How Deep Learning and Artificial Intelligence Can Complement Rules-Based Machine Vision

As artificial intelligence and deep learning (AI/DL) machine vision software joins traditional rules-based machine vision software, understanding what technology works best for each application and defining best practices for integrating each solution are critical to developing optimized machine vision systems.

In general, machine vision solutions automatically inspect manufactured goods as part of industrial quality assurance and automated assembly. These solutions are in high demand. According to *Grand View Research*, "The global machine vision market size was valued at $12.29 billion in 2020 and is expected to expand at a compound annual growth rate (CAGR) of 6.9% from 2021 to 2028." Much of this growth will be driven by the demand for enhanced quality, production, and automation — all of which can be improved with AI/DL technology as part of machine vision solutions.

According to a study by McKinsey & Company, AI-powered quality inspection can increase productivity by up to 50% and increase defect detection rates by up to 90% compared to manual inspection.

However, a clear understanding of how AI/DL technology differs from traditional rules-based machine vision — including the strengths and limitations of each approach — is critical for designers to efficiently create camera-based automated inspection systems for quality control, material handling, and assembly.

This tech note defines the primary benefits and challenges of traditional machine vision solutions and convolutional neural network (CNN)-based AI/DL solutions and compares the two approaches. Additionally, this article outlines how to use these technologies to align with specific manufacturing goals to develop a successful vision solution.

What Is Machine Vision?

Traditional machine vision uses rules-based inspection software that runs on some kind of computational engine, such as a PC, embedded system, or cell phone. The software analyzes images, which are typically acquired from industrial cameras. Rules-based machine vision solutions are used in applications with well-known defects that can be defined mathematically. And since the process needs to be mathematically defined, the fewer variables the easier it is to design a successful solution. Therefore, traditional machine vision solutions typically include a number of physical, optical, and software-based constraints that limit the number of variables the machine vision system needs to solve. These constraints, ranging from enclosures to limit the effects of uncontrolled environmental lighting to mechanical fixtures that present parts to the camera the same way every time, make it possible to teach computers to "see" a difficult task at best.

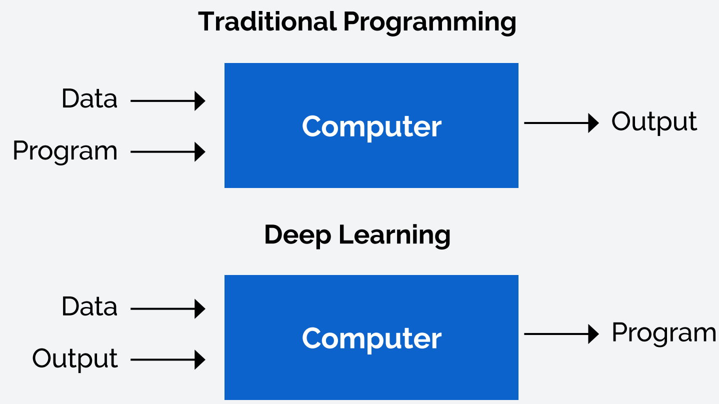
> **Traditional machine vision solutions** are good at making measurements, detecting edges, and determining whether parts, defects, and/or features are present in an image. **Rules-based machine vision technology** is often used to automate the inspection of products at the end of a manufacturing step to increase quality and production speed, reduce labor, and improve overall quality and reliability.

Traditional machine vision solutions struggle in applications with difficult-to-define variables or constraints. For example, inspecting a smartphone for port placements, geometric dimensioning and tolerancing (GD&T) or the presence of a certain feature in the image may work well with machine vision. However, determining whether a line on a cell phone cover is a fingerprint or a crack can severely challenge traditional machine vision technology. When defects vary a lot, it is difficult to define them consistently using numbers. This is where traditional machine vision solutions struggle. For example, inspecting a smartphone screen for scratches is difficult when scratches occur in random places on the screen and vary in geometry. This limitation in traditional machine vision resulted in decades of research on CNNs, leading to new AI/DL solutions.

