Leading Artificial Intelligence Use Cases in Manufacturing

How AI delivers business value for today's manufacturers

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Executive Summary

Industry 4.0 represents the next industrial revolution in advanced manufacturing and smart, interconnected, collaborative factories.

While Industry 4.0 relies upon a synthesis of emerging and maturing technologies, perhaps none holds as much promise to enable truly new ways of doing things within manufacturing environments as artificial intelligence (AI).

In fact, AI is on the brink of mass adoption, with forecasts anticipating a 57.2% CAGR creating a $16.7B USD market by 2026—*in the manufacturing sector, alone!*

Broadly speaking, where there's data there's the possibility of leveraging AI to improve how something is done by making it faster, more accurate, more cost-effective, etc. Within manufacturing environments, four leading use cases will drive AI adoption.

As manufacturers increasingly turn to AI, "explainability" features that reveal how an AI model works and why it has made a particular decision will be especially important—for a few reasons.

First, explainability makes the development, maintenance, and extension of AI-powered solutions both more effective and more efficient—helping manufacturers to introduce better solutions, sooner, to maximize lifetime ROI.

Second, some manufacturing use cases leverage explainability as part of their operational implementation, literally revealing to an operator in real time the reasons why a particular decision—for example, an inspection outcome—has been made and forever logging that information in an auditable database.

And third, because of concerns about bias, privacy, security, and other factors, many regulators are introducing rules that govern the use of artificial intelligence. As a result, businesses subject to such legislation—which includes many manufacturers—may not be able to use AI solutions that lack explainability features.

DarwinAI specializes in developing high-performance, explainable deep learning solutions that are smaller, that have higher density, and that are more accurate than those produced by any other AI offering. These solutions are already trusted by Fortune 500 companies, proving the value of AI in manufacturing and representing the very early stages of AI's enabling role in Industry 4.0.

TOP AI USE CASES WITHIN MANUFACTURING ENVIRONMENTS

1 Anomaly Detection

Leveraging visual (images, video) and auditory data, AI can recognize deviations from expectation. While this capability has obvious utility in quality control and inspection applications, it can also be used to detect malfunctioning equipment and other errant behavior.

2 Adaptive Factory Automation and Equipment Process Optimization

The ultimate goal for this use case is a fully automated facility in which AI complements skilled workers. AI helps to achieve this outcome by enabling:

- Automated equipment work instruction;
- Predictive maintenance;
- Adaptive robotic picking;
- Federated equipment learning.

3 Human Workflow Optimization

By optimizing the division of labor between human operators performing primarily value-added work and automated machines that handle non-value-added functions, manufacturers can maximize production efficiency.

4 Adaptive Logistics and Supply Chain Management

While applying AI to supply chain logistics is a vast topic, two applications in particular hold tremendous promise:

- Using supply and demand data to provide direction to logistics operations;
- Optimizing material flow within a production facility or warehouse.

The Future of Manufacturing

The global manufacturing sector is constantly evolving, as competitive pressures and market demands create powerful incentives that drive innovation.

By introducing new technologies, manufacturers have enabled new processes, unlocked new efficiencies, delivered remarkable products—and earned higher revenues.

The new paradigm: Industry 4.0

Characterized by the interconnection of industrial equipment which accesses and analyzes centralized operational data, Industry 4.0 is the new manufacturing paradigm. It represents the next industrial revolution in advanced manufacturing and smart, interconnected, collaborative factories and relies upon a synthesis of enabling technologies including artificial intelligence (AI), automation, the Industrial Internet of Things (IIoT), cloud services, and centralized management systems.

The role of artificial intelligence

Among Industry 4.0 technologies, AI represents perhaps the greatest leap from what was to what will be. Because of its enormous potential and broad range of applications, AI is on the brink of mass adoption: in the manufacturing sector alone, Markets and Markets values the AI opportunity at $1.1B USD and forecasts that it will reach $16.7B USD by 2026. This astonishing growth—a CAGR of 57.2%—will be driven by *"the increasing number of large and complex datasets (often known as big data), evolving Industrial IoT and automation, improving computing power, and increasing venture capital investments."* [1]

However, the path forward is not without potential hurdles, including general societal discomfort about machines making decisions—particularly when the reasons behind these decisions are not understood.

