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Autonomous Cars: Developments, Technical Challenges and Opportunities

Jacob Joel
Altran

Abstract: Machine Language is being used in technological advancement in all the domains nowadays, automotive domain being one of them. But practically implementing the ML has its own challenges in the automotive domain since it concerns the lives of people in the car, pedestrians and other vehicles. Even though AI had been in existence for long, the challenges are so high that still we are not in a stage where Level 5 autonomous cars can be deployed in any part of the globe. Here we look into the various challenges faced in the Autonomous cars and different implementations performed.
Index Terms: Autonomous cars, Artificial Intelligence, Machine Learning, neural network

I. INTRODUCTION

The increase in population and standard of living has led to a multifold increase in cars and rising complexity on the roads. In turn it has resulted in higher number of accidents wherein human error had always being a constant factor; human error itself contributing to 94% of the accidents. [1]

Autonomous cars had been in existence from 1980's and machine learning also had been newly introduced. There are lots of challenges being faced in this area with respect to its technological advancement and hence regulation and safety standards are yet to be finalized and agreed upon. Many of the OEMs are at its inception stage wherein Level-0-2 is being monitored by human being and Level 3-5 is where the vehicle is responsible for the environment monitoring. Tesla claims it would achieve Level 5 [2] by the end of 2021, while other OEMs are also in the race for it.

II. CHALLENGES FACED

In the present scenario even after rigorous traditional testing for the software and hardware, every year millions of vehicles are recalled from different regions of the globe. Moreover, in the case of autonomous cars, we are working on a black box while working with ML algorithms [3]. Few of the key challenges [4] which are being faced and which could vary from region to region are:

A. Road Conditions
B. Traffic conditions
C. Weather conditions
D. Accident Liability

Road conditions could vary from place to place and countries would employ either left-hand drive or right-hand drive. The training sets also needs to be implemented based on the various regions of the globe.

Various hazards can occur like the weather and environmental hazards for e.g. rains, fog, storm, snow, smoke and tornadoes could affect the performance of the sensors and lidars. Different scenarios in the traffic conditions like cars violating traffic lights and crossing the signals or pedestrians ignoring the zebra lines and crossing the road could affect the behavior of the autonomous cars. There could be even untoward incidents like cattle's or deer and moose crossing the roads or it could even be locust attacks.

A. Future of Predictive Diagnostics in Asian Countries

When it comes to Asian countries, there are lot more other challenges and constraints, especially in countries like India where the roads could be curvy, narrow, with speed breakers or with abrupt turns and public not adhering to traffic rules. India ranked 20th in AVRI (Autonomous Vehicle Readiness Index) among the 25 countries. [5] Due to these congestion and other hindrances, vehicles in metro cities take 1.5 hrs more to commute compared to other parts of the globe for the same distance. Here in such conditions, more ADAS features such as traffic jam assist and collision avoidance type of regression tests needs to be more deeply looked into.

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Typical scenarios even need to be understood such as protests or roadblocks being held. How is learning affected when traffic signals are stolen or how does machine learning infer from the placards in the protests or even its behavior when effigies as well as religious processions are being carried? On the other side, countries such as Singapore also in Asia has been ranked second globally (and first in Asia) when it comes to AVRI by KPMG Global.

Even faults can be induced knowingly or unknowingly in the system, for example if jammers are placed in any area it could affect the functioning of the radar or other devices functioning in the car. Here also in case of adverse conditions like a tyre burst or the malfunctioning of a component or software behavior too, the system needs to provide corrective measures or bring the car to a safe state.

