LANDING AI

Redefining Quality Control with AI-Powered Visual Inspection for Manufacturing

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Introduction

The Evolving Industrial World

At the end of the last century, the availability of cost-effective computing and digital cameras led to mainstream adoption of traditional machine vision automated inspection systems. Such machine vision solutions analyze photos of objects, identifying and locating defects based on a set of human-defined rules created in a standard computer programming environment.

While it reduces human error for many assembly and quality inspection applications, traditional machine vision lacks the capacity to detect complex defects. Traditional machine vision also struggles with changing environmental conditions both inside the manufacturing plant and outside, in areas such as agriculture and remote sensing, for example.

Today, more sophisticated artificial intelligence (AI)–based vision systems, including machine learning (ML) and deep learning (DL), are enabling more powerful visual inspection solutions. These solutions can handle complex applications with less engineering time compared to traditional machine vision solutions. But even with this new automated inspection solution capability, only 5% of manufacturing companies have a clearly defined strategy for implementing AI in manufacturing and quality assurance applications.

The Cost of Quality Is Real

Visual inspection still relies heavily on human inspectors or traditional machine vision solutions with their inflexible, rules-based analysis methods. As a result, the upfront and hidden costs of sending defective pieces to customers — in terms of both company reputation and recalls — remain a primary concern for manufacturing companies around the globe.

One important piece to expanding the adoption of AI/ML/DL solutions lies in a workflow tool set that makes this powerful technology available to all manufacturing customers — not just companies with teams of engineers and data scientists.

From Proof of Concept to Production

Manufacturing companies can successfully create a proof of concept (PoC) of an AI-based deep learning visual inspection system in a few weeks or even a few days. But getting a deployable solution ready for production and then scaling it across lines, departments, and far-flung facilities can bring a project to a standstill.

Arriving at a PoC — which generally takes the form of off-line tests run under highly controlled conditions — is a major milestone, but developers are still a long way from successful deployment. At this point, manufacturers have less than 10% of the software needed for the first deployment, and the first deployment is a small fraction of the work needed to scale to multiple production lines. Teams need to carefully plan, prepare, and execute each step of AI deployment.

Too often, companies fail to scale solutions beyond an initial project or two. This is particularly pervasive in manufacturing due to the complex and unique nature of projects. In conventional detection built on rigid rules, manufacturers need to invest massive amounts of time and money to adapt thousands of lines of code to account for small details and variables. AI visual inspection systems also present a uniquely complex set of obstacles to deployment and scaling.

Obstacle 1: Limited Clean Data Sets

The manufacturing industry is focused on preventing defects. For that reason, it can be difficult to acquire enough defect samples to implement AI because defects happen only a fraction of a percent of the time. Unlike consumer web companies such as Google and Amazon, which can apply data from billions of users to train powerful AI models, manufacturers find that collecting massive training data sets is often not feasible.

More than 58% of research respondents report that the most significant barrier to deployment of AI solutions is a lack of data resources. For a specific defect, a manufacturer may have only 10 or fewer images. In automotive manufacturing, where Lean Six Sigma practices are nearly universal, most OEMs and tier-one suppliers strive for fewer than three or four defects per million parts. Tools designed to work for big data have difficulty functioning reliably and repeatably when the model is created from such a small amount of data.

Using only a few examples of a problem, AI models are difficult to train. This prevents companies from scaling or solving for natural variance in environments.

Solution

Manufacturers need a portfolio of techniques to overcome the small data challenge. When trying to build a high-accuracy AI/DL/ML system from only 10 examples, it is crucial that these examples be labeled clearly and unambiguously. The notion of clean (non-noisy, accurately labeled) data is critical in small data settings.

In contrast, using 100,000 examples, noise would be more tolerable, since AI can "average out" the noise. According to the theory of ML, if just 10% of data is mislabeled, manufacturers might need almost twice the data (around 1.88 times as much) to achieve a certain level of accuracy. If 30% of the data is mislabeled, manufacturers need 8.4 times as much data compared to a situation with clean data.

What causes labels to be noisy?