Such concerns are not without merit, as poorly designed and insufficiently audited solutions can introduce biases, suffer from blind spots, and be very difficult to troubleshoot. For these reasons and others, many jurisdictions have introduced legislation requiring algorithmic transparency and explainability.

Nevertheless, the promise and potential is such that widespread implementation of AI within manufacturing is a matter of "when" rather than "if"—and the first-movers will gain valuable competitive advantages in the global marketplace.

While the uses of AI within manufacturing are broad—where there's data, there's a possibility of leveraging AI—four applications stand above all others:

- Anomaly Detection;
- Adaptive Factory Automation and Equipment Process Optimization;
- Human Workflow Optimization;
- Adaptive Logistics and Supply Chain Management.

1. The report is available at Markets & Markets

USE CASE 1

Anomaly Detection

AI solutions are adept at recognizing when a data sample or set deviates from expectation, even for complex input/output relationships and at high rates and volumes. In manufacturing environments, such solutions usually leverage one or more of the data inputs.

AI-BASED MANUFACTURING SOLUTIONS CAN LEVERAGE A VARIETY OF DATA INPUTS

Image

Manufacturers can take a high-quality picture of a part/component and allow an AI-enabled program to create an ideal model of what that part should look like.

An AI-based utility within the production line then assesses images of parts under inspection to detect abnormalities by identifying deviations from the model.

Video

Video is essentially a rapid flow of still images; by applying similar visual recognition techniques as above, video input data can be used to detect abnormalities.

Audio

AI models can create an audio profile of what a particular manufacturing process should sound like.

In a production environment, a program can then pause production or flag a human operator if something sounds unusual, allowing for proactive repair and ensuring defects do not leave the process they were built in.

"Applying AI for quality inspection within high- or medium-throughput operations typically automates tasks, but not entire jobs."

With these seemingly simple building blocks, enormous value can be unlocked in a wide range of manufacturing environments. For instance, image-based anomaly detection is already used within:

- PCB board manufacturing (~40,000 units/day) to detect and categorize defects on unfinished and finished boards;
- Automotive manufacturing (~1000 units/day) to spot problems on partially built and fully built vehicles;
- Large welded parts manufacturing (~10 units/day) to find flaws with weld beads.

Applying AI for quality inspection within high- or medium-throughput operations typically automates tasks, but not entire jobs, allowing manufacturers to re-allocate personnel away from repetitive (and potentially dangerous) work into value-added functions that generally provide greater growth opportunities and higher satisfaction for employees—and contribute to better overall performance for the company.

For low-throughput and highly complex operations, quality inspection automation supports inspectors with highly complex parts/operations. For instance, sometimes a part is either too large or too complex for the human eye to inspect, or parts may be impossible or too dangerous for humans to see (e.g. weld beads inside a 30-meter welded tube). In these scenarios, having an AI-powered visual inspection system looking for abnormalities can show the human where attention is needed or can provide a virtual image of hard-to-reach places.

In all of these scenarios, the addition of an AI solution increases the confidence that the correct inspection decision has been made.

USE CASE 2

Adaptive Factory Automation and Equipment Process Optimization

The ultimate goal for this use case is a fully automated facility—but, contrary to popular belief, that doesn't mean a facility devoid of human personnel.

In a facility that's automated, human involvement is still required, but primarily as skilled labor; for instance, overseeing operations, troubleshooting issues, and maintaining/repairing equipment.

> "AI takes information it has learned from its audits to dynamically adjust production output to meet a stated goal."

In such environments, AI complements these roles and enables new heights of performance.

Automated equipment work instruction

When instructions to the equipment are automated, the AI takes information it has learned from its audits to dynamically adjust production output to meet a stated goal. From a macro-view perspective, AI can make decisions about what equipment should do based on input from any source.

