



# **A QUICK GUIDE TO DEPLOYING DEEP LEARNING IN SPOT WELDING INSPECTIONS**

**COGNEX**



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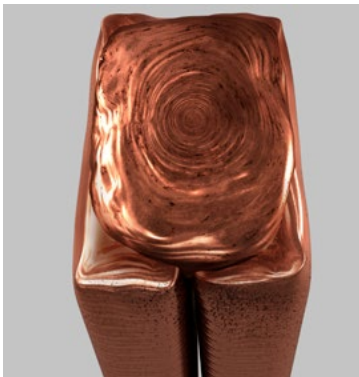
Deep learning uses neural networks to learn by example, just like humans. This is an attractive solution to a vexing production challenge: automating the inspection of terminal spot welds.

Terminal spot welds join metallic components in electrical devices. Strong, durable spot welds extend the lifespan of electrical components like sensors and stators, improving quality and reducing return costs for manufacturers, especially in the automotive industry.

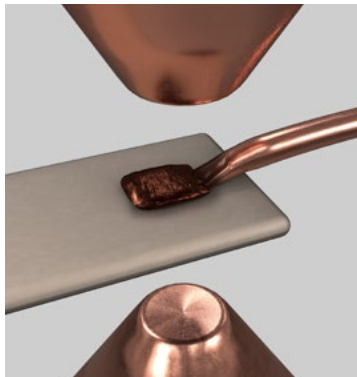
However, there are too many welds, too few people, and insufficient benefits to justify the costs of manual inspection for most manufacturers. Thus, they have strong incentives to automate spot weld inspections.

Deep learning-based inspections can scrutinize every weld on every part—a feat few manufacturers can hope to achieve with common inspection solutions. This makes deep learning an attractive technology for terminal spot weld inspections.

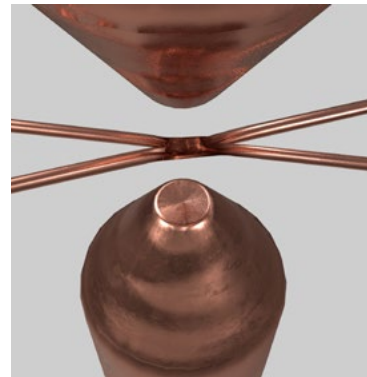
## Types of spot welds



*Pin to pin*



*Wire to pin/pad*



*Wire to wire*

Deploying deep learning in spot weld inspections boils down to four phases:

1. **Prototyping.** The opening phase captures everything a human inspector sees and prepares this insight for replication in a deep learning application.
2. **Factory validation.** The second phase confirms that the deep learning application is successfully detecting defective spot welds.
3. **Production deployment.** The manufacturer puts the deep learning application to work on the factory floor, implementing pass-fail inspections that detect spot weld defects.
4. **Classification for process control.** The application developer classifies defects to inform decision-making for tasks such as rerouting bad parts and addressing upstream faults in the production process.

This guide provides a concise summary of the phases. Understanding the core principles behind each phase increases the likelihood of successfully using deep learning to automate spot welding inspections.

### Automotive components using spot welds



*Stator*



*Starter switch*



*Sensors*



*Motor core*



*Solenoid*



*Alternator rectifier*

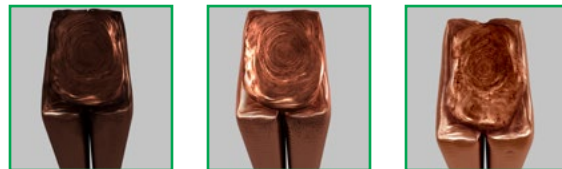
# APPOINTING A QUALITY EXPERT AND ESTABLISHING GROUND TRUTH

To start, every deep learning application needs an independent Quality Expert for two crucial tasks:

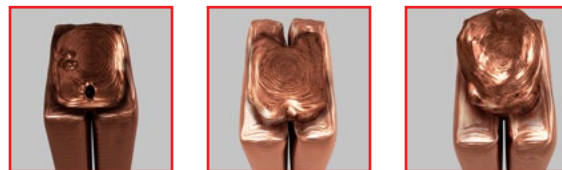
- Distinguishing between passing and failing spot weld inspections
- Establishing the “ground truth”

Even so, a deep learning application must have unbiased data to generate accurate statistical models. The Quality Expert’s assessment of Ground Truth—a digital representations of reality—must be as reality-based and bias-free as possible. Any errors in the Ground Truth phase will degrade the results of everything that follows.

