectancies - https://www.sciencedirect.com/science/article/abs/pii/S1369847808000570?via%3Dihub
Follow up Questions	1. Are drivers who were selected from around Corvallis, OR representative of an ordinary urban driver or metropolitan city driver and their visual behavior? 2. Does the number of years that a driver has had their license affect the visual behavior and risk for a RH crash? 3. Does the speed that the car approach the intersection affect the ATFD of drivers on bicyclists and how does it affect crash rate? 4. How would the ATFD change for truck drivers on semitrailer trucks?

[Patent #2] Vehicle Detection System – 9/24/22

Source Title	Vehicle Detection and Alert System with Blind Spot Elimination Function
Source citation (APA Format)	Chang, C.-J. (2009). *Vehicle Detection and Alert System with Blind Spot Elimination Function* (Patent No. US2009059403 (A1)). https://worldwide.espacenet.com/publicationDetails/biblio?FT=D&date=20090305&DB=EPODOC&locale=&CC=US&NR=2009059403A1&KC=A1&ND=3
Original URL	https://worldwide.espacenet.com/publicationDetails/biblio?CC=US&NR=2009059403A1&KC=A1&FT=D&ND=3&date=20090305&DB=EPODOC&locale=
Source type	Patent
Keywords	Blind Spot Alert System, Blind Spot, Vehicle, Mirror, Driver Safety

Summary of key points + notes (include methodology)	This patent invents a structure for an automatic rear view mirror on cars with a blind spot alert system. The invention has a lens on the mirror that can change its angle and a sensor to detect oncoming objects. This improves safety as it optimizes the visible angle from the driver.
	
	Notes:
	- Vision of drivers blocked by pillars, front, back, left, right blind spots
	- Drivers may think there is no oncoming cars but they are in the blind spots
	- Collisions occur because of limited viewing angle from mirrors
	- Sensor is installed in rearview mirror to detect things around vehicle
	    - When object approaching, mirrors would widen the angle to improve view on blind spots
	- System on rear-view mirror
	    - Lens/mirror
	    - Driving motor to change angle of lens
	    - Sensor to detect oncoming objects
	    - Control chip module to control driving motor
	- Control chip connects to a signal wire which is controlled by a signal light
	    - Control chip changes angle of the lens
	    - Can also be connected to the gear shift
	        - Ex. When car is put in reverse, mirrors change

	- Can memorize multiple viewing angles for custom adjustment - Can be connected to other controls: buttons, knobs, sticks, etc. - Can communicate wired or wirelessly with signal - When sensor detects oncoming object, the rear view mirrors would open outwards to eliminate blind spots - Alert system can also alert drivers to check mirrors for oncoming traffic - Can also include a display to show real time oncoming traffic from rear view mirrors
Research Question/Problem/ Need	What methods can be developed to alert drivers of oncoming objects in a vehicle's blind spot?
Important Figures	 This figure is a 3D model for the rear view mirror of a car with a blind spot elimination and vehicle detection system.

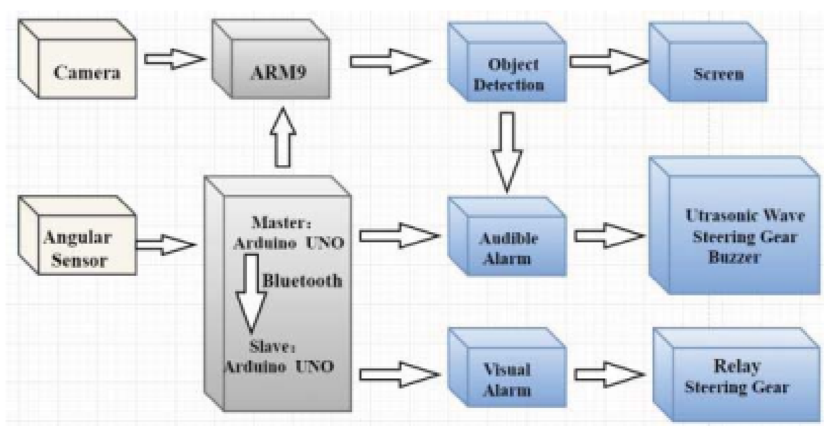
	 FIG. 2 This figure shows the regions that would be covered with the change in angle of the lens.
VOCAB: (w/definition)	Control module - a single entity that controls something with parts such as sensors, controllers, actuators, etc. Signal light switch - turn signal Driving motor - a motor that converts electrical energy to mechanical energy Digital image display unit - a screen that can display media typically found in the center of the car
Cited references to follow up on	Lane departure warning mirror - https://worldwide.espacenet.com/publicationDetails/biblio?DB=EPODOC&II=2&ND=4&adjacent=true&FT=D&date=20070830&CC=US&NR=2007200689A1&KC=A1 Automotive blind spot safety system and method - https://worldwide.espacenet.com/publicationDetails/biblio?DB=EPODOC&II=0&ND=4&adjacent=true&FT=D&date=20060316&CC=US&NR=2006056086A1&KC=A1
Follow up Questions	1. What type of sensors are used to detect oncoming objects? 2. How can the sensor detect oncoming objects?

	3. Can a camera sensor be used to detect oncoming vehicles with greater accuracy? 4. How could the center rear view mirror be adjusted to improve blind spots?

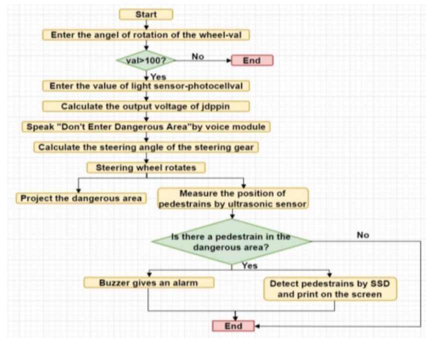
[Article #20] Arduino Warning Device – 9/25/22

Source Title	Design of Arduino-Based In-vehicle Warning Device for Inner Wheel Difference
Source citation (APA Format)	Zhang, Q., Wei, Y., Wang, K., Liu, H., Xu, Y., & Chen, Y. (2019). Design of Arduino-Based In-vehicle Warning Device for Inner Wheel Difference. *2019 IEEE 2nd International Conference on Electronics Technology (ICET)*, 301–304. https://doi.org/10.1109/ELTECH.2019.8839372
Original URL	https://ieeexplore.ieee.org/document/8839372
Source type	Scientific Conference Article
Keywords	Inner-wheel difference, visual blind area, blind spots, blind spot detection

