Traffic Lights Detection and Recognition using Machine Learning or Deep Learning

Traffic lights detection is essential for drivers and driverless vehicles. The motivation is to provide sustainable, safe, convenient, and congestion-free transport. The challenges of this AI development include infallible recognition of traffic lights, signs, unclear lane markings, pedestrians, etc.

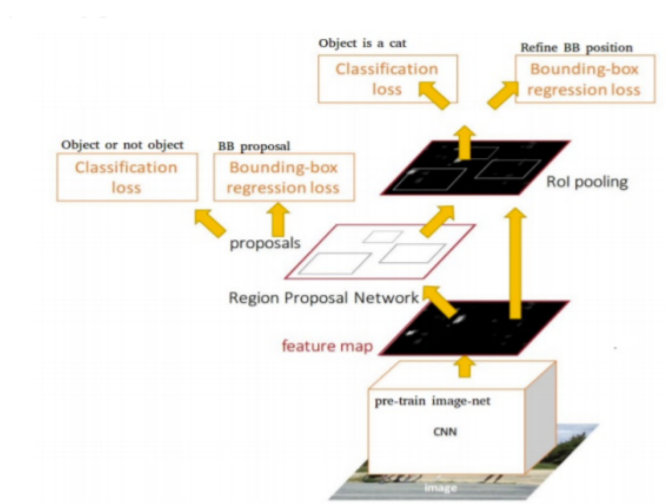
These problems can be overcome by using Deep Learning, Computer Vision, methods including R-CNN, the Inception model, Yolo, and Reinforcement Machine Learning.

Methodology

Faster R-CNN

Faster R-CNN identified the region proposal step as the bottleneck for real-time object detection and proposed a way to combat that.

From Rural. K [1] study, the dataset is from Indian streets. The authors adopted the Faster R-CNN Inception-V2 model. The model was trained on the NVIDIA GEFORCE 940M GPU using TensorFlow. The computation time is costly. The training included 120,000 iterations which took nearly 12 hours, with a loss in the range of 0.01. The model successfully detects the traffic light and classifies it according to its type.



Learning-based methods are also widely adopted for image detection. Girshick et al. brought forth the framework of region proposal-based CNN (called R-CNN). Later, Fast R-CNN and Faster R-CNN were proposed to improve the performance of object detection. YOLO is one of the ground-breaking studies on deep regression networks for object detection.

Generalized Harr filter based CNN

The deep-learning network comprises 11 convolution layers, four max-pooling layers, and one softmax layer. For the reduction of memory consumption, several low-level features are shared by localization and classification channels via conv1~ pool4. The authors use Harr-like filters in object detection owing to their strong representation and high efficiency instead of using a fixed number of rectangles and configuration types.