This makes the Quality Expert one of the most crucial roles in the development of deep learning applications.



*Good spot welds*



*Bad spot welds (from left to right):  
pitting, undersized, oversized*

## PHASE 1: PROTOTYPING

Automating terminal spot weld inspection starts with prototypes built on a comprehensive understanding of everything a human inspector does when accepting or rejecting a part in production. The deep learning application must have all the same visual data that’s available to the inspector.

Machine vision systems accomplish this with digital cameras built specifically for industrial automation. Deep learning software then analyzes visual data from these cameras to replicate the inspector’s work.

Prototyping happens in three steps:

**1. Configuring image collection.**

Cameras on the production line must photograph a comprehensive range of spot welds from multiple angles. Lighting must be optimized to reduce glare, limit shadows, and produce sharp digital images. Flawed or defective welds are rare in high-quality production environments, so extra care is required to separate the good from the bad welds.

**2. Collecting image data.**

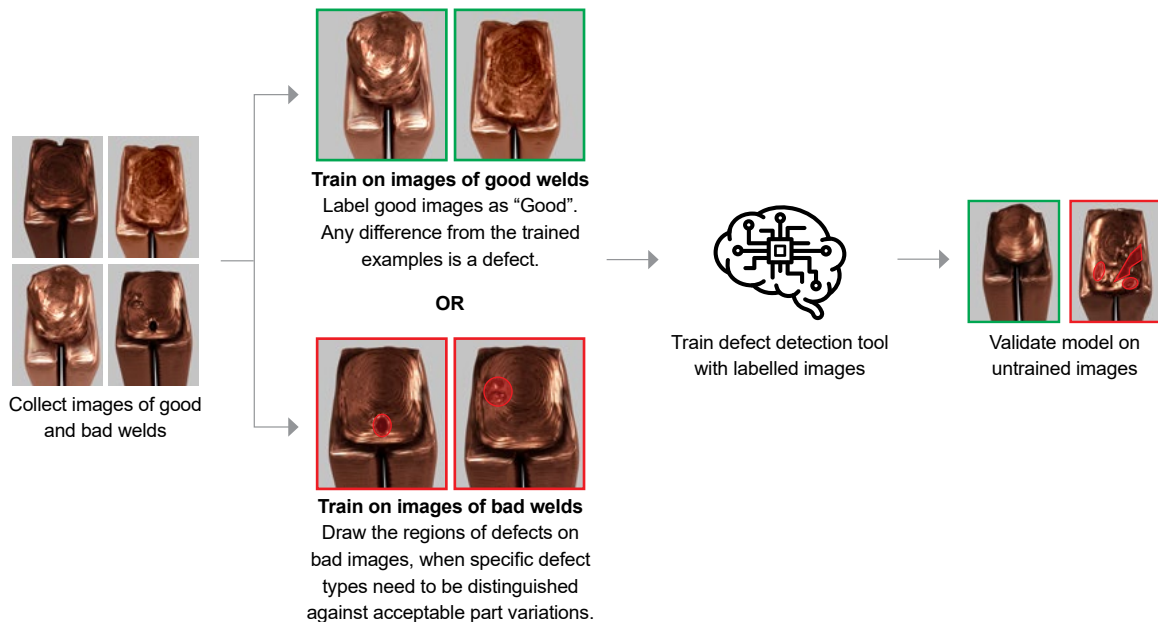
Application developers take pictures to track all the decisions of a human inspector. Hundreds of digital images are recorded, time-stamped, and separated by part type and weld variety. This provides digital data that connects human decision-making to the processes the deep learning system uses to simulate human inspections.

**3. Labeling.**

In the labeling phase, a Quality Expert identifies spot welds that pass or fail inspection. Images that include pitting, misshapen welds, and other flaws must be labeled to help the deep learning application assign pass/fail classifications to parts in production.