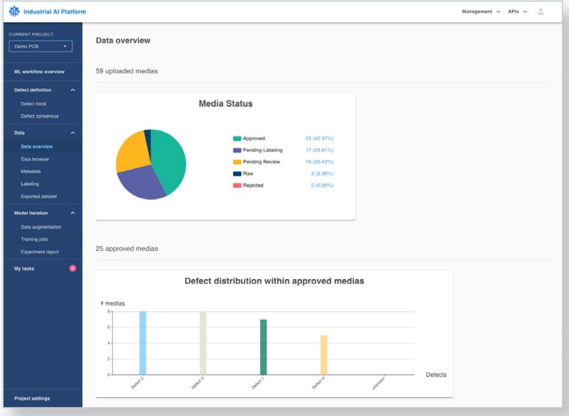
What Is Deep Learning?

DL is not programmed using specific numerical inputs into traditional math algorithms and convolutions. Instead, DL "programs" itself by analyzing a database of images that have been labeled and categorized by human experts. DL software is datacentric; it creates a mathematical model with data on miniscule image variations and other clues that humans use to determine if something is "good" or "bad." That model is then used to inspect new products for quality. In this way, DL systems learn much like humans do — by acquiring knowledge from an expert and repeating successful operations.

Because AI/DL solutions are data-centric, designers are smart to focus on the quality of the labeled images before quantity. Training an AI/DL system involves tagging and labeling images of defects. This process is computationally intensive and usually conducted in the cloud before deployment to a production line. The deployment process is called inference. While creating an AI/DL model is computationally expensive, inspecting products with the model is not. It can be done with small computers or even smart cameras.



To develop the best solution for any given application, designers need to understand the general differences between traditional and AI/DL machine vision solutions as well as the individual steps that go into making an AI/DL model. In most cases, a final machine vision production system will use traditional machine vision software to acquire images and will filter and prepare those images for analysis with an AI/DL model, which offers better defect classification than a traditional, algorithm-based machine vision solution.



Data quality is critical for AI/DL solutions

Four Steps to AI/DL Success

AI/DL machine vision solutions have enabled many applications that traditional, rules-based machine vision approaches could not handle. Although companies may not need to adopt AI/DL for every application, employing AI/DL in the right applications creates a competitive edge. Common considerations when adopting AI/DL solutions involve:

1. DATA

Better data, better AI/DL results

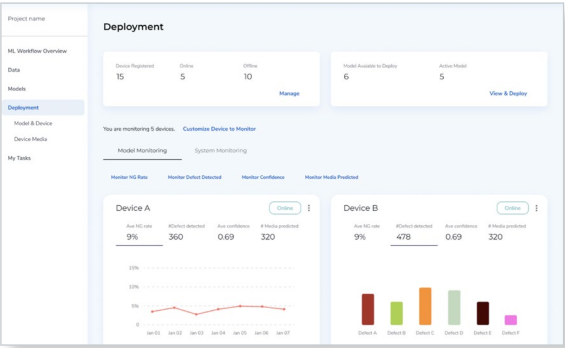
Consider a known process where variables are limited and well understood and where training set data collection is feasible without interrupting existing production. Data-centric AI/DL solutions need expertly labeled data — the more the better, provided that data quality is consistent and accurate. The more examples collected, defined, and accurately categorized during development, the better the AI/DL model and the more effective the solution when deployed. And since each defect needs its own training dataset plus an additional set of labeled sample images to test the model, the fewer defects a product has, the smaller the necessary dataset. So start with an application that is well-defined, accessible, and not too complex.

To combat a lack of data, AI/DL design environments often include pretrained models and the ability to expand datasets by creating simulated defect images. The defect images are typically created by changing the location, size, and orientation of real defects found in the original dataset.

2. TRAINING

In a recent Landing AI survey, 56% of respondents said the main issue with their current visual inspection method was false calls (good parts being marked as defective and vice versa). **False results can cripple a machine vision project.** If just 10% of the data in an AI/DL model is inaccurate, optimizing the model involves three times more data. For system integrators that develop dozens of projects per year, managing data accuracy is paramount and requires AI/DL design tools that identify incorrectly labeled images and inconsistencies among different expert human labelers. Landing AI's labeling features — including automated outlier identification and labeler-to-labeler consensus building — can speed up the labeling process by as much as 50% over competing AI/DL design environments.