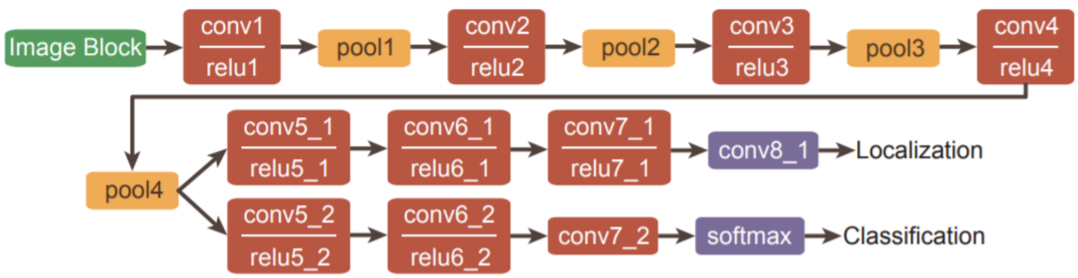
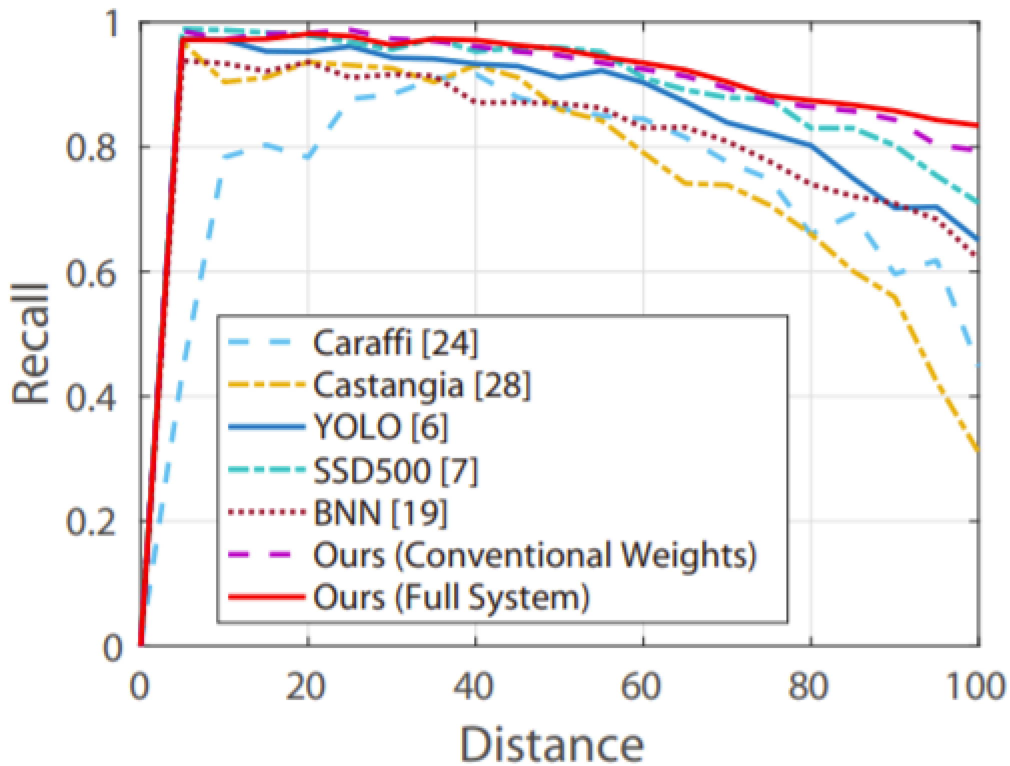
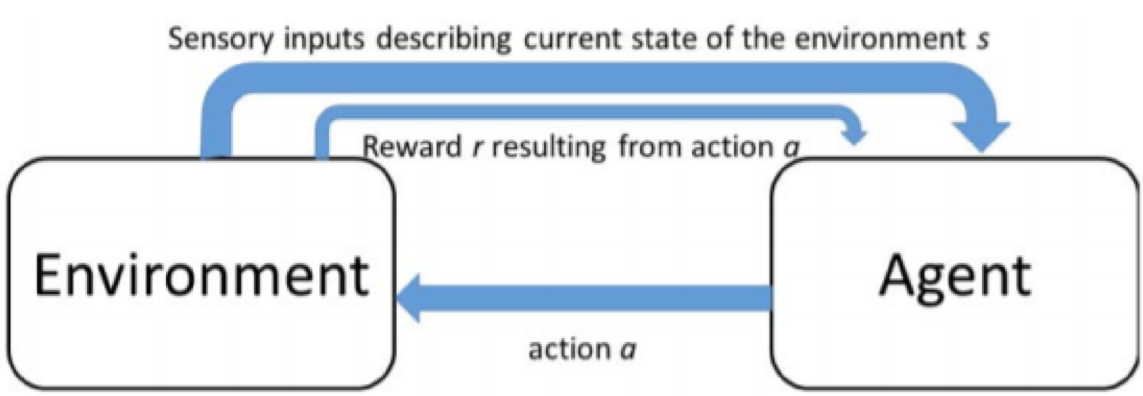


Fig. 1. Architecture of the Deep Networks.

Performance evaluation of different vehicle distances indicates the recall drops significantly for longer distances.