The value of automated work instruction is clear:

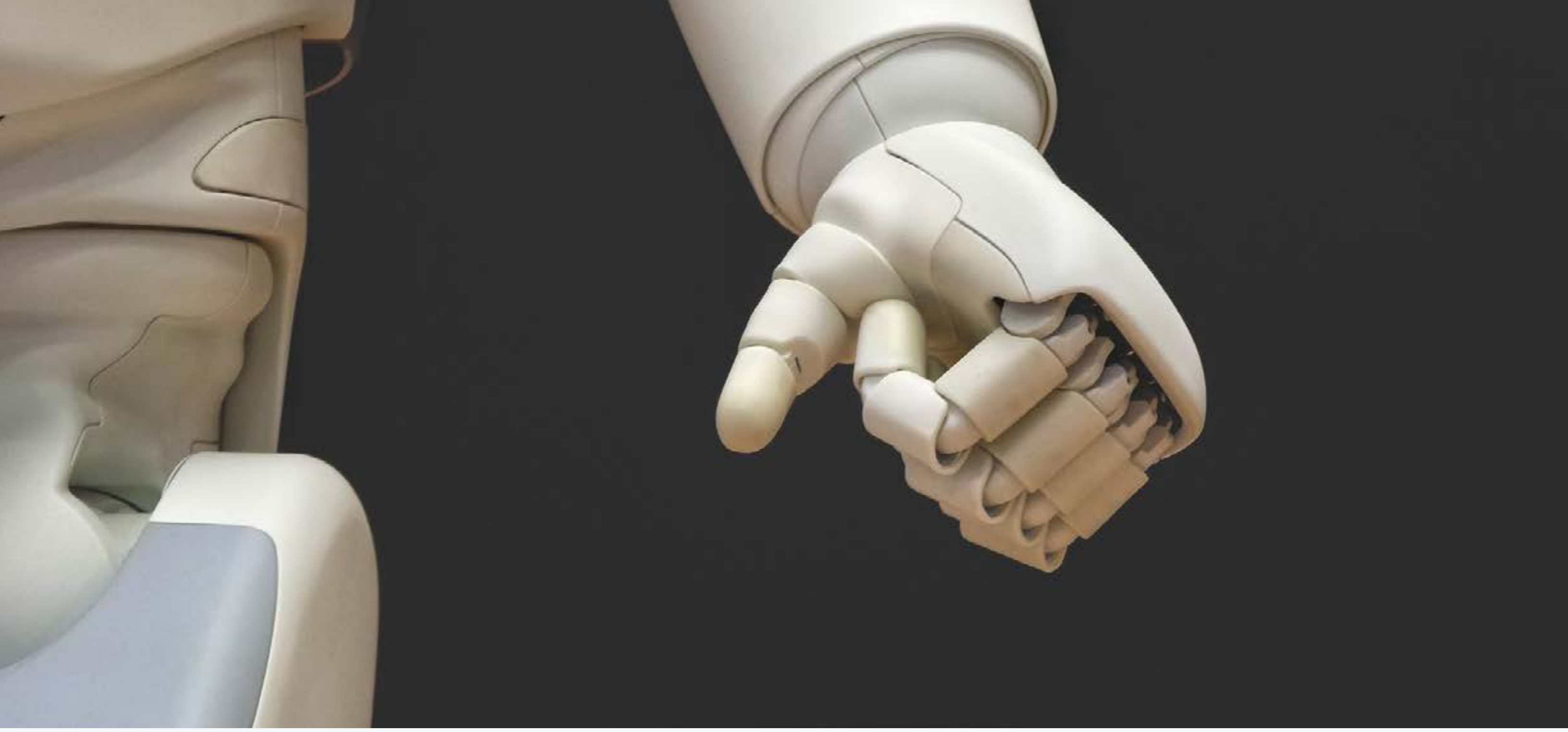
1. It requires minimal human intervention—only skilled workers are required to manage equipment uptime;
2. Where there is no manual work required, there is further optimization and operational productivity.

Predictive maintenance

By monitoring heat, sound, vibration, and energy consumption data from industrial IoT sensors and analyzing this stream of information in the context of historical trends, AI solutions can predict when machine failure is more likely to occur.