3. COMMISSIONING AND VALIDATION



Commissioning and validation

Commissioning and validation involve installing a system in a production environment and testing it against existing inspection systems and methods. While working with an experienced integrator can ease commissioning and validation challenges, the right design environment can help ensure success. For example, LandingLens' Human-in-the-Loop features make it easy for customers to check the efficacy of automated solutions against the work of manual inspectors. As stated earlier, most machine vision solutions involve a combination of traditional machine vision technology for acquiring and optimizing images and AI/DL models for improved defect classification and inspection. A trusted integrator can leverage the best features of each software and hardware component and make sure that critical data is available for improving future manufacturing operations.

4. SCALE

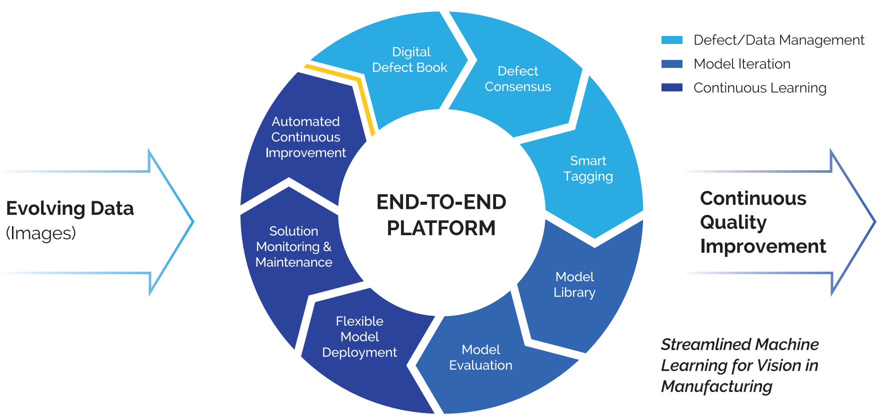
Transition challenges continue through the scaling of projects. Each deployment has its own unique challenges, so scaling is not as easy as just copying a pilot solution. Ambient conditions, variations in production equipment, and variation among components from different suppliers can all affect the performance of a machine vision solution.

While scaling may not be the focus at the start of a pilot, it is beneficial to think and plan in phases. For example, a platform from Landing AI provides access and communication features that speed model deployment by up to 67%. This is possible through streamlining processes such as labeling with comprehensive, user-friendly features, ensuring that the most accurate models are used for training the AI system and making it easy to iterate models and track deployments. Continuous learning tools also make it easier to modify existing AI/DL models to include new product variations, helping system designers and enterprises with centralized engineering support.

There are many challenges with AI/DL and machine vision and many differences between them. As the market grows, the first step in a technology adoption plan is to develop a relationship with a technology provider or vendor that is knowledgeable and responsive. "Deep learning–based, machine vision techniques in smart manufacturing will see an annual growth rate of 20% between 2017 and 2023," according to ABI Research, so companies that do not have a relationship with a provider or vendor should start now. As these solutions are adopted, companies with successful pilots will expand into increasingly more complex applications. Companies with successful adoption projects will drive industry production speed and cost.

LandingLens

Landing AI's industrial AI platform consists of a suite of interconnected tools that enables users to build, deploy, manage and scale AI solutions for visual inspection in an end-to-end workflow.



About LandingLens

LandingLens is an industry-first data-centric artificial intelligence (AI) visual inspection platform. It helps improve inspection accuracy and reduce false positives. The end-to-end platform standardizes deep learning solutions that reduce development time and scale projects easily to multiple facilities across the globe. Our focus remains on our customers and continual product innovation to solve the real-world problems of the manufacturing audience. To learn more, visit: www.landing.ai and follow Landing AI on Twitter and LinkedIn.

About Landing AI

Landing AI™ is pioneering the next era of AI in which companies with even limited data sets can realize the business and operational value of AI and move AI projects from proof-of-concept to full scale production. Guided by a data-centric AI approach, Landing AI's flagship product is LandingLens™, an enterprise MLOps platform that offers to build, iterate, and operationalize AI powered visual inspection solutions for manufacturers. With data quality being key to the success of production AI systems, LandingLens™ enables users to achieve optimal data accuracy and consistency. Founded by Dr. Andrew Ng, co-founder of Coursera, former chief scientist of Baidu, and founding lead of Google Brain, Landing AI is uniquely positioned to lead the development of AI from a technology that benefits a few to a technology that benefits all.

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