From Keyu Lu's [2] study, the authors use a generalized Harr filter-based CNN, which is suitable for object detection tasks in traffic settings. The From Sahar. An etc. [3], the authors focus on Reinforcement Learning and Q-learning. Reinforcement learning is a subfield of valuable machine learning in unknown environments. This learning method exploits environmental feedback as a reward or punishment. In reinforcement learning, the learning algorithm is simple, and an agent can learn an optimal policy without predicting the impact of its actions. The Q-learning algorithms store the expected reinforcement value associated with the watch state-action pair represented by Q(st, at)



One of the most common aims in traffic light signal control is to increase the number of vehicles crossing the intersection per unit of time. Traffic is a dynamic setting, so a flexible approach to the management of traffic signals is necessary. The proposals include a transition model that estimates the waiting time of cars in different states. A function approximation method is applied as a mapping between shapes and signal timing. The applied reinforcement learning is suitable to predict the overall value of the optimization objective given the vehicle's states.

YOLO:

Deep learning techniques have recently begun achieving highly robust results for object detection. One such technique is the "You Only Look Once" (YOLO) family of Convolutional Neural Networks (CNNs) that can achieve the highest quality results with a single end-to-end model that can perform object detection in real-time. As the name suggests, it's a very efficient object detection technique.

Included in this report is a link to a tutorial that will teach users about the YOLO-based CNN family of models for object detection, including the most recent version of YOLO called YOLOv3. Furthermore, it will include the best-of-breed open source library implementation of YOLOv3 for the Keras deep learning library and use pre-trained YOLOv3 to perform object localization and detection on new photos. [4]

Using YOLO for Object Detection:

Object detection is a difficult task requiring successful object localization to locate and draw a bounding box around objects in an image and object classification to predict the correct class of thing localized in each respective bounding box. This approach uses a single deep CNN and divides the input into a grid of cells that each predict a bounding box and object classification, creating a large set of bounding boxes combined to make a final prediction in the post-processing stage.

The result is a highly accurate model. While not as precise as some other CNNs, such as Region-Based Convolutional Neural Networks (RCNNs), YOLO-based CNNs are highly efficient, producing results in real-time.

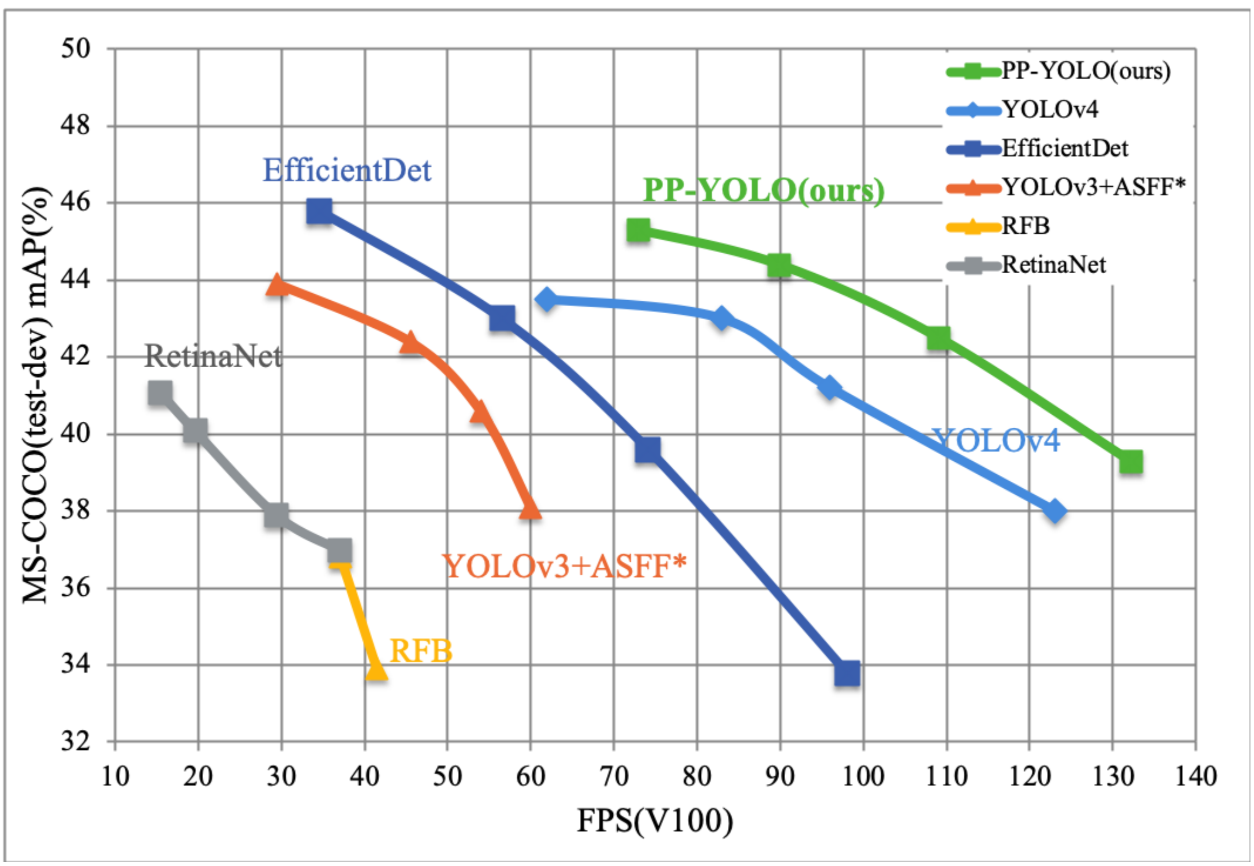
Single Shot MultiBox Detector (SSD)