This foresight provides a number of benefits, including:

- **Proactive intervention** by giving skilled maintenance staff the opportunity to perform proactive measures (e.g. replacing parts, greasing joints, etc.) to prevent equipment failure—every manufacturer recognizes that machine failure can lead to operational disruption and downtime, either of which can be extremely expensive (especially if the issue leads to a chain reaction of supply shorting which can cause a plant shutdown);
- **Personal fulfilment** by allowing personnel to spend more time doing thoughtful, planned work and less time in stressful downtime situations;
- **Avoiding delays** by enabling parts and components to be ordered within comfortable lead times, instead of getting into a pinch when a part is needed but not available.



Adaptive robotic picking

A common approach today is to combine an external computer vision system with 'dumb' robots to enable robotic picking. In this scenario, the computer vision system localizes a part and determines what it is, then tells the robot where it is and instructs the robot to pick it.

In the past, this method was 'chosen' somewhat by default, because vision systems required significant computational resources that weren't available on most industrial robots.

However, advances in AI have led to high-performance vision systems that require far fewer computational resources than their predecessors, introducing the very real option of incorporating intelligent decision-making into practically any device—including industrial robots. These new capabilities are no mere convenience: they allow truly new implementations and scalability, now that the edge devices can be decoupled from server farms and cloud systems.

When manufacturers integrate advanced robotics for the purpose of automated part picking, they enjoy two tiers of value:

1. **AI assists with complex human work:** a robot can pick parts based on a pick sequence for the purpose of assembling a bin of sequenced parts or for building sub-assemblies.
2. **Workers can be reassigned:** some tasks will no longer require a human, so team members can be reassigned to new work.

Federated equipment learning

What one robot sees, learns and predicts can be shared with all the other equipment in the facility, so that cell automation results in the whole facility having shared automation. Shared learning helps the equipment work as a cohesive unit so that anomalies are not replicated. If an anomaly is detected or a part variation is found which potentially causes an error with one robot, the AI tells the other robots what to expect in order to prevent that same error from reoccurring.

There are two major points of value:

1. Because the equipment can learn and adjust accordingly, then share its parameterized adjustments with the rest of the facility equipment, the automated operation becomes self-sustaining with minimal human intervention;
2. There is no manual work needed to optimize operational productivity.

IMAGE COURTESY OF
Aspire Food Group and Next Generation Manufacturing Canada

Introducing a Ground-Breaking Protein Production Facility

The Aspire Food Group will use DarwinAI's Explainable AI for intelligent industrial automation and quality optimization as part of their new production facility that will help to address global food insecurity.

As project partners, DarwinAI is providing high-performance Explainable AI technology in Aspire's operations that will employ industrial automation and robotics, IoT, and deep learning—the first time Industrial IoT, sensors, automated storage and retrieval systems (ASRS), and AI will be deployed in climate controlled, indoor vertical agriculture with living organisms.

> When you think about us trying to build a facility that will be the smartest indoor protein-production—fully automated facility in the world—you begin to realize that each one of those adjectives has a deep level of expertise behind it.
>
> **MOHAMMED ASHOUR, CEO, ASPIRE FOOD GROUP**

USE CASE 3

Human Workflow Optimization

By optimizing the division of labor between human operators and automated machines, manufacturers can maximize production efficiency—this approach is especially applicable to human-led environments in which certain tasks cannot be automated.

SEGMENTING DIFFERENT TYPES OF WORK WITHIN MANUFACTURING OPERATIONS

Value-Added Work

Work that adds value to the product that the end customer is willing to pay for, for example:

- Tightening a bolt;
- Welding two parts together;
- Soldering a capacitor onto a PCB.

Non-Value-Added Work

Work that does not add direct value to a product, for example:

- Walking to pick up a part;
- Setting a part on a table to pick up a tool;
- Waiting for a machine to complete its task;
- Lifting a bin of parts onto a staging rack.

A first step to achieving this outcome is to consider every process within a manufacturing operation as being one of two types of work: value-added work and non-value-added work.