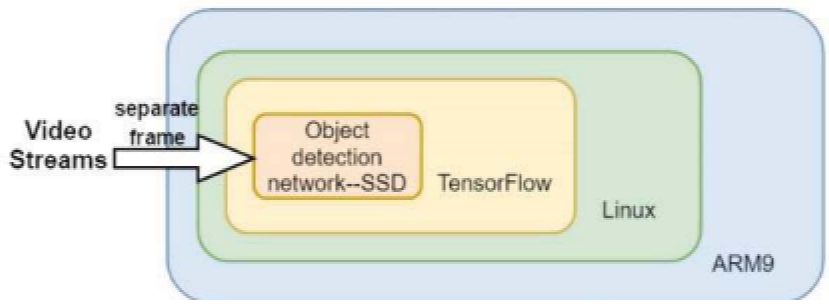
Summary of key points + notes (include methodology)	This study aims to solve the problem of inner-wheel difference blind zones in large vehicles. An arduino-based warning device is developed with a object detection model to locate pedestrians.
	
	Notes:
	- Demand for larger vehicles increase with growing economies
	- Pedestrians, cyclists, and electric vehicles often are crushed by turning larger vehicles
	- When inner wheel difference occurs there is a blind zone and the driver cannot see
	- Small radius turns do not have proper infrastructure
	- Current methods to prevent inner wheel difference:
	    - Laser-based warning device (harmful to body)
	    - Ultrasonic detection + video display (Driver may not be alert to the video)
	- New method: Arduino warning device with light warning + video deep learning object detection
	- Components/modules
	    - Angular sensing module
	        - Connected to the inner front wheel and detect turn angle
	    - Warning module
	        - Receive signal by Bluetooth for visual alerts
	        - Laser is emitted with reflection device to warn pedestrian
	        - Audio alarm when object in area with ultrasonic sensor for pedestrian and driver
	        - When obstacle is too close an alarm will sound

<table>
<tr><td></td><td>
- Camera and screen used to show area to driver
- Object detection module
  - Video from camera is processed into fames
  - Passed into SSD deep neural network on ARM9
  - SSD model has feature extractor VGG16
  - Has two outputs: classification confidence and bounding box
  - Trained on Pascal VOC dataset with Tensorflow
- Arduino module
- When vehicle turns the angle sensor sends signal, calculates inner wheel difference, calculates steering angle and controls it, gives visual warning, uses object detection model, and shows it on the screen
- Two angular sensors are used on each front wheel
- Maximum steering angle of front wheel is 40 degrees
- Easy ot install with low update cost
- Reduces power consumption
- Device can cover blind zone on both sides
</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>How can the inner-wheel difference blind zone of a large vehicle be resolved to prevent collisions and improve the safety of pedestrians?</td></tr>
<tr><td>Important Figures</td><td>


This figure describes the process the system takes to recognize objects in blind spots using an Arduino.
</td></tr>
</table>

<table>
<tr><td></td><td>


This flowchart describes the process taken to control devices and check blind spot.



This figure describes a high level module diagram to show how videos are passed through object detection networks.
</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>ARM9 Processor - 32 bit small processor with 4 cores

HC-SR04 Ultrasonic sensor - devices that generate ultrasonic waves to detect distance from objects

Pascal VOC - a common object detection dataset

SG90 - mini steering gear motor</td></tr>
<tr><td>Cited references to follow up on</td><td>The PASCAL Visual Object Classes (VOC) Challenge - https://link.springer.com/article/10.1007/s11263-009-0275-4</td></tr>
<tr><td>Follow up Questions</td><td>1. By how much has the demand increased of large vehicles in China?
2. How fast are predictions made by the SSD model on the ARM9 processor?
3. Can the ARM9 processor make real-time continuous predictions and what would the speed of the predictions be?
4. Can ultrasonic ranging modules make false detections with road side obstacles?
5. What is the predicted cost of this system and installment?</td></tr>
</table>

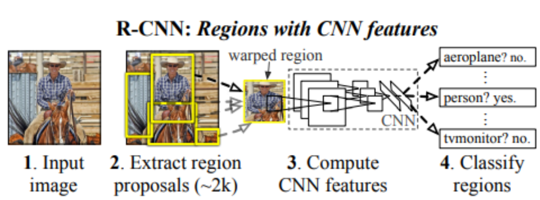
[Article #21] RCNN – 9/28/22

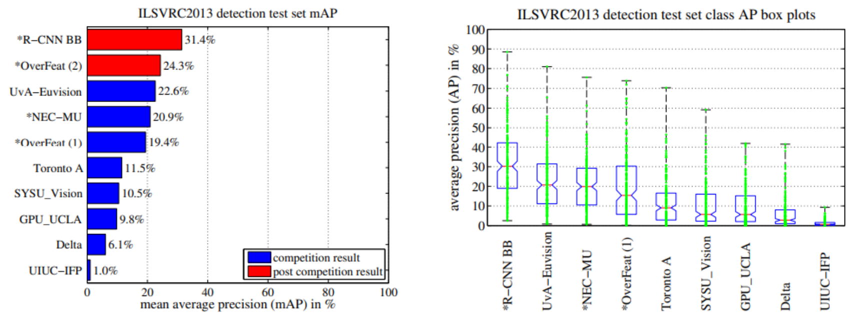
Source Title	Rich feature hierarchies for accurate object detection and semantic segmentation
Source citation (APA Format)	Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. *2014 IEEE Conference on Computer Vision and Pattern Recognition*, 580–587. https://doi.org/10.1109/CVPR.2014.81
Original URL	https://ieeexplore.ieee.org/document/6909475
Source type	Scientific Journal Article
Keywords	CNN, Deep Learning, Image Processing, Object Detection, Pascal VOC, Region Proposal Network, Semantic Segmentation

Summary of key points + notes (include methodology)	This article proposes a new algorithm for object detection that is scalable and accurate. This algorithm uses convolutional neural networks, region proposals, pre-training, and fine-tuning to detect objects. This model performs significantly better than other algorithms in terms of accuracy.
	