- Unclear defect definitions
- Unclear labeling instructions
- Labeler inconsistency

With a large data set, even if each data point is noisy, trends are clear. But this isn't possible with small data, which requires a clean, non-noisy data set. The solution is to adopt a disciplined process of data labeling and organization to avoid unclear defect definitions, unclear labeling instructions, and labeler inconsistencies. Clean data ensures that small data is not the hurdle.

Obstacle 2: Ambiguous Defect Requirements

Identifying a defect can be subjective, and it's common for two inspectors to disagree. One inspector may consider a scratch to be problematic, while another thinks the same scratch is small enough to be ignored. When even experts disagree, how can we expect AI trained by humans to perform well?

Unlike big data acquisition methods used by the software industry, which can average the responses of millions of "inspectors" (users), a manufacturing application may depend on the judgment call of just two or three experts. Manufacturers sometimes opt for traditional machine vision to compensate for the shortcomings of human inspection, but this comes with its own trade-offs. Given its low accuracy, traditional machine vision forces users to permit high false-positive rates (the percentage of products marked defective that are actually acceptable) to prevent false negatives (the number of bad parts that aren't caught).

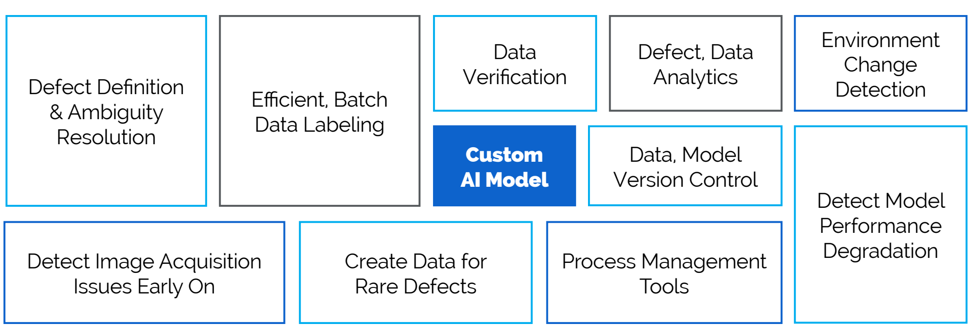
The rate of false positives could be as high as 40% for many manufacturers, which forces inspectors to physically inspect rejected parts on the manufacturing line.

Solution

Manufacturers need practical, objective dashboards that systematically help human inspectors visualize and identify clear defect definitions, categorize defects, and decrease their ambiguity. Factories that continue to rely on human inspectors often defer to paper "defect books." In the modern era, an AI dashboard should support a digital version of the defect book, which can be updated in real time to adapt to shorter product cycles and frequent changes.

Human inspectors also make errors. Many studies set error rates for manual inspections between 20% and 30%, meaning that only 70% of defects might be caught by human inspectors.

Further, the AI platform containing the digital defect book should automatically flag ambiguities and labeling inconsistencies. For example, inconsistent labels of discolorations may signal that the definition of discoloration is unclear and should be corrected. By helping domain experts clarify and express what should be deemed okay to the AI system, inspectors can deliver significantly more accurate results.



In addition to a custom-built AI model, to deploy an AI inspection system, manufacturers need a long list of custom capabilities and tools.

Obstacle 3: Changing Environments and Requirements

Manufacturing doesn't operate in a vacuum, but many traditional vision models address visual inspection as if it does. When changes in the external or internal environment occur, performance of AI/DL/ML systems degrades. Suppose an AI system is inspecting smartphones for scratches. The system must be able to respond to changes, such as seasonal changes causing lighting levels in the factory to shift, a new manufacturing process that makes scratches that were previously silver in color appear darker, or a stained camera lens that causes images to suddenly blur. Manufacturers also regularly change product requirements, but an inspection team might have already labeled data according to the original requirements. For example, a factory may previously have considered 1 mm scratches acceptable but then changed the requirement to permit only scratches under 0.8 mm.

Solution

Manufacturers need to ensure that changes to products or environments do not harm inspection operations or quality. In the past, hard coding a traditional machine vision system to cope with unpredictable changes was either impossible or required thousands of lines of code. Intelligent AI systems are more forgiving and flexible in changing environments, and a robust AI platform can simplify the process of overcoming key challenges. To do so, an AI visual inspection platform needs to perform a few key tasks.