Accurate, thorough prototyping is essential. Any misstep in the prototype phase can create problems that cascade through the development process, potentially undermining the accuracy of automated inspections.

## Process flow for training a deep learning solution





## PHASE 2: FACTORY VALIDATION

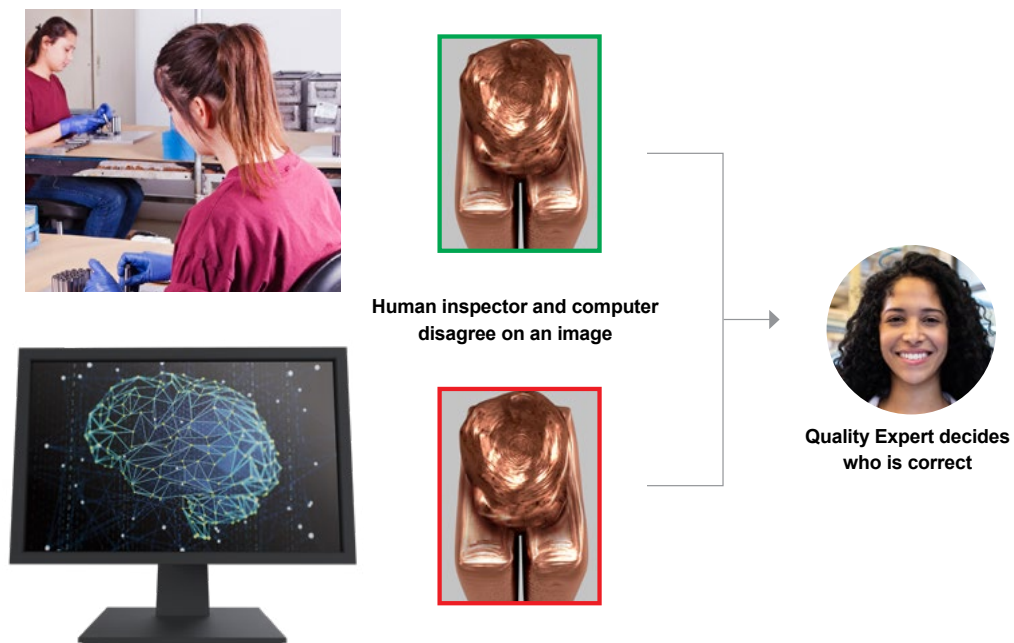
Once the prototype is developed, its real-world effectiveness must be validated.

The deep learning application scans every spot weld on every part coming down the manufacturing line, while human inspectors continue their work. The application developer then creates a process to compare the accuracy of the people vs. computer.

The key is to find discrepancies between human and machine perception. If the computer and the inspector agree on a passing (or failing) grade, that usually indicates the system is working as expected.

The most useful insights, by contrast, typically arise when the computer and the human inspector look at the same images and disagree on what they see. Here, the Quality Expert intervenes and decides who was correct.

### Human inspectors vs machine perception



If the human inspector is correct, more images may need to be added to the neural network to train it to perceive the flaw. If the deep learning application is correct, then this data becomes the statistical baseline to assess the accuracy of future spot weld inspections.

This same data can help determine the return on investment in deep learning inspections. It can also help establish tolerances that make the system even more accurate in the future.

## PHASE 3: PRODUCTION DEPLOYMENT

After the application developer has a validated model, it must be tested in a live manufacturing environment. Operational factors, like the variety of spot weld flaws emerging from different shifts and production lines, are assessed.

As inspection data is returned, manufacturers must decide whether to fully automate all inspections or to merge the insights of human and machine inspectors. Many manufacturers choose a two-tiered system that's programmed to deliver ambiguous results to human inspectors who can better decide whether a spot weld passes or fails. Images from these inspections can also train the neural network to become better at spotting subtle flaws.

Deployment is also the time to assess what to do when the deep learning application makes a mistake, which can take one of two forms:

- **Overkill (false negatives):** This occurs when good spot welds receive a failing grade from the deep learning algorithm. Overkill incurs avoidable expense by unnecessarily rerouting good products out of the production system.
- **Underkill (false positives):** This occurs when bad spot welds receive a passing grade from the algorithm. Underkill leads to product returns