	Notes:
	- Past visual detection tasks have been based on SIFT and HOG
	- Object detection is tested on PASCAL VOC dataset
	- Past methods are histogram based representations which detects features based on various areas
	- CNN's and training for stochastic gradient descent have better image classification accuracies which were trained recently on ImageNet
	- Past methods have more commonly used SVM (support vector machine) methods
	- CNN can significantly increase performance in object detection with two parts: localizing networks and then classifying them
	- Object detection needs to localize objects in an image and find bounding boxes
	    - Past methods include:
	        - Regression method
	        - Sliding window detector
	        - Many convolutional layers
	- New method: Generate region proposals and extract feature vectors then classifies each region with an SVM
	- RCNN is compared to OverFeat detection system on ILSVRC2013 dataset

- RCNN is better with mAP of 31.4% v.s. 24.3%
- Labeled data is uncommon and hard to find to train a large CNN – uses supervised pre-training and then fine-tuning on smaller dataset is effective
- Has 54% mAP with fine-tuning
- Uses regression method to predict bounding boxes
- Can also work for semantic segmentation problems
    - Use PASCAL and additional data to train dataset
    - Full strategy - find features based on window without accounting for irregular shape
    - FG strategy - find features based on a foreground mask
    - Full + FG - combine strategies to segment objects (best performance on PASCAL)
- THREE MODULES:
    - Module 1: Region Proposals
        - Selective search used to generate region proposals
        - Find 2000 region proposals – ~90% is recall
        - Score feature vector for each region with a SVM model
        - Filters out regions that overlap with other regions that have a higher score
    - Module 2: CNN
        - Pre trained on ILSVRC2012 class annotated data
        - Fine tuned CNN using SGD on warped region proposals
        - Replaced ImageNet 1000 class classifier with N+1 classifier with N object classes and 1 background
            - VOC - N=20
            - ILSVRC2013 - N=200
        - Training is biased towards positive region detections because they are rarer compared to background positives
    - Module 3: SVM
        - Used to classify object regions
        - Optimized on VOC2012 trainval dataset
        - Linear regression model to predict detection window given feature vector + region proposal
- Feature Extractor
    - Input image is 227 by 227 RGB
    - Forward prop image through 5 conv layers and 2 FC layers
    - Extracted 4096 dimension feature vector from each region proposal
    - Frst layer filters find edges and opposite colors

	- Later filters fire on more high level features: dog faces, dot arrays
	- RCNNs are scalable - many object classes does not increase time complexity that much
	- Are much more accurate with less complex algorithms
	- Performance
	    - mAP of 0.314 on ILSVRC 2013
	        - Second best result is 0.243
	- Different usages of CNNs can result in various different results
	- RCNN feature extractors perform better than DPM feature learning methods - .2 mAP higher
	- Network architecture has strong affect on performance
	- Fine-tuning does not reduce variability of AP but improves low and high of AP test
	    - Improves various features that change an image
	- ILSVRC2013 Dataset
	    - Val and test set are annotated with bounding boxes, training data only classify image type
	    - To pretrain model val set was heavily used and train images were positive examples
	- Training data for object detection used for fine-tuning, SVM training, and bounding-box regression
	- mAP on val and test sets were similar
	- RCNN performs 0.209 mAP when only pretrained on ILSVRC2012 – fine-tuning + expanding training set + bounding box regression makes mAP to 0.31
	- OverFeat is similar to RCNN but uses a different method of region proposals – pyramid of square regions, one single bounding box regressor
	- OverFeat is ~9x faster than RCNN
	- Speeding up RCNN is future work
	- 30% relative improvement on PASCAL VOC 2012

Research Question/Problem/ Need	How well do CNN techniques used with ImageNet work with object detection with the PASCAL VOC challenge?
Important Figures	 This figure shows the general process that the RCNN applies to an image.

	 This figure shows the performance of the R-CNN compared to other image processing techniques in terms of mAP and AP on the ILSVRC2013 dataset.
VOCAB: (w/definition)	Scale Invariant Feature Transform (SIFT) - an algorithm that detects and locates features in an image Dropout regularization - reduce overfitting on training data by thinning weights Feature vector - a vector of numerical data of observations and features Non-max suppression - technique of selecting best bounding box out of many proposals Half-wave rectification - a rectifier that only allows half of a wave to pass Bounding box regressor - refine and predict bounding boxes by regressing from region proposal or to use anchor boxes OverFeat - type of CNN architecture used for image classification Second order pooling (O_2P) - a pooling method that finds richer features Support Vector Regression (SVR) - a regression and clustering regression algorithm
Cited references to follow up on	The PASCAL Visual Object Classes (VOC) Challenge - https://link.springer.com/article/10.1007/s11263-009-0275-4 ImageNet classification with deep convolutional neural networks - https://dl.acm.org/doi/10.1145/3065386 OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks - https://arxiv.org/abs/1312.6229

Follow up Questions	1. Can numerous SVM classifiers for each class be changed to a single classifier for efficiency? 2. How does the number of fully connected final layers affect the accuracy? 3. How can noramlization be implemented in the RCNN to improve generalization to validation tests? 4. How are SVM classifiers trained and on what dataset?

[Article #22] CNN Trade-offs – 10/3/22

Source Title	Speed/accuracy trade-offs for modern convolutional object detectors
Source citation (APA Format)	Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Fischer, I., Wojna, Z., Song, Y., Guadarrama, S., & Murphy, K. (2017). Speed/Accuracy Trade-Offs for Modern Convolutional Object Detectors. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 3296–3297. https://doi.org/10.1109/CVPR.2017.351
Original URL	https://ieeexplore.ieee.org/document/8099834
Source type	Scientific Journal Article
Keywords	Convolutional Neural Networks, Object Detection, COCO detection metrics

Summary of key points + notes (include methodology)	This study investigates the performance of various object detection models in terms of speed, memory, and accuracy. Various meta-architectures and feature extractors were tested such as Faster RCNN, RFCN, and SSD systems as well as VGG and ResNet. Results showed the optimal model for speed and another optimal model for accuracy based on COCO detection metrics.
	
