Artificial Intelligence:
Quality Control Driven By Self Learned Vision Algorithms

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Executive Summary

Automation driven by computer vision software is a powerful method for gaining efficiency, saving costs and optimizing yield in a production chain. Vision is increasingly being used in all kinds of quality control applications from agricultural to medical inspection. Many inspection processes that are currently accomplished by workers can effectively be transferred to vision algorithms, freeing up the human operators to perform other tasks, and increasing the consistency and accuracy of yield.

Vision automation sensors use predefined algorithms to analyze images taken with cameras. These algorithms are programmed into a sensor by an expert and can accurately detect features. These sensors provide binary results, for example, the output might consist of good vs bad product. These sensors can be easily programmed to detect rigid objects of a known size with tight tolerances. There are many applications where features can be nonspecific and difficult to articulate, making algorithm development near impossible. Situations like this normally require vision experts to participate in a long and expensive R&D project because off the shelf systems are unable to detect what is required.

An Ideal Solution Meets These Requirements:

- *Does not require expensive R&D*
- *Is flexible enough to handle the most challenging cases*
- *Replaces experts with artificial intelligence*
- *Field proven technology*
- *Demands little to no human intervention*
- *Operates fast and accurately*

Case Study in Agriculture

“We use a machine learning technique that allows us to develop vision software in a very quick way, but also in a way that’s highly accurate, which allows us to go into niche agriculture markets, but also markets that are a little bit more complex.

”So one of the crops that I talked about in my presentation yesterday was the date. The date is a small, niche agricultural market, but it’s also a complicated market. Dates actually grow to a certain point and then they start to shrivel as they mature. And that maturity is hard to gauge. So, traditionally it’s been done by hand: once the fruit is harvested, it’s sorted by hand. That works, obviously, but it is becoming increasingly expensive for growers to be using hand labour. So they’re switching to mechanical labour.

“So they need something that will help them do vision assisted sorting, because it is a niche product and because it’s complex, they need a sophisticated system. In addition to shrivelling, as it grows, dates also rot from the inside out. It makes it really hard to tell a rotten fruit. The ladies who are doing the sorting, they can tell instantly, they can tell the difference between a rotten fruit and a good fruit. But I can’t. And if I ask them what the difference is, they can’t articulate it to me, they can’t describe it to me. Which means that I can’t write an algorithm for it, I can’t create a vision system for something I can’t articulate. But using a machine learning technique, we can.

”As we feed the machine learning technique lots of images of the good fruit and the bad fruit, it actually iterates an algorithm of its own. So we were able to develop a vision system that had the same results or better than hand sorting.

“So we use the same technique, whether we’re looking at avocados or garlic or dates, so we’re not reinventing the wheel every time, but we do get a highly custom system every time.”

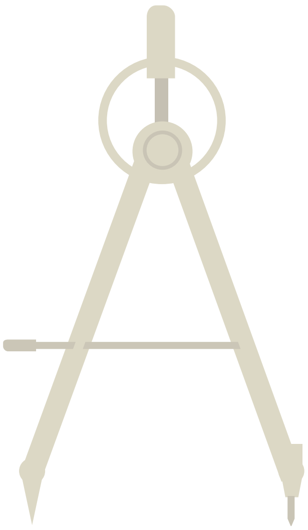
- BreAnn Washburn
Ag Inovation Showcase

Existing Turnkey Solutions Fall Short

Advancements in hardware, image processing, and pattern recognition have made automatic visual inspection a low cost and efficient solution for industrial processing applications. Visual inspection-based systems can be employed for defect detection, and quality grading.

Many vision systems allow for size, shape and color inspection, however, they fall short when presented with complicated criteria.

- Product is not ridged
- Classification is difficult to program
- Criteria is not easily articulated
- Visually subjective elements



Designing Custom Vision Solutions is Time Consuming and Expensive

The economic benefits of implementing a vision solution are more than worth the investment, many companies do not have the resources to endure an R&D process that may or may not yield the required results.

While vision technology would revolutionize their automation process, it is out of reach. The fact is that human vision engineers are expensive.

Machine Learning is the Way

Machine learning is a type of artificial intelligence. It endows computers with the power to learn without being explicitly programmed by an expert. Recent developments in this field are uncovering use cases in every industry. When applied to vision automation, an entirely new set of possibilities are unleashed.

> "Computer vision coupled with machine learning has driven the real-time optimization of production processes for our customers."
>
> ***-Bruce Taylor, Laitram Machinery***

Researchers at Brigham Young University have been working for years on novel ways of combining machine learning with image processing. They have developed a powerful method for vision processing that does not require human interaction to select key features in images. Vision algorithms can now be generated by a computer, completely cutting out the human expert.