III. TECHNICAL CHALLENGES FACED

Challenges faced are innumerable since we are talking about Stochastic systems. From the technical perspective some of the major issues being faced are:

A. Standard Designs or Architectures

Distributed architecture will be followed for the different systems involved, hence failure in sensor response of one system could adversely affect the system functioning of the other systems or decision making. If we look from the hardware perspective following are the hardware sensors being utilized mainly:

1) 4 cameras for traffic signal, lanes, vehicle and pedestrian, curb & drivable area as well for image recognition
2) 1mm RADAR, 14 layer and 32-layer LiDAR for curb and drivable area, pedestrian and vehicles and unknown obstacles are being used. Mostly 6 long-mid radars are placed at the front and back and 4 short range radars are placed at the corners. It is used also for enhancement for position of Simultaneous Localization and Mapping (SLAM)
3) Ultrasonic sensors used for parking assistance and blind spot detection
4) GPS measures position of the vehicle and
5) Inertial Measurement Unit (IMU) which measures the acceleration and rotational movement of the vehicle using gyroscope and accelerometer.

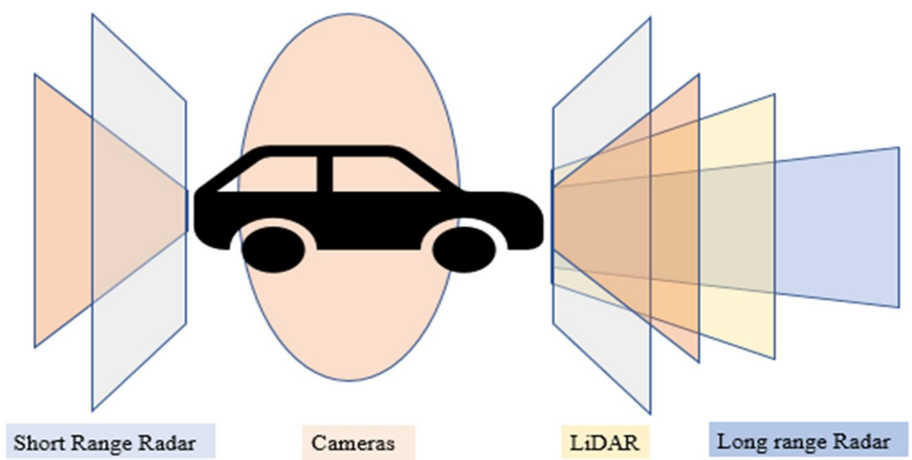

Fig. 1: Sensors in Autonomous Cars

This set being used is closest to Google's. while Tesla does not employ a LiDAR. From the software perspective Autosar lite is being used in Autonomous cars.

B. Computational Complexity

While GPUs or TPUs [6] are being used for computations, several systems have to simultaneously work to achieve its purpose for eg. When a vehicle is moving inside a tunnel GPS might not give accurate results and IMU (inertial measurement unit) results needs to be taken into consideration. LiDAR's could also introduce noise in the case of fog, rains or dust. Similarly, 8 1080p cameras would generate around 1.8GB of data per second. Hence localization, object detection and tracking employ CNN [7]. Also for eg. object detection utilizing AlexNet deep loading workloads needs to process 2800 images/s.

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C. Accuracy & Reliability affecting Black Box Behavior

ML techniques are difficult to explain and interpret. The training set should be exhaustive and extensive in nature, at the same time we have to be cautious of not over-fitting the model. Here in the case of autonomous cars, the frames are moving and changing rapidly along with the speed of the autonomous vehicle. For eg, while taking the pedestrians into account various possibilities has to be looked into, pedestrian walking, changing directions and even on skateboard, crutches as well as on wheelchairs. Training of AI algorithm takes time which could lead to failure in adverse conditions. Also the accuracy and reliability can vary due to different climatic conditions and scenarios from region to region.

D. Safety

Majorly five distinct areas of safety [8] is covered:

1) Behavioral safety
2) Functional safety
3) Crash safety
4) Operational safety
5) Non collision safety

Event data recorders need to be in place, so that data can be retrieved in case of accidents or other unforeseen incidents. These criteria are being met by Waymo also for their development.