Non-value-added work is where automation and AI are most valuable, as value-added work often consists of human tasks that are too complex for available automation technology.

In practice, in a human-led process it's very hard to eliminate all non-value-added work. Even the manufacturers that do the best job at optimizing the segmentation and balance between value-added versus non-value-added work have this problem. But what if a manufacturer could tap into the process by assigning data to each movement? This would allow them to:

- Use that data on a macro level (across the whole operation) to pinpoint areas within the operation that are the least efficient;
- Subsequently use a historical time-series of that data to recommend areas of improvement;
- Predict machine failure within those processes (assuming equipment is attached to the device used to collect and process data).

Having a good understanding of each process in an operation, as well as all processes together at a macro level, allows management teams to identify areas for improvement and to optimize operational productivity.

Distinguishing between value-added and non-value-added work will lead to process rebalancing, whether for full processes or partial processes, which can lead to additional cost savings.

USE CASE 4

Adaptive Logistics and Supply Chain Management

Applying artificial intelligence to supply chain logistics is a vast topic that spans everything from operational performance optimization and fleet management to warehouse management. Within this diverse range, two applications in particular hold tremendous promise.

Using supply and demand data to provide direction to logistics operations

Understanding historical data and assessing active supply or demand data such as supplier parameters, part shortages, part demand, and other outside factors that impact supply (such as weather patterns) allows AI to generate valuable insights and/or automated planning and decision making that enable manufacturers to avoid operational downtime.

Beyond monitoring active supply chain operations, manufacturers can use this data when planning new product production. They can also provide planning teams with insights and predictions, shedding light on areas to focus on and helping to mitigate supply chain disruptions.

> "AI can help enterprises leverage intelligent predictions to avoid operational losses and gain a competitive edge."

For example, what if precautions could have been put in place to avoid extreme weather-impacted buying patterns as well as halting production plans? AI can help enterprises leverage intelligent predictions to avoid operational losses and gain a competitive edge.

Optimizing material flow within a production facility or warehouse

There are companies that build products to help optimize and automate material flow within a facility. Using autonomous mobile robots (AMRs) is a whole other field of evolution and progress.

Extending beyond AMRs, using AI-enabled video monitoring of all factory assets can help monitor material flow while continuously assessing flow efficiency and providing management teams with reports. Those reports can help adjust route planning for manually-operated material flow or provide input to fleet management software to optimize automated material flow.

For supply chain management, AI-enabled risk mitigation can help to avoid operational downtime for manufacturers.

For operations within a manufacturing or warehouse environment, continuously monitoring material flow efficiency helps customers immediately identify areas within their material flow operation where waste can be removed, which leads to process rebalancing.

Deep Learning and the Importance of Explainability

In all of these examples, AI uses data to build a model that can audit production data within facilities—even in real time.

The most advanced form of AI is deep learning. This approach is based on artificial neural networks, which are virtual constructions that emulate the cognitive capabilities of the brain, and it allows machines to perform functions—like detailed, contextual visual analysis—that were previously the exclusive domain of humans.

The explainability imperative

Deep learning is transforming organizations and industries alike, and lines of business have begun outsourcing important decisions to these intelligent—but mysterious—systems.

While neural networks behave in ways that reflect the data they're trained against and the human labelers who annotate the training data (incorporating selection and human biases along the way), all too often it remains unclear how they reach particular conclusions.

The consequences are far from trivial: "explainability"—illustrating how the black box in AI works—has important implications for the reliability, efficacy, and ethics behind deep learning.2 If an organization leverages deep learning, these implications extend to these facets, including the ability to design AI solutions in a rapid, robust, and ethical manner.

Explainable AI (XAI) is more than a great feature that creates confidence, builds trust, and strongly contributes to better business outcomes—it will soon be an imperative. As intelligent systems and algorithms become ever more ubiquitous, many jurisdictions around the world are introducing legislation requiring explainability as part of efforts to evaluate safety, ensure fairness, and preserve privacy.