	Notes:
	- Many object detection models are deployed in consumer products
	- Architectures that are best suited for various tasks is difficult to decide
	- mAP is not an all inclusive metric, does not account for running time and memory usage
	- Speed/accuracy trade off is not discussed much
	    - Depends on feature extractor, input image sizes, etc
	- Test-time performance is evaluated
	- Created implementations of Faster RCNN, RFCN, SSD in Tensorflow
	- Using less proposals in Faster RCNN can make it much faster without losing much accuracy
	- SSD is less dependent on accuracy of feature extractor for accuracy of detections
	- Meta-architectures
	    - RCNN is computationally costly
	    - Fast-RCNN - first feature extracts from entire image and then crops from intermediate layer

- Region proposals can also be generated from anchor boxes and class predictions
- Faster-RCNN used multibox anchor boxes to improve accuracy and computation speed
- SSD uses one forward pass to predict object locations and classes

- Faster RCNN
    - First RPN with a feature extractor and predict predict box proposals
    - Next box proposals crop features and then pass through more feature extraction to predict class
- R-FCN
    - Pushes cropping features to the last layer to minimize computation
- Experimentation Setup
    - Past studies used various different metrics and various training sets making them hard to compare
    - This study conducted on Tensorflow
    - Can swap feature extractors, loss functions
    - Can deploy anywhere
- Feature Extractors
    - VGG16
    - Resnet 101
    - Inception V2
    - Inception V3
    - Inception Resnet v2
    - MobileNet
- Number of proposals is varied between 10 and 300
- Loss function
    - Matching
        - Groundtruth boxes and anchor boxes need to be matched
        - Use (two-to-one) Bipartite or (many-to-one) Argmax matching
    - Box encoding
        - Encode groundtruth box with matching anchor
    - Location loss
        - This study uses L1 loss function
- Each model is tested with various image sizes
    - High resolution model – M=600
    - Low resolution model – M=300
- Trained and evaluated each model using COCO Detection API
- Timings for predicting from image are averaged over 500 tested images of size MxM
- Measure memory usage for each model when making predictions

	- Faster RCNN/RFCN - most feature extracotrs use batch norm after convolutional layers and used weights from ImageNet
	- SSD - use batch norm in all new layers and initialize weights with normalized distribution
	- Testing
	    - IV: Meta-architectecture, feature extractor, stride, input resolution, number of proposals
	    - DV: GPU time, memory usage, # parameters
	    - Total 147 models
	- RFCN and SSD models are faster than Faster RCNN
	- Faster RCNN are generally more accurate, but can be faster if number of region proposals are limited
	- SSD + InceptionV2 or MobileNet are most accurate in fastest models
	    - MobileNet is 2x faster than InceptionV2 but slightly worse accuracy
	- R-FCN have balance between speed and accuracy
	- Faster-RCNN + ResNet can have good speed if limited number of proposals to 50
	- Investigated correlation between performing well on classification and detection
	    - Faster RCNN and RFCN detection performance seems to depend more on feature extractors
	    - SSD models have less dependencies
	- Investigated affect of object size
	    - SSD models perform terribly on small objects
	    - RCNN + RFCN perform better on smaller objects
	    - Are better at detecting larger objects
	- Investigated impact of resolution
	    - Decreased resolution decreased accuracy and decreased inference time
	    - High resolution models perform much better on smaller objects
	- Investigated GPU Time
	    - Calculate FLOPS to reduce hardware dependency
	    - Bigger feature extractors have longer running times and bigger memory usage
	    - MobileNet uses less than 1gb of memory
	- Investigated affect of IOU threshold
	    - Higher and lower threshold does not change much
	    - 0.75 IOU is good benchmark for all IOUs

Research Question/Problem/ Need	How can you choose an object detection model based on given speed, memory, and accuracy requirements?

Important Figures

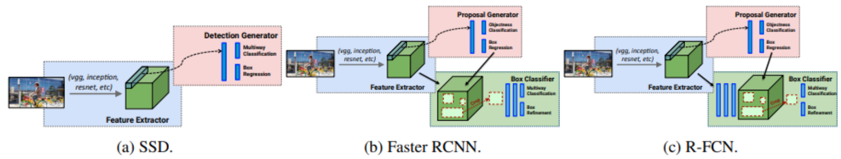
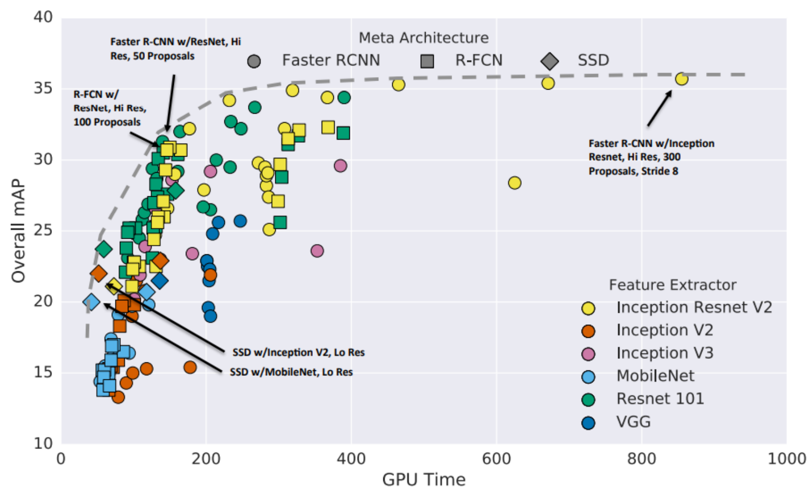
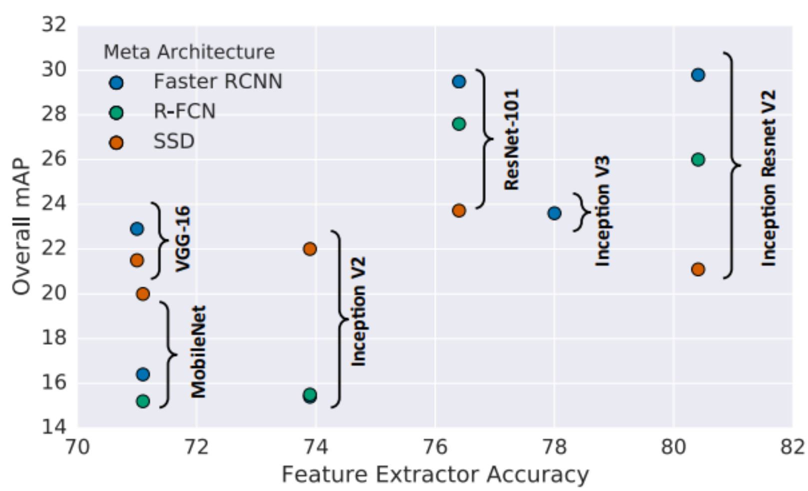


Figure 1: High level diagrams of the detection meta-architectures compared in this paper.

This figure shows some higher level block diagrams that show how each tested meta-architecture works.