Single Shot MultiBox Detector (SSD) removes the region proposal step often present in other approaches.

Instead, a set of default bounding boxes in many different sizes and aspect ratios is used. The network products the presence of an object in those bounding boxes, as well as adjustments to the bounding box

Summary:

Methodologies for traffic light detection include several Convolutional Neural Networks, including Regional Convolutional Neural Networks (RCNN), Fast RCNN, Faster RCNN, Mask RCNN, You Only Look Once (YOLO), and Single-Shot MultiBox Detector (SSD). While these methodologies can be pretty effective, problems have emerged in recent years while detecting different states because of a lack of balanced datasets. This is due to the high prevalence of red traffic lights relative to other lights. This problem highlights the need for robust data. One of the many challenges in autonomous vehicle safety is accurate traffic light detection. Real-time detection of the state of traffic lights is the ultimate goal to deliver a robust and precise traffic light model.



Reference:

[1] https://machinelearningmastery.com/how-to-perform-object-detection-with-yolov3-in-keras/
[2] http://csl.arizona.edu/sites/default/files/Yolov3_0.pdf

[3] https://ywpkwon.github.io/pdf/18itsc.pdf
[4] https://towardsdatascience.com/yolo-v4-or-yolo-v5-or-pp-yolo-dad8e40f7109

Relationship Between New Features and Risk Events - Running Lights and Cornering

Methodology: collect stats/articles for the relation between new features and risk events
Question: What features should be added in running lights and cornering?

The current features to estimate the motor scores include brake, acceleration, stop situation, tailgating, cornering, and vehicles. We want to add features essential to motor scores, specifically emphasising features such as running lights and cornering.

Features in the event:

```
EVENT_SEVERITY_TABLE: Dict[str, float] = {
    # brake and accel event severities
    "brake_6mph": 1,
    "brake_halfg": 2,
    "brake_oneg": 3,
    "accel_6mph": 1,
    "accel_halfg": 2,
    "accel_oneg": 3,
    # stop sign event severities
    "full_stop": 0,
    "rolling_stop": 0.5,
    "no_stop": 3,
    # tailgating event severities
    "tailgate_time_to_collision_1.5-1.0s": 0.75,
    "tailgate_time_to_collision_1.0-0.5s": 1.75,
    "tailgate_time_to_collision_<0.5s": 3,
```

```
    # cornering event severities
    "cornering_6mph": 1,
    "cornering_halfg": 2,
    # vehicle safety system event severities
    "vss_abs": 1,
    "vss_traction": 1,
    "vss_stability": 1,
}
```

Running Lights

Nearly a third (28%) of crash fatalities at intersections with traffic lights are due to drivers going through a red light. In the United States, Arizona has the highest rate of red-light running deaths, while New Hampshire has the lowest rate. About 46% of such fatalities were passengers or people in other vehicles, while more than 5% were pedestrians or cyclists. Over 35% of the fatalities were the drivers who ran the red light.