While the specifics vary, in general these regulations demand that explainability:

- **Removes subjectivity** to minimize the role of human interpretation and intuition;
- **Applies to industry and commercial contexts**, rather than exclusively within strict academic or laboratory settings;
- **Be direct, global, stable, and verifiable** to maximize utility and the scope of the explanations provided.

Businesses subject to regulatory and compliance guidelines—which includes many manufacturers—may be unable to apply deep learning solutions lacking sufficient degrees of explainability.

DarwinAI's Generative Synthesis

DarwinAI specializes in developing high-performance, explainable deep learning solutions. Within DarwinAI's proprietary GenSynth technology, AI builds better AI, resulting in deep learning models that are smaller (which lets them run on less-powerful equipment), that have higher density, and that are more accurate than those produced by any other AI offering.

> "DarwinAI specializes in developing high-performance, explainable deep learning solutions."

DarwinAI's proprietary approach gives concrete explanations and actionable insights that quantitatively reflect an AI's decision, while other solutions such as LIME and SHAP provide subjective explanations about what may relate to the AI's decision—and which are sensitive to how the solutions are configured.

2. For a detailed exposition of explainability, including comparisons of different approaches, please see Dark AI and the Promise of Explainability

In general, with DarwinAI's proprietary explainability, manufacturers get:

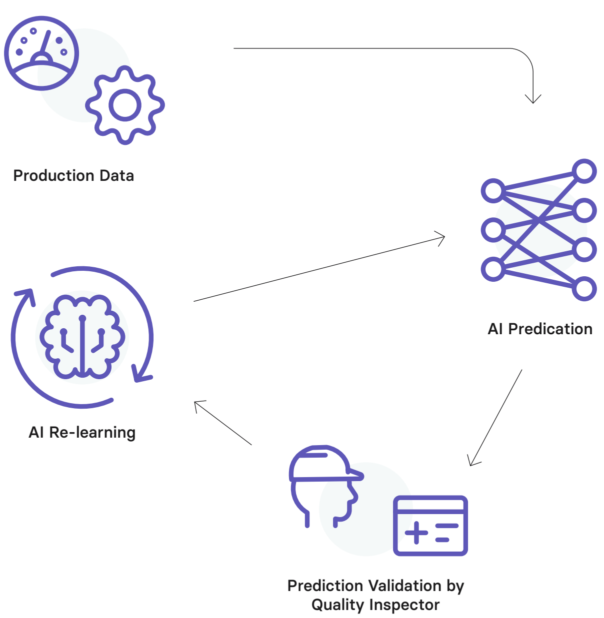
- **Insights that allow for higher precision and reliability** than open source offerings;
- **The ability to do more with less training data;**
- **Localized explainability that shows root causes with context**, to make better human-in-the-loop decisions; these insights help to catch defects that otherwise go unnoticed and lowers the barrier for people to do inspections—meaning humans learn from the AI, too.

Beyond providing an operator with an explanation as to why the model has made the decision it has made, DarwinAI's solutions enable a feedback loop that can be used to make a one-time model self-sustainable over time (essentially reteaching itself) by incorporating user feedback to improve known abnormalities and to automatically learn about new abnormalities the model has never seen before.

As far as what the feedback looks like, it depends on the type of model that was built for the application. For example, there are different kinds of results that can be programmed as a desired output, including:

- **Segmentation:** detecting different types of defects—not just 'good' or 'no good'—which is tremendously valuable in manufacturing contexts
- **Binary:** for applications that will place less value on knowing the kind of defect and more on knowing that it is a defect

These results double as feedback that can influence the relationships between particular inputs and outputs, and that can identify potential blind spots.



Proven value

The DarwinAI team is already working with enterprises and developing leading AI products for a variety of manufacturing use cases.

For example, a global aerospace and defense manufacturer was experiencing difficulties with the existing inspection process for printed circuit boards, including:

- **High lead time:** 40%+ of defects found during inspection could have been detected two days earlier during PCB soldering.
- **High scrap:** Entire batches are scrapped when defects are found, wasting thousands of dollars of raw materials.
- **Penalties:** manufacturing delays can incur significant penalties from customers.