This chart compares the mAP of a model with the GPU time to make predictions. Each color represents a different feature extractor. Different marker shapes represent different meta-architectures.



This figure compares the accuracies in mAP of various feature extractors tested on various meta-architectures.

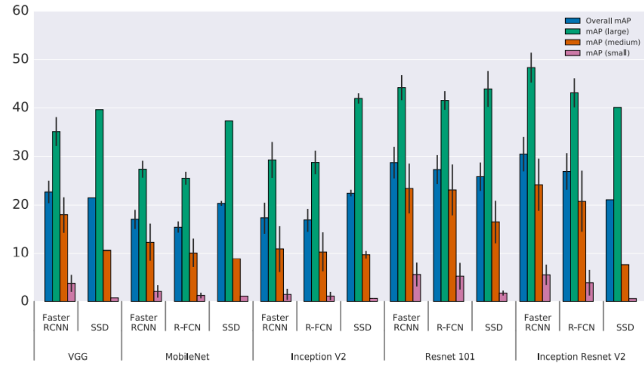
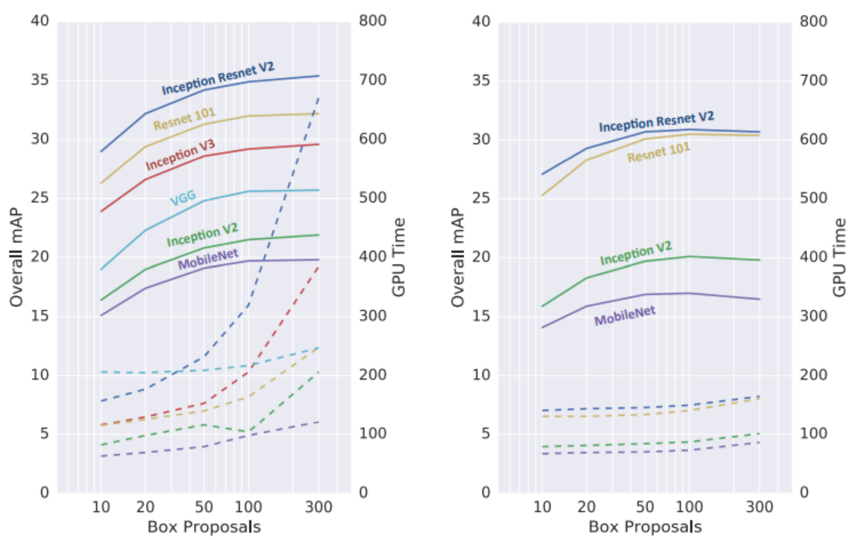
<table>
<tr>
<td></td>
<td>


Figure 4: Accuracy stratified by object size, meta-architecture and feature extractor, We fix the image resolution to 300.

This figure compares the accuracies for each architecture and feature extractor with mAP for different object sizes.



(a) FRCNN (b) RFCN

This figure compares the accuracy in mAP of each model testing over a range of box or region proposals. By decreasing box proposals to 50 from 300, mAP only loses a little bit but runtime is significantly decreased.
</td>
</tr>
<tr>
<td>VOCAB: (w/definition)</td>
<td>
Discrete class prediction - predicting classes within an intermediate layer of a neural network

Groundtruth box - box that is “correct” and is from training data

Positive anchor - if a groundtruth box can be matched with an anchor

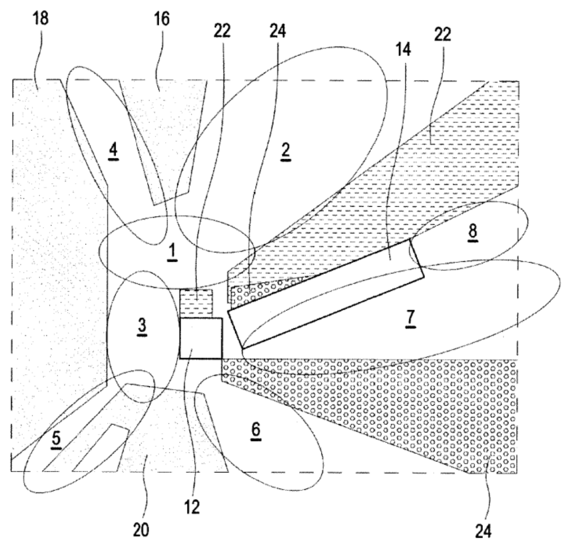
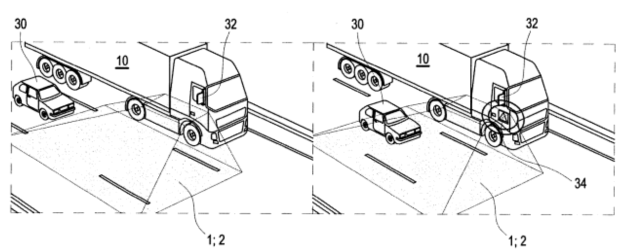
Negative anchor - if there is no match between anchor and groundtruth box
</td>
</tr>
</table>

	FLOPS - Floating point operations per second or number of multiply and add computations
Cited references to follow up on	Contextual priming and feedback for faster r-cnn - https://link.springer.com/chapter/10.1007/978-3-319-46448-0_20 Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks - https://ieeexplore.ieee.org/document/7485869
Follow up Questions	1. How well does InceptionV2 compare with InceptionV3 for feature extraction? 2. How can mAP be increased if box proposals increased? 3. How can FLOPS be converted to GPU or CPU time? 4. Is GPU, memory, or CPU the greatest limiting factor when making inferences or training? 5. How does training time compare with each model?

[Patent #3] Blind Spot Warning Device – 10/18/22

Source Title	Blind Spot Warning Device And Blind Spot Warning System
Source citation (APA Format)	Victor, T., & Larsson, P. (2013). *Blind spot warning device and blind spot warning system* (United States Patent No. US20130169425A1). https://patents.google.com/patent/US20130169425A1/en?q=truck+blind+spot&country=US
Original URL	https://patents.google.com/patent/US20130169425A1/en?q=truck+blind+spot&country=US
Source type	Patent
Keywords	Inter-vehicle communication, blind spot, warning system

Summary of key points + notes (include methodology)	This patent outlines a blind spot detection system that is attached to a vehicle. This system can show warnings if objects are outside the vehicle based on its position to the vehicle.
	