New feature considerations:

- Speed - Effects of speed on crashes and crash severity
- Speed limitation - the maximum speed limit of the road
- Presence of alcohol, medicinal, or recreational drugs
- Color blindness
- Poor eyesight of road users
- Driving in darkness
- Running a red light at an intersection (counts for a third of crash fatalities)
- Mounted overhead (How the traffic light is mounted)
- Ego Driver going forward (no turns)
- Driver fatigue, stress and emergencies
- Driving too fast and unable to stop the vehicle

The above feature lists derive from reported essential factors contributing to the fatality of running lights and corner events. We can classify four features in the following categories: the environment/vehicle and the other is related to the drivers' conditions and drivers' demography.

Related to environment/vehicle

- Speed of vehicle
- Speed limit of the road
- Poor eyesight

- Driving in darkness
- Weather conditions
- Running a red light at an intersection (counts for a third of crash fatalities)
- Mounted overhead (How the traffic light is mounted)

Related to drivers

- Presence of alcohol, medicinal, or recreational drugs
- Driver fatigue
- Driver inattention
- Ego Driver going forward (no turns)
- Driver fatigue, stress and emergencies
- Driving too fast and unable to stop the vehicle

Driver demography

- Gender
- Age
- Driving experience

Distracted Driving:

Types of Distraction

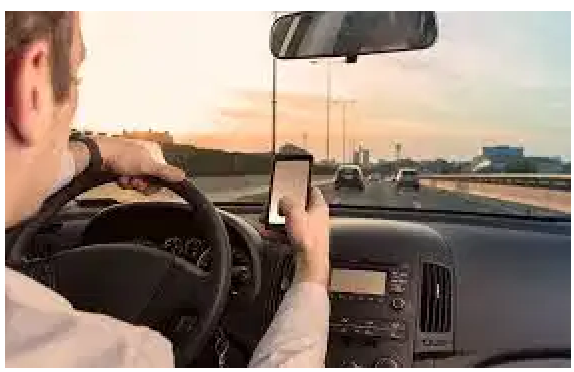
Anything that takes your attention away from driving can be a distraction—sending a text message, talking on a cell phone, using a navigation system, and eating while driving is a few examples of distracted driving. Any of these distractions can endanger you, your passengers, and others on the road.There are three main types of distraction:

- Visual: taking your eyes off the road
- Manual: taking your hands off the wheel
- Cognitive: taking your mind off driving2

<u>Illegal Red Light Example:</u>

Not stopping at red light:

Distracted Driving:

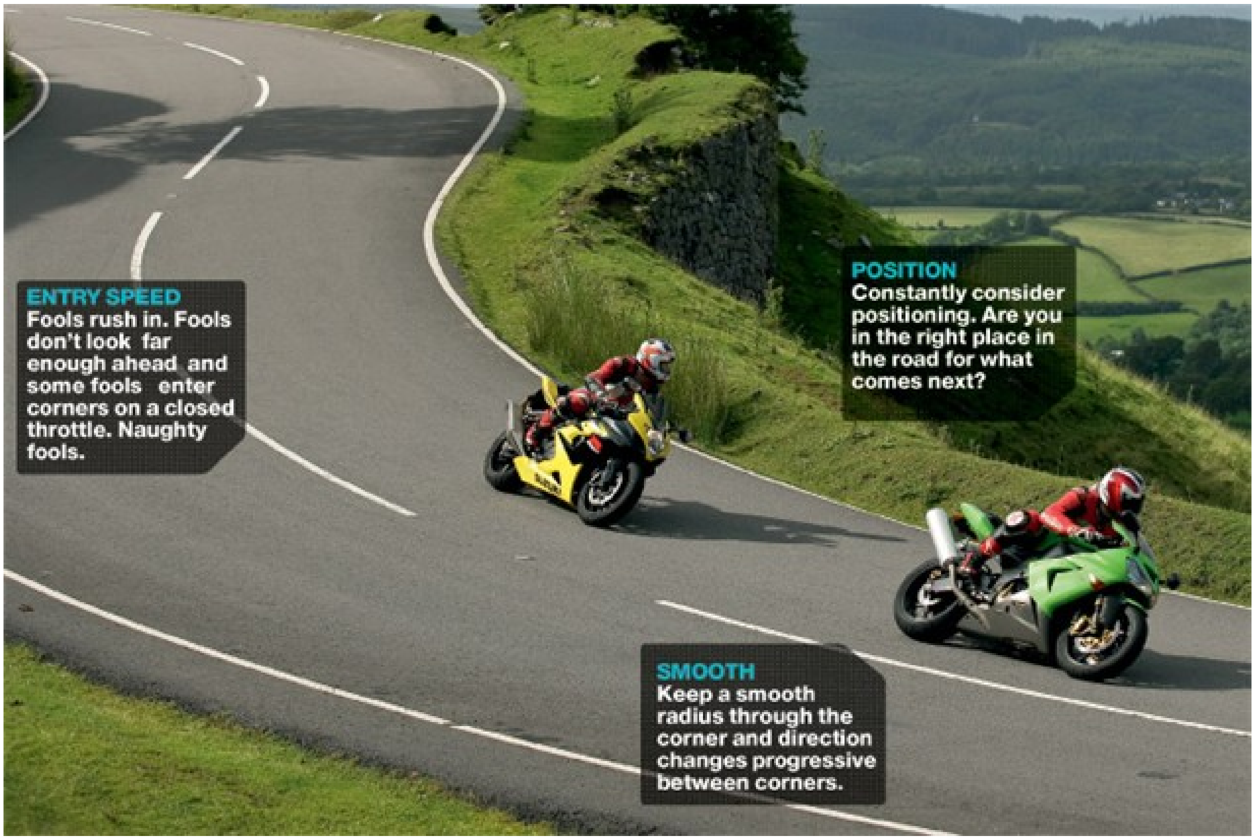


Cornering

New feature considerations

- Off path or out of control on curb [1]
- “Run off road on a curb” - pushed/pressured “off road” by another vehicle [1]

- Accidents on curves [1]
- Left cornering events - likely left turns
- At intersections only
- Right cornering events



From Reckless cornering fatality statistics in an Australian study,

Australian states don't record reckless cornering as a behavioral cause of accidents. However, New South Wales, Western Australia, and Victoria all record and report data on accidents that occur on or around corners or curves.

The following table presents the number of fatalities recorded for these accidents as a percentage of road fatalities for the relevant year, where data is available.

	2012	2013	2014	2015	2016	Avg
NSW1	22%	27%	22%	25%	22%	24%
VIC2	8%	11%	9%	10%	14%	11%
WA3	28%	24%	27%	28%	–	27%

1NSW fatalities recorded as "Off path or out of control on the curb." 2VIC fatalities recorded under "Run off-road on a curb." 3WA fatalities recorded as "Accidents on curves."
This article addresses the cornering events based on statistical analysis. The authors identify cornering events in NSW, VIC, and WA from 2012 to 2016,
WA experienced the highest number of cornering events among the three places. It seems worth investigating the typical locations of cornering events and include the pertinent features in the motor score estimation.
This is an extract from another article showing the dangers of speeding and lists the top 10 dangerous cities for speeding. We can collect the information of town vs. motor score to determine the weighting factor of speeding better.

References:
https://www.who.int/violence_injury_prevention/road_traffic/activities/roadsafety_training_manual_unit_2.pdf
https://ubicar.com.au/blog/the-fatal-impact-of-reckless-cornering/
https://www.iihs.org/topics/red-light-running
https://www.npr.org/2019/08/29/755441473/deaths-from-red-light-running-at-a-10-year-high-aaa-study-finds
Top 10 Dangerous city for speeding: https://ncsrsafety.org/
https://ncsrsafety.org/national-speed-fatality-map/