Key Tasks

- **Keep track of slowly** changing operating metrics, so operators are alerted if performance changes
- **Collect data continuously** and then systematically organize it to ensure accessibility for human auditing and AI retraining
- **Enable easy (one-click) retraining**, so an operator can easily trigger the AI system to relearn based on the newest data and make sure it performs according to new specifications
- **Validate new models** before redeployment to reduce the chance of failure during scaling
- **Detect any abrupt changes** and alert the appropriate teams — for example, if a camera is suddenly knocked askew and part of a product is no longer visible

Obstacle 4: Compounding Complexities

For visual inspection to reach its full potential, manufacturers need to be able to deploy their solutions across many factories and projects. Without the ability to scale, global manufacturers encounter prohibitive costs by maintaining small deployments unique to each task, plant, or region.

But scaling AI solutions across a global manufacturing footprint introduces the problem of compounding complexities. That is, when applying an already complex AI project across many stations, assembly lines, and factories, complexities build on each other. For example, a manufacturing company may decide to implement AI-powered visual inspection solutions in 100 factories to inspect hundreds of products, and each product could have 100 potential defects. This can easily result in thousands of unique AI software models, each trained on 10 to 1,000 images of a particular defect. No engineering or quality team has the bandwidth to continuously update software models to align with new protocols and definitions, let alone continuously track changes of this magnitude.

Solution

An AI platform that provides end-to-end workflow visibility, organization, and collaboration can help companies scale across the state, country, or world, allowing each piece of data and each software component to be systematically developed, deployed, tracked, maintained, and monitored.

Landing AI's platform enables customers to create, deploy, manage, and scale industrial AI solutions. The platform is able to reduce overall AI project development time by up to 67% and speed up the labeling process by as much as 50%.

AI/DL/ML platforms eliminate the need for a plant operator to run between dozens of production lines to spot problems, enabling operators to aggregate statistics. Instead, the head of manufacturing for a large multinational can access an overview of deployments from around the world.

But more than top-level visibility, the next-gen AI platform must also allow appropriate teams to drill down into specifics at the factory, product, line, or even defect level. For example, a quality engineer must be able to see whether a particular defect is becoming a common pattern across plants and then take appropriate corrective actions.

Conclusion

Modernizing manufacturing means accelerating efficiency through the implementation of new tools that boost productivity while protecting human workers. AI-powered models that accurately detect defects empower workers by giving them more time to solve the root causes of defects. Thus workers add more value while companies save costs and boost efficiency, creating a more profitable future for all.

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AI/DL/ML technology offers powerful new tool sets for manufacturers. However, trying to solve applications without a measured framework and workflow often results in failed projects.

AI isn't right for every instance. Conventional machine vision is still the best option in cases like gauging and precision, while AI excels at cosmetic inspections, part location, and assembly verification.

A custom end-to-end platform is the best solution for implementing AI-powered visual inspection projects. It solves for all issues presented, enables acceleration and scale, and provides a continuous learning infrastructure. Manufacturers need tools such as end-to-end AI workflows, with digital defect books, data labeling tools, and data generation software that work in harmony.

Landing AI's platform LandingLens is an integrated visual inspection platform designed to help manufacturing companies improve their quality efforts. Developed as an end-to-end platform to help manage and build consensus on your defect data and iterate on your models, LandingLens is helping to ease and expedite project deployment.

Additional information is available at landing.ai.

20% predicted CAGR in deep learning–based machine vision techniques in smart manufacturing between 2017 and 2023

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About Landing AI

Landing AI empowers customers to harness the business value of AI by providing enablement tools that help transform you business. One of the company's core products is LandingLens, an end-to-end AI platform specifically designed for industrial customers to build and effectively deploy AI visual inspection solutions. Founded by Dr. Andrew Ng, co-founder of Coursera, former chief scientist of Baidu, and founding lead of Google Brain, the team at Landing AI is uniquely positioned to help companies across the globe successfully move their AI projects from proof-of-concept to full-scale production.

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