	Notes:
	- Traffic accidents are related to blind spots
	    - Lane changes / turns
	    - Front blind spots
	    - Backing up
	- More mirrors is bad for aerodynamics and makes driving more complex
	    - Mirrors are hard to adjust
	    - Mirrors provide distorted view
	- Blind spot detection systems neglect warning the person in the blind zone
	    - Warning decals
	- Sensor systems are expensive and very hard to deploy onto a vehicle
	- Blind spot warning device has warning if target vehicle is in blind spot / close to the vehicle
	    - Actively triggers / turns off
	    - Increases awareness of other drivers to vehicle blind spots
	- Can be deployable onto all vehicles
	- The warning would pop up when an object comes within the blind zone and alert the driver
	- The system would show some light source onto the object to help them identify the blindspot
	- Can be attached to a vehicle exterior body

	- Device could be decorated with more luminescent materials to make it more perceptible - Could have an auditory system for making sound alerts to driver or object - Could also send signal to GPS / computer system
Research Question/Problem/ Need	Drivers are not aware of the blind spots of other vehicles which causes safety concerns.
Important Figures	 
VOCAB: (w/definition)	BSODS - blind spot object detection system Ultrasonic parametric array - a direction-based speaker that produces ultrasoun
Cited references to follow up on	Truck light warning system - https://patents.google.com/patent/US6133851A/ Warning system for a turning vehicle and a vehicle comprising such a warning system - https://patents.google.com/patent/US20160221496A1

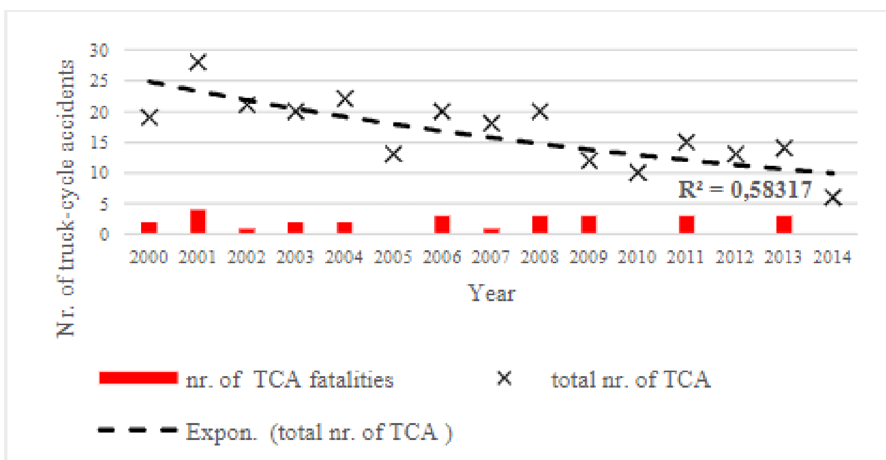
Follow up Questions	1. How would this device differentiate between pedestrians, cyclists, or motorcyclists? 2. How expensive would a visual system be to implement? 3. Would this visual system cover the inner-wheel difference blind spots made in turns?

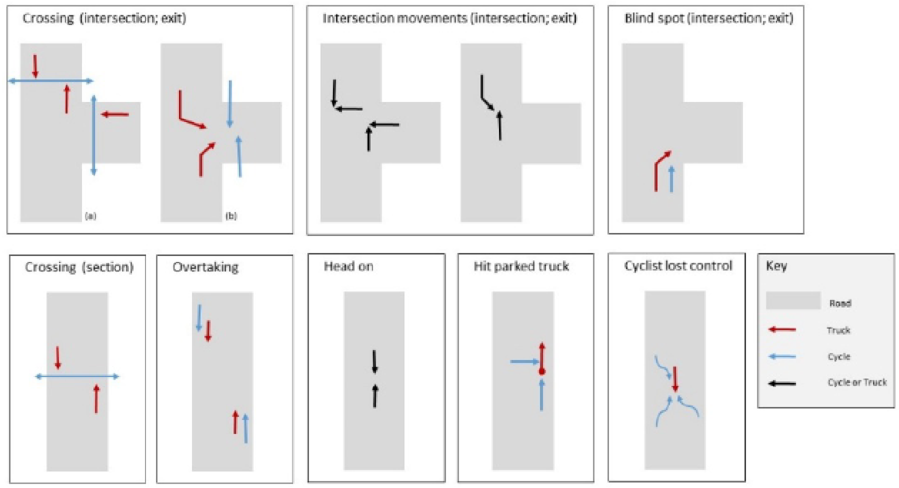
[Article #23] Truck-Cyclist Accidents – 10/21/22

Source Title	Accidents between freight vehicles and bicycles, with a focus on urban areas
Source citation (APA Format)	Pokorny, P., Drescher, J., Pitera, K., & Jonsson, T. (2017). Accidents between freight vehicles and bicycles, with a focus on urban areas. *Transportation Research Procedia*, 25, 999–1007. https://doi.org/10.1016/j.trpro.2017.05.474
Original URL	https://www.sciencedirect.com/science/article/pii/S2352146517307810?via%3Dihub
Source type	Scientific Journal Article
Keywords	Road safety, urban areas, cyclists, freight traffic, accident analysis

Summary of key points + notes (include methodology)	There is an increase in concerns for bicyclist safety as freight truck demand increases.This study aims to find the risk factors of accidents between trucks and bicycles using data from accident records in Norway. The results show that poor road surfaces and visibility from blind spots are leading causes of truck-cyclist accidents.
	
	Notes:
	- Safety concerns are increasing
	- Concern for truck v bike accidents because they are severe
	- Paper investigates infrastructure risk factors
	- Conditions in Europe are improving for cycling, hope for more cycling for transportation
	- In Norway, studies show that there is much higher risk of injury with cyclists than cars or buses –3x more risk
	- Trucks are big factor of risk for cyclists
	    - More severe injuries
	    - Blind spots
	    - Occur in urban areas and driving maneuvers
	- Analyzed police accident records in Norway and National Databse of Road Data (NVDB)
	    - 271 TCA
	    - 10% of these were fatal
	    - Issues with data
	        - Underreporting cyclist accidents for nonsevere injuries
	        - Estimated only 54% of accidents are reported
	        - Injury severity is less detailed than AIS
	        - Actual speeds + time is unknown, but speed limits can be inferred

	- Quality of description is variable
	- Analyzed each accident report with Google Maps, made collision diagrams, and annotating each accident
	- Results
	  - 77% of accidents occured in urban areas
	  - 70% of fatal accidents occured in urban areas
	  - 56% of accidents occured in intersections
	  - 12% of accidents occured in blind spots but injury severity was much higher
	    - Occured mostly at intersections and roundabouts
	    - Mostly right-hand turns
	  - Road surfaces were significant in determining the fatality risk of an accident
	- Intersections should be designed to improve visibility and be safe
	- Lack of separated bike lanes could be cause for cyclist accidents
	- Gender differences is possibly a risk factor
	- Physical health could affect accidents but was not documented
	- Decreased visibility from road conditions is the cause for more accidents
	- More studies should show that there are infrastructure problems which causes accidents

Research Question/Problem/ Need	What are some of the most prominent risk-factors in truck-cyclist accidents in Norway?
Important Figures	 This graph shows the number of truck-cyclist accidents as they decrease throughout the years. Additionally, the fatalities are labeled in the red column chart and the X represents the total numbe of TCA each year.