> "DarwinAI's solutions enable a feedback loop that can be used to make a one-time model self-sustainable over time"

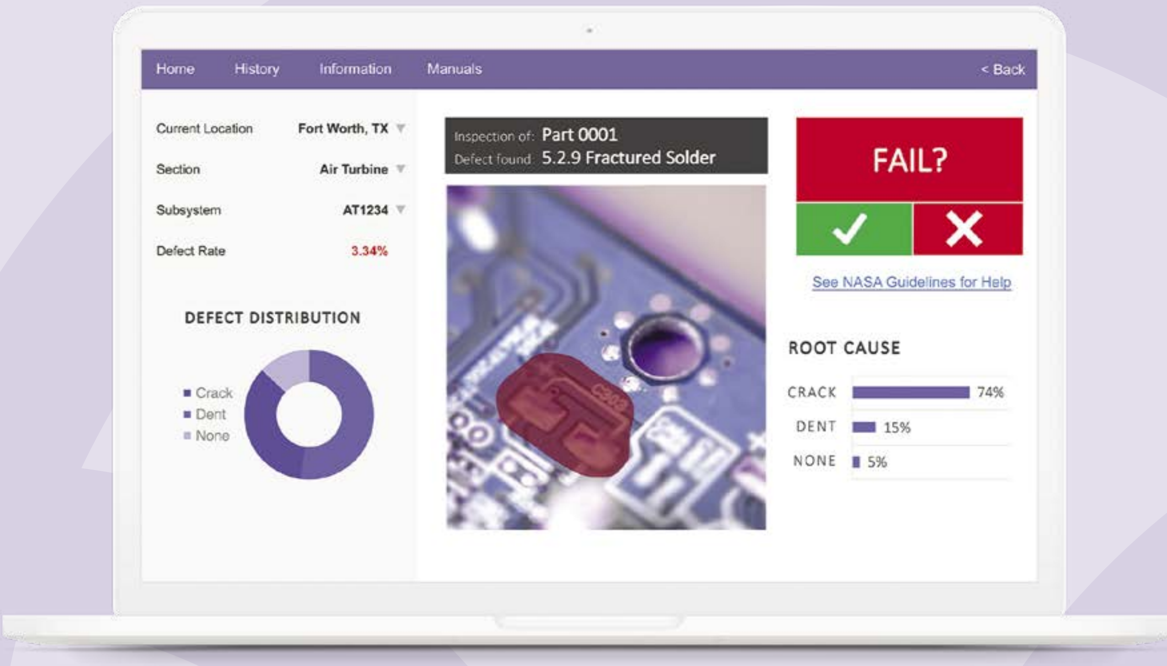
In just a few weeks, DarwinAI worked with the manufacturer to implement a purpose-built inspection system that:

- **Quickly detects and categorizes solder joint defects** based on NASA standards (which require over 20 types of surface defects to be distinguished and reconciled)
- **Shows the root cause behind defects**—allowing operators to validate the system's predictions and make it smarter over time
- **Requires only a few data samples of defects to get started**—a fraction of what traditional systems demand
- Not only does this solution assist operators, but it also enables a faster production process by catching 40% more defects before final inspection and lowering lead time by 29% by reducing rework—delivering a return on investment in only three-months.

And this pilot project applied to one production line within one of the manufacturer's 50+ plants—only scratching the surface of the potential value of such solutions.

The future of manufacturing is bright indeed.

DarwinAI, an explainable AI company, enables enterprises to build AI they can trust. Founded by renowned academics at the University of Waterloo, DarwinAI's Generative Synthesis technology makes explainability real, allowing developers to understand, interpret and quantify the inner workings of a deep neural network. Based on years of distinguished scholarship, the company's patented explainability technology accelerates advanced deep learning design and unlocks new possibilities for the commercial uses of deep learning.



For assistance or more information, please reach out at info@darwinai.com

Learn more about our solutions at darwinai.com/manufacturing →

Trusted by Fortune 500 Companies for AI in Manufacturing

Providing vision inspection systems for heavy, light and additive manufacturing—proven to help improve product quality and reduce manufacturing costs

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