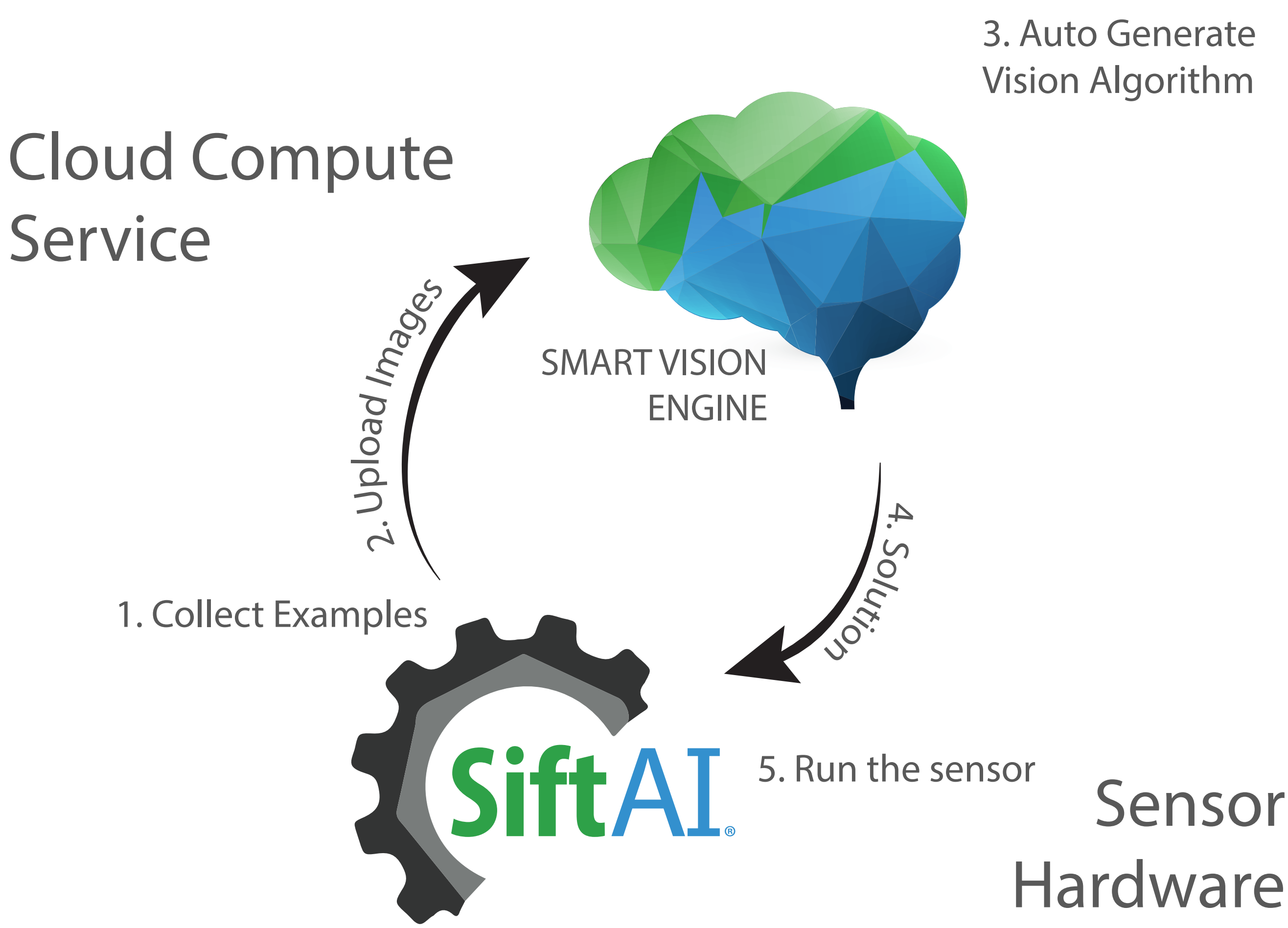
Using **Machine Learning**, algorithm development can be realized in minutes rather than weeks.

SiftAI® is the Means

The SiftAI is a computer vision sensor designed to evaluate product on a conveyor belt using models generated by a machine learning cloud compute service known as the Smart Vision Engine. Starting out is easy and does not require the help of a vision expert.

The process begins by workers sorting product as they usually do. The SiftAI then captures images of the different classes of product. Once a sufficient number of samples are collected, the images are then uploaded to the Smart Vision Engine. An image processing algorithm is autonomously generated using machine learning. When ready, this generated model is loaded onto the sensor and is ready for use.

Savings come as workers are replaced or repurposed by a more cost-efficient solution that increases production quality, yield and speed.



Return On Investment

• Faster Processing Time

- Depending on operation parameters a single sensor can classify up to 30 objects per second or more.

• Increased Quality and Accuracy

- Algorithms typically have a 95-99% accuracy, significantly outperforming the accuracy and consistency of manual sorting by a landslide.

• Labor Cost Reduction / Utilization

- Workforce size is either decreased or valued employees can be moved into more skilled positions as production volume increases

• Saves Local Jobs

- Avoid facility relocation as a labor cost reduction measure. Improved throughput capabilities will increase the bottom line.

• Remain Competitive

- Gaining or maintaining a competitive edge requires innovation that drives costs down while boosting profits. Increased throughput or labor cost reduction will enable companies to push the envelope.

SiftAI is the clear choice.

Contact Smart Vision Works for a free evaluation at

info@smartvisionworks.com

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