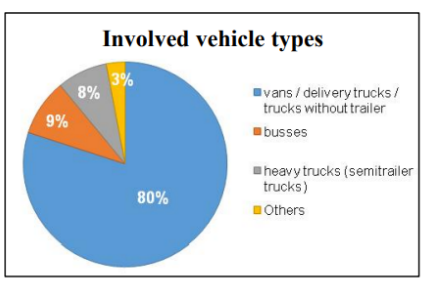
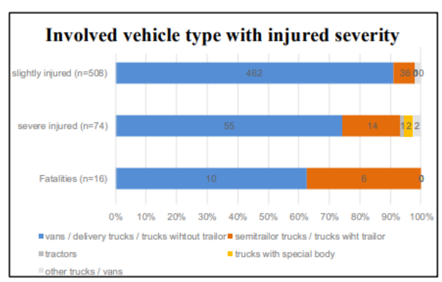
	 This figure represents the 8 types of accidents that could occur between a truck and a cyclist from the data.
VOCAB: (w/definition)	TCA - truck-bicycle accident Right-hand rule - stay to the right when driving Signalized intersections - an intersection that uses various signals to separate vehicle flow and give spacings in time
Cited references to follow up on	Development of a Test Procedure for Driver Assist Systems Addressing Accidents Between Right Turning Trucks and Straight Driving Cyclists - https://www.researchgate.net/profile/Benjamin-Schreck/publication/310966374_Development_of_a_Test_Procedure_for_Driver_Assist_Systems_Addressing_Accidents_Between_Right_Turning_Trucks_and_Straight_Driving_Cyclists/links/583bf21608ae3d91724233f2/Development-of-a-Test-Procedure-for-Driver-Assist-Systems-Addressing-Accidents-Between-Right-Turning-Trucks-and-Straight-Driving-Cyclists.pdf Pre-Crash Analysis of accidents Involving Turning Trucks and Bicyclists - https://www.ivi.fraunhofer.de/content/dam/ivi/en/documents/paper/pre-crash-analysis-ircobi-2015.pdf
Follow up Questions	1. What are the correlations between the different types of trucks and TCA accidents? 2. Are there any similar datasets available for the U.S.? 3. How does the severity of injuries from night-time comapre to day-time TCAs? 4. How does the length of the truck correlate to injury severity in TCAs?

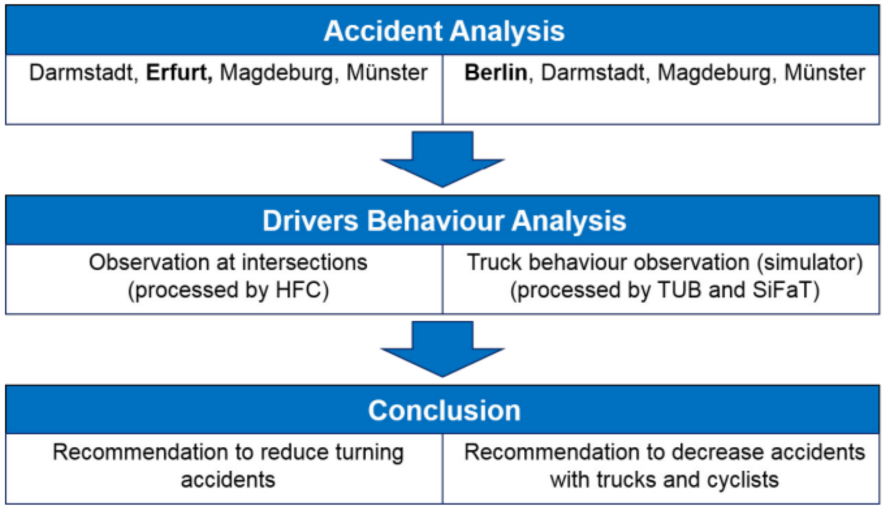
[Article #24] Right-Hook Accidents – 10/22/22

Title	Turning accidents between cars and trucks and cyclists driving straight ahead
Source citation (APA Format)	Richter, T., & Sachs, J. (2017). Turning accidents between cars and trucks and cyclists driving straight ahead. *Transportation Research Procedia*, *25*, 1946–1954. https://doi.org/10.1016/j.trpro.2017.05.219
Original URL	https://www.sciencedirect.com/science/article/pii/S2352146517305203
Source type	Scientific Journal Article
Keywords	Accident analysis, cycling, turning accidents, infrastructure, behavior observation, blind spot, traffic safety

Summary of key points + notes (include methodology)	Cyclist collisions in turning accidents with large vehicles are often severe. This study analyzes accidents in Germany from a driver and external perspective. The results show that trucks are significantly associated with severe truck-cyclist accidents.
	
