

*Artificial Intelligence Tests for Certification of
Autonomous Vehicles*

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Vehicle automation is receiving strong support as a transformational strategy to improve road safety. Autonomous vehicles (AVs), in particular, and their potential use for shared rides as a form of public transport for first and last-mile travel, have the potential to address many of the global challenges facing urban mobility, transform our communities and provide significant road safety, economic and social benefits (Dia et al, 2020).

While there is considerable excitement about their potential, regulators around the world still face big challenges in developing uniform technology-agnostic AV tests to evaluate their performance based on road safety readiness and outcomes. Vehicle manufacturers and technology providers, who are investing heavily in the Artificial Intelligence (AI) self-driving software and sensors, have already started to trial their highly automated vehicles on public roads but without meaningful guidance from regulators. They remain largely self-regulating particularly with the means by which they determine if their AI software and sensors are safe enough for open roads (Marshall, 2019). The regulators also don't have robust safety evaluation criteria or procedures for making such determinations. This has resulted in some unintended consequences over the past few years, with trials on open roads causing numerous road crashes including a fatality in the USA when a vehicle driven in an automated mode killed a pedestrian (Dia, 2018).

In California, where AV trial permits have been issued to a large number of companies to test their vehicles on public roads, the readiness of self-driving software (measured by the software's rate of disengagements per distance traveled) was found to vary significantly between different providers (in some cases by a factor of 5,000) but regulators remained without reliable means to benchmark self-driving performance (DMV, 2021). These issues are further complicated by the fast pace of developments in the industry and the adoption of different types and configurations of sensors and algorithms for developing the AI software, making it difficult for regulators to develop uniform tests that are applicable to all different automation and technology variations and combinations. To be effective, AV regulations under uncertainty requires rigorous yet flexible and agile approaches focused on road safety outcomes without stifling innovation. If such tests to certify AV performance are not developed now, regulators risk impacting public safety as the industry presses ahead with more open road trials.

When reviewing the current state of vehicle automation development and readiness, a key immediate issue for regulators becomes clear. Legal opinions by road safety regulators such as the US National Highway Traffic Safety Administration, already consider the AI self-driving software that controls autonomous vehicles to be the “driver” for regulatory purposes (Marshall, 2019; Dia, 2016). And therein lies the challenge. Which procedures can be used to verify the software's safety readiness and that it has been trained to an adequate level and compliance? Should the AI self-driving software pass a benchmark test, developed specifically for autonomous vehicles, before it can be recognised as a legal driver? Should there be a gradual licensing or certification scheme where different levels of software readiness would be required for certain road or weather conditions? Who should develop such tests and what should they include?

This short article aims to answer these questions by presenting an embryonic concept for a comprehensive testing framework that is inspired by advances in the assessment of vision-based AI systems (Geman et al, 2015; Dia, 2016) and human driver licensing criteria (Cummings, 2019). This framework could serve as a potential solution to address these challenges and can help regulators assess AV readiness before trialing or deployment on public roads. The article also provides reflections on the topic and a reality check on why AV deployment will remain hindered until these issues around their safety readiness are properly addressed.

It is important to start by acknowledging some complexities of autonomous driving systems (Bagloee, 2016). The AI self-driving software, considered the brain of intelligent vehicles, is developed using “deep neural networks” which include millions of virtual neurons that mimic the human brain. The onboard computers that process this information in real-time have impressive supercomputing power packed inside hardware the size of a laptop computer.

The neural networks do not include any explicit programming to detect objects in the world. Rather, they are trained to recognise and classify objects using millions of images and examples from data sets representing real-world driving situations collected either from field studies or simulations. Object detection alone, however, does not encapsulate all aspects of the driving task which is much more complex than object detection and classification. Also, detection is not the same as understanding. For example, if a human is driving down a suburban street and sees a soccer ball roll out in front of the car, the driver would probably slow down or stop immediately since a child might be close behind. Even with advanced AI, would a self-driving vehicle know how to react? What about those situations where an accident is unavoidable? Should the car minimise the loss of life, even if it means sacrificing the occupants, or should it protect the occupants at all costs? Should it be given the choice to select between these extremes? These issues are not routine instances but are considered as ‘edge cases’ that are important to get right. Lacking a large set of examples, they would be relatively resistant to deep learning training. Therefore, how can such situations be included in a benchmark test?

The key premise of our proposed certification framework is based on the Turing Test. The question of whether a machine could “think” has been an active area of research since the 1950s, when Alan Turing first proposed his eponymous test. The basis of the Turing Test is that a human interrogator is asked to distinguish which of two chat-room participants is a computer, and which is a real human. If the interrogator cannot distinguish a computer from a human, then the computer is considered to have passed the test. But the conventional Turing Test has many limitations and is now considered obsolete. In more recent research, however, a Visual Turing Test (Figure 1) has been developed in which computers would answer increasingly complex questions about a scene which would be more suited to today’s AI evaluations (Geman et al, 2015). The test calls for human test-designers to develop a list of certain attributes that an image might have. Images would first be hand-scored by humans on given criteria, and a computer vision system would then be shown the same picture, without the “answers,” to determine if it was able to pick out what the humans had spotted. A modified Visual Turing Test can potentially be used to test the self-driving software if it’s tailored to the multi-sensor inputs available to the car’s computer, and is made relevant to the challenges of urban driving. Rather than evaluating the AI-based computer vision system only by its object detection and classification accuracy, a Visual Turing Test can provide far richer descriptions about images and their safety context (Geman et al, 2015).

Another key differentiating aspect of this approach is that it would be based on a hierarchy of AI-based digital tests combined with human driver licensing criteria (Cummings, 2019). A graduated licensing scheme for AVs will first be identified to provide clear restrictions on



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|---|--------|
| 1. Q: Is there a person in the blue region? | A: yes |
| 2. Q: Is there a unique person in the blue region?
(Label this person 1) | A: yes |
| 3. Q: Is person 1 carrying something? | A: yes |
| 4. Q: Is person 1 female? | A: yes |
| 5. Q: Is person 1 walking on a sidewalk? | A: yes |
| 6. Q: Is person 1 interacting with any other object? | A: no |
| ⋮ | |

Figure 1: Sample questions posed in a Visual Turing Test. Wikimedia Commons, CC BY-SA

permissible conditions under which a licensed AV is allowed to operate. This could include, for example, criteria inspired by the graduated driver licensing system for human drivers e.g. L (Learner permit), P (Provisional) and F (Full) license. The results from the AI digital tests are then used to decide the level of licensing. For example, if the results show that the self-driving software is well-developed and can be tested on open roads with no restrictions and without human intervention, it will receive a Graduated License Level “A”. If the results show that it should only be tested during daylight and good weather conditions, it will receive license level “B”. Similarly, if the results show that it can only be tested in confined environments, then it will receive a lower certification such as license level “C” where the vehicle may only be used inside a physical testing facility, with a human test driver and no public interaction. Together with the AI-digital test, the combined approach provides rigorous and transparent

tests to allow regulators to determine which self-driving systems are ready to be tested on open roads and under which conditions.

While the proposed concept seems simple, it represents a radical departure from existing self-driving software evaluations that are mainly based on object detection. However, the proposed tests which are crucial for certification of safety-critical systems in autonomous vehicles are quite complex and would be challenging to put together requiring years of research and development. This is further complicated by the ethical questions of self-driving cars and other challenges in managing the interface between driver and computer when an acceptable response requires broader knowledge of the world. It is further suggested that such evaluations can be integrated with mixed-reality test environments where the proportion between virtual and real testing can be varied for individual dimensions of the test setup. Research would be needed to test common standards to describe data formats for environment representation and driving scenarios to perform data exchange in real time thus comprehensively implementing the test environment.

In summary, policy and regulations will remain the last major hurdle to widespread deployment of AVs. As with other fast-moving innovations, policymakers and regulators who are struggling to keep pace need to be supported by rigorous and transparent certification tests for consistent evaluation of the AV safety readiness regardless of the technologies used. Regulators also need to engage the public to create a legal framework for compliance verification that is easily understood and accepted while ensuring that it remains flexible but robust. The testing concepts we present in this paper will go a long way to addressing these challenges and progressing the widespread deployment of a very promising technology that could reduce road crashes drastically and save millions of lives each year. Without this, the potential promise of fully autonomous vehicles would not be realised.

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