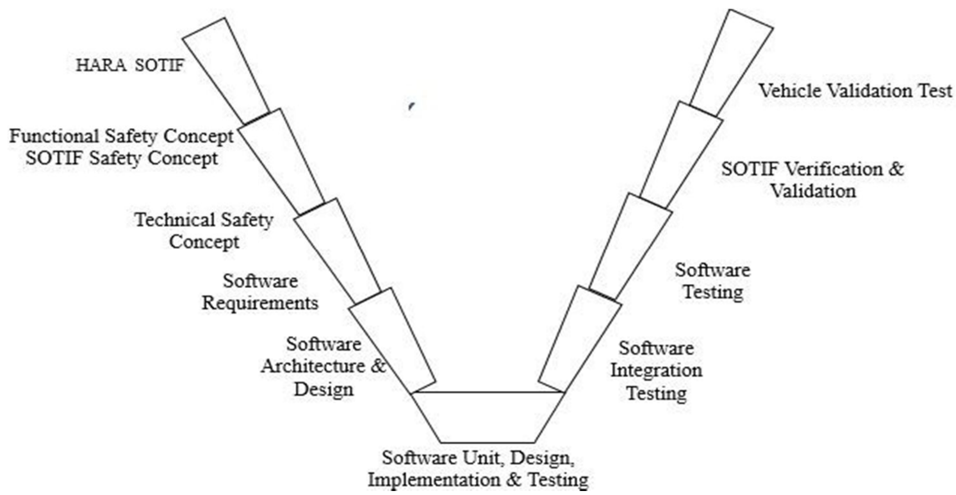

Fig. 2: V Model

While considering electrical components for Autonomous cars ISO26262 and IS/PAS21448 are in place which takes the requirements and performs validation. The hazards and scenarios are taken into consideration based on which the failsafe mechanism is being implemented. Safety needs to be incorporated at different stages like safety by design and utilizing SOTIF as well as Functional Safety standards. [9] Safety by design primarily uses FMEA, FTA and other techniques. Since Safety is being also related to Security, hence

E. Security & AI

Cyber security plays an important role in achieving Safety Standards, when Vehicles are moving from L2 towards L5 level. Autonomous vehicle has to be in compliance with SAEJ3061. With the advent of V2V communication, self-driving cars could be hacked from external vectors such as other cars or accessing OBD II remotely. Since the data is uploaded and retrieved from the cloud, also the data is transferred between connected cars, hence the security could get comprised and get exposed to different vulnerabilities. In order to avoid the same more rigorous penetration tests need to be done and avoid all kind of remote possibilities. It can be introduced for eg. with fake lanes or understanding how autonomous cars behave when tested by exposing it with stickers or graffiti. Also fault injections are being done in order to cover the scenarios of ageing sensors or unpredictable events occurring. [10] Here the image could get blurred due to ageing camera lens or tiny flecks could get injected into the system due to noise. To counter such practical issues small perturbations could be introduced into the raw input of policy. It could be in the form of black box or white box attacks

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F. Ethics & AI

Ethics & AI is a cross discipline between human psychology, machine learning and social policies. Regulations are being implemented by different countries and so is the technology getting more mature. Autonomous vehicles may sometimes have to decide on preferential killing ie. killing of one person over another. For eg. If a narrow road is being blocked by man on the left and a child on the right; to which side should the Autonomous car swerve in order to avoid hitting one of the persons immediately. Should AVs be taught to ignore gender in cases involving inevitable accident? In this regard Germany had already formulated ethical rule which states. In the event of unavoidable accident situation, any distinction based on personal features (age, gender, physical or mental constitution) is strictly prohibited. It is also prohibited to offset victims against one another"

Fig. 3: Adversial Attacks

[11]. In a poll too "people preferred self-driving cars to not consider gender (92.6%), fitness (88.8%) or status (84.7%)."
[12] Out of Distribution (OOD) models are provided apart from the training sets to bring more confidence into the system. Technology is even directing towards eye contact in a car in order to decipher whether there the pedestrian will cross the road or turn back.