	Notes:
	- In 2014, 25% of all accidents in Germany were related to cycilsts
	    - Were often severe or fatal
	- Turning accidents account for 20% of all cyclist accidents
	- Vehicles are supposed to yield to straight-going cyclists
	- This study is divided into two projects
	    - First project is about conflicts on left/right-turning vehicles and straight-going cyclists
	    - The second project is about right-turning trucks and through-going cyclists
	- Past research and suggestions to improve bicycle safety
	    - Bicycle stop line after car stop line
	    - Cyclists get green light before other vehicles
	    - Trixi mirrors – mounted on traffic poles
	    - Protected bike lanes are bad
	    - Stop at red light before turns
	- Most turning accidents are due to mistakes to turning process
	    - Drivers looked poorly
	    - Cyclists used wrong way
	    - Ignoring traffic lights
	- Older age shows higher risk of getting in accident
	- Most accidents happen during rush hour

	- ⅔ of turning accidents are right-hook
	- ¾ of turning accidents occur at signalized intersections
	- Obstructive view found at many intersections
	    - Vehicles, trees, bus stations, etc
	- 10% of turning accidents involve trucks
	    - 80% of TCA have injuries
	    - 2% of TCA have fatalities
	    - 10% have severe injury
	    - 67% slight injury
	    - 8% of turning accidents are semi-trailer trucks
	        - These TCA are very severe
	    - Main cause is incident turning maneuver
	- Both truck and bicyclist approach intersection at same speed and cyclist stays in the blind spot – high risk
	- Study observed intersections using cameras
	    - Intersections with worser visibility had higher conflict rate
	- Look over right shoulder decreases risk of accident
	- Most conflict when driver starts driving from red light and cyclist passes through without stopping
	- Study also used driving simulator
	    - Half of drivers were informed of oncoming cyclists
	    - Results show that drivers look more at cyclists when lanes get closer
	- Bicycle infrastructure should be clearly marked
	- Intersections should be easily understood
	- Broken signaling for make pause between cyclist signal and traffic signal

Research Question/Problem/ Need	What behaviors and infrastructure features are risk factors to turning accidents with through-going cyclists?
Important Figures	  This figure highlights the prevalence of fatal or severe accidents in semitrailer trucks or HGVs. This emphasizes the need for safety measures for these potential accidents.

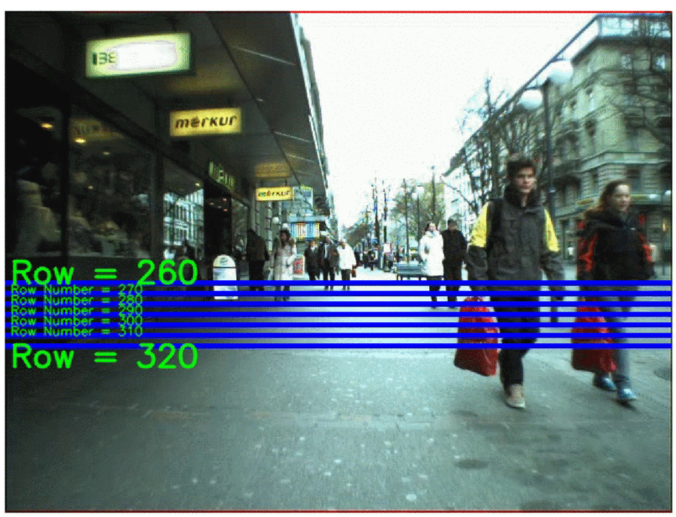
	 This figures provides a graphical outline for the paper.
VOCAB: (w/definition)	Incident turning maneuver - when a turn is executed poorly and overlaps with the cyclist lane a lot Separated signalization - when signals for cyclists and turning vehicles are separated to allow for time Angle of collision - the angle between the direction of target and original vehicles
Cited references to follow up on	N/A
Follow up Questions	1. How did injury severity differ between left and right-turn crashes? 2. How can obstructions be mitigated to prevent sight disabilities? 3. How long does the look over right shoulder glance take and at what moment of the maneuver is it most effective? 4. Does the length of the vehicle determine the effectiveness of the look over the right shoulder action?

[Article #25] Object Detection Metrics – 11/25/22

Title	Object Detection in Real-Time Systems: Going Beyond Precision
Source citation (APA Format)	Sobti, A., Arora, C., & Balakrishnan, M. (2018). Object Detection in Real-Time Systems: Going Beyond Precision. *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 1020–1028. https://doi.org/10.1109/WACV.2018.00117
Original URL	https://ieeexplore.ieee.org/document/8354221
Source type	Scientific Conference Paper
Keywords	Object Detection, Real-time detection, CNN, mAP, evaluation criteria

Summary of key points + notes (include methodology)	This study investigates some new metrics, other than mAP and fps, for evaluating real time object detection systems. A select number of the most common object-detection frameworks are compared in terms of their Frame Processing Rate (FPR).
	
	Notes:
	- Most object detection algorithms are analyzed with precision and recall metrics over IoU
	- May not be good for evaluating real-time systems where more detections is usually better
	- Early detections should be rewarded
	- Decision distance can be analyzed based on when the model can detect something how far away
	- This study evaluates pedestrian detection in three categories
	  - Object Detection
	  - Tracking
	  - Evaluation metrics
	- Evaluated detectors over two conditions
	  - Infinite resource setting
	    - Find the limit of how good these object detectors can do
	    - Detections are run offline and then fed through tracking algorithm
	  - Resource constrained setting
	    - Only processes limited number of frames
	    - Constraints of cost, energy, performance
	      - Which has the most significant effect?
	- Used Multi-object Tracking Challenge training dataset
	- Used pixel values to predict the presence of people
	  - Faster people used less intermediate detections
	  - Slower people used more intermediate detections

	- Used row number to say how far people are (Figure below)
	- Four run configurations
	  - CPU + GPU
	  - High end CPU
	  - Low end CPU
	  - ARM Processor
	- Results:
	  - Entropy of the video effects a lot the accuracy – the speed of people change tracking algorithm a lot
	  - mAP is a good criteria of performance if all detectors ran the same mAP
	  - More false positives at longer distances / smaller row numbers
	  - Accuracy depends on how fast a neural network is, not only how big it is and its mAP
	  - SSD MobileNet performs well on lower power
	  - Smaller applications need smaller models who can run much faster
	  - Higher mAP may not be best choice when power and time is limited
	  - Faster detectors perform better on smaller platforms

Research Question/Problem/ Need	How can evaluating object detection real-time systems be improved?
Important Figures	 This figure shows how the lesser the row number the farther away the person is. This is necessary to scale how fast people are moving in the frame.
VOCAB: (w/definition)	FPR - Frame Processing Rate - Rate at which frames are being processed by the detector

Cited references to follow up on	A system for real-time detection and tracking of vehicles from a single car-mounted camera - https://ieeexplore.ieee.org/abstract/document/6338748 How Far are We from Solving Pedestrian Detection? - https://ieeexplore.ieee.org/document/7780510
Follow up Questions	1. How would the EfficientDet detector compare against the tested models? 2. Would post-quantization of models make accuracy decrease in real-time application? 3. How does video size affect detection accuracy?