

The Importance of Data Quality When Training AI

With artificial intelligence (AI) on the rise and making its way more and more into our daily lives, companies of all kinds have also started exploring what AI has to offer. In imaging applications, AI has become widespread in assisting with the analysis of complex images. The challenge in deploying a trustworthy AI-based system is not necessarily just with the machines themselves. The quality of the training that can be provided to the AI can also have a major impact.

The Prerequisite for a Trustworthy AI

A crucial factor in properly training an AI is the quality of images that are used in the process. Instead of focusing on resolution, even though clarity in images is useful, quality in AI image sets is strongly proportional to variation. For example, in a traffic application an AI needs to be trained to understand various vehicles. To do this, a data set of images must be provided to visualize what the AI should be looking to identify. In Figure 1, images of different vehicles are captured as they pass by the camera. By including a variety of vehicle types in these images, the AI can be better trained for the types of vehicles that will likely show up in a real-world scenario. This is done by flagging each image to provide context for each vehicle.



Figure 1 – A set of images used for training an AI for traffic imaging.

Once enough images are gathered to show a significant variation in the data, the training can start. This produces an AI that can recognize variations in images by itself. The quality of the data used to feed the system is crucial for success. An example of good data would be adding in images of similar subjects, but taken at a variety of angles. In the case of using a traffic camera mounted on an elevated pole on the side of a road, the angle would be quite different than a camera attached to a UAV. These variations can cause issues if the system is not trained specifically in the same environment as the final application. Therefore, having images that reflect the subjects from behind, above, adjacent, and other angles (see Figure 2) can produce an AI that can more accurately interpret images on the fly. The outdoors also poses new challenges (changing illumination from the sun, reflections off surfaces, different seasons, weather patterns) that can all affect the quality of an image.



Figure 2 – Traffic images from a data set showing a variety of angles and subjects for improved results.

The types of images captured by a vision system will change over time and the data set used to train an AI should reflect all the possibilities. The basic functionality of the system is usually quite easy to set up and in most cases after setting up a system the majority of images processed will match the data provided. The challenge comes with predicting corner cases. This is when the system is most likely to fail. For example, if a system is trained for a traffic application, but the training data does not include images of traffic in rain, then the system has the potential to work great on a nice day, or perhaps even on a cloudy day, but may fail on rainy days.

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Another example of a corner case in traffic imaging is a type of vehicle that the system has never been trained on, such as the construction vehicle shown in Figure 3. In these images the system was able to identify the cars, including the large truck. However, unique vehicles that do not match a common shape, like the yellow vehicle, can cause an issue.



Figure 3 – Images of vehicles being detected (Expect a corner case with a construction vehicle).

An AI vision system does not fail in these corner cases because the AI algorithm is faulty. These systems fail when they are not trained properly. The key to a successful system is having images that represent the real-world that the cameras will capture. Having a diverse set of images that represent the various vehicle shapes, colors, number of doors, and a lot of other possibilities helps improve the effectiveness of the training. In Figure 4, not only are there uncommon vehicles such as a motorcycle and a garbage truck, but there are also examples of trailers of varying sizes such as an enclosed box trailer or an open flatbed trailer. All of these require a license plate on public roads and, therefore, would need to be captured as they pass by a traffic camera. However, many datasets already exist that engineers can use instead of collecting their own images. With these datasets engineers can ensure they can properly train their system.



Figure 4 – A set of vehicle images that show a variety of design types.

Judgement in Image Analysis

Consistency of judgment is the final measure of how well a system has been trained. The difficulty comes from the human judgement that is required to identify each image to use in training. All the images used in training must be labeled based on the judgement of someone in order to allow the AI to understand which images pass or fail the criteria. An example of this is with traffic toll monitoring. The images from the camera need to be analyzed and identified whether they are good enough to pass quality control. However, it is important to consider outliers and how they may affect the results of the inspection. For an AI, if the training is based on a narrow set of images, then it may not judge correctly when something outside of that set of images appears. To ensure that the subject being inspected is judged correctly, it is valuable to include a large enough sample size where the people judging the sample images observe true variety in the data. By seeing a greater variety of possible images of what could pass by the toll system, the system will be able to more accurately identify if the objects in the images are vehicles with a license plate. If an AI system is training and it only sees sedans and SUVs driving by the toll, it may not know what to do or where to look for the license plate if a truck

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drives by. In Figure 5 the system does not recognize the truck, but manages to identify all the other vehicles. If the system would be able to recognize the truck as a vehicle it might have difficulty locating the license plate. Unlike most standard cars where the license plate is located near the rear bumper, there are large trucks and trailers that have their license plates located at the top of the vehicle.

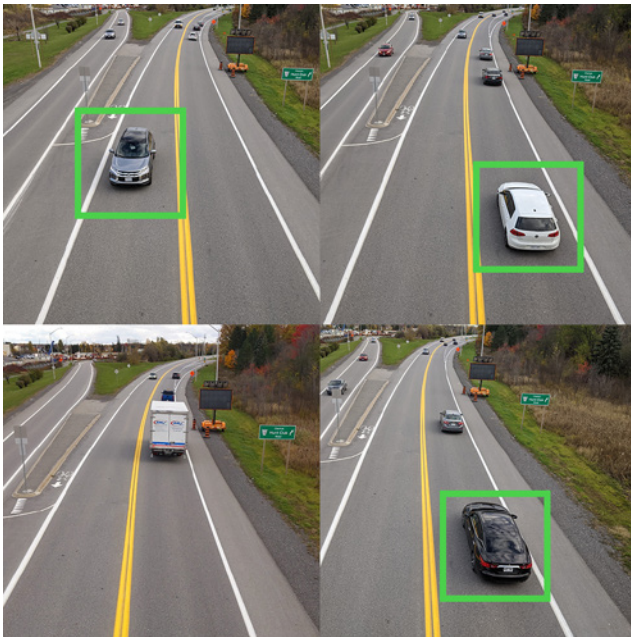


Figure 5 – A set of vehicles all being identified except for a large truck.

For a human, a camera with incorrect white balance will likely not hide a car driving by, but for an AI these settings can be crucial for correct identification because of the training. However, there are instances where weather can drastically affect visibility and an individual may incorrectly judge one of the sample images used for training. Whether or not the AI makes the correct judgement call in these situations ultimately comes from the analysis of the people who judged the images used to train the AI.

For instance, if someone is manually inspecting images and is presented with an image of questionable quality, human interpretation and judgement may still allow it to be approved. However, in the following week a similar low-quality image may be presented to that same individual or even a different individual and this time it may fail. This difference in judgement may be from something as simple as someone being tired or distracted during one of the tests. Whatever the reason, the result is a slightly different conclusion.

This type of inconsistency is what will confuse an AI. The more erroneous evaluations that are made while training the system, the more difficult it will be for the AI to perform correctly. It may be easier for a person to deal with these types of situations, but for AI, without consistent judgement their foundation falls apart. Therefore, the system all comes down to training, and the foundation of that training is a well-labeled set of diverse images.

To learn more about finding the best camera for your application, visit the Teledyne DALSA website or reach out to our imaging experts.

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