IV. MACHINE LEARNING IN AUTONOMOUS VEHICLE

A generic set of training data would provide varied results across different regions of the globe and also different OEMs could behave in a unique manner. Here scenarios need to be understood wherein how the system would behave when training data is fed with white swan pictures because in reality there are black swans [13] too and how it would respond when encountered with unfamiliar data. Even unpredictable scenarios could happen when there is a locust attack in a particular area in turn affecting the quality of the images received from sensors and cameras.
Semantic segmentation at pixel level will be performed to classify objects into different categories of pedestrian, vehicle, vegetation etc. In neural networks Relu is being currently employed which supersedes the Sigmoid function and is an old school. Also for detecting lanes Hough transform (ARHT) is being used. Machine learning algorithms mostly used in Autonomous cars involve:

1) Localization & Mapping -SLAM
2) Sensor fusion & Perception
3) Navigation & Decision making

SLAM implementation would check the corners of an object from one frame to another to identify the object of the previous frame. For sensor fusions the inputs are taken from the different sensors and if there is a discrepancy then current observation and future prediction are taken into account by the use of Kalman filters
Most commonly AI Algorithms being Employed are:

A. Support Vector Machines

The most popular and most tested methods used for road sign recognition are the SVM methods. The support vector machines (SVM) with histograms of oriented gradients (HOG) and principle component analysis (PCA) are mostly used recognition algorithms in ADAS. The SVM can be used as an initial verification and double check with trained neural networks. SVM as a classifier would determine whether a pedestrian could pose a threat to the autonomous car or not. Such double checks are quite useful when the cars are travelling at high speeds. Even for situations such as lane change and pattern recognition also SVM [14] algorithm is being employed.

B. YOLO (You only look once)

Yolo is 12 layered and it compensates for its incredible speed of 45 frames per sec, even though it is poor in performance. Time to frame using YOLO model is 0.0222 s wheras Simplenet takes 0.09 s YOLO can used in combination with SVM to enhance the classification performance. Based on the performance if the SVM is able to classify the vehicle or a pedestrian with better performance then SVM is chosen, otherwise if YOLO is able to identify the pedestrian with better performance then the algorithm chosen is YOLO. [15] In addition YOLO is able to see the entire image and does not suffer from the issues in R-CNN like mistaking background images for objects.

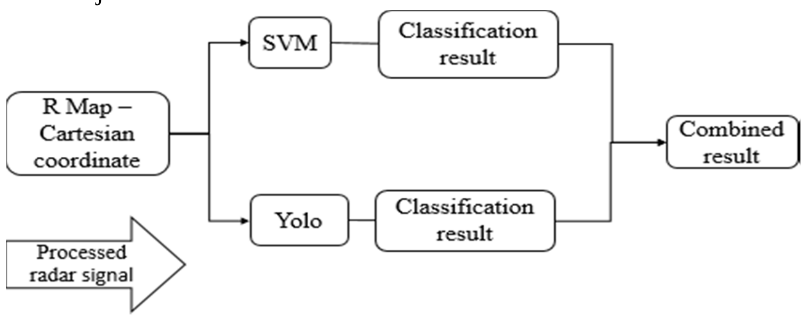

Fig. 4: SVM, Yolo Classification Model

C. RCNN & Fast R-CNN

CNN is used not only in image classification but also for object detection and semantic segmentation. In the case of RCNN it uses RPN which provides cropped and warped images to CNN layer, hence RPN runs CNN for each of them, later on which the classification is done using SVM. In fast RCNN [16] the advantage is that the CNN is run first once and then looked for RPN, thus reducing the time for running separate CNN for each ROI. Fast R-CNN works on region proposal and it employs MobileNet architecture to build base convolutional layer. RPN makes it possible to detect multiple classes of objects along with different aspect ratios. There is Faster RCNN also which takes lesser time for execution than fast RCNN [17]

V. CONCLUSIONS

Although immense technological advancements had been done in autonomous cars industry, lot more still needs to be done before it can be commercialized and rolled of into the market by various OEMs. Standardization of procedures for testing is still to be accepted and agreed upon and before it could be deployed on to the road. On the one hand there are technical challenges such as sensor management and decision making, actuation and security as well as there are other issues on the diversity and cost of the vehicles, policy and ethical consequences. Even though the researches have proved to be reaching us to our goals but still it is still early to speculate when it comes to the commercial phase, which will be overcome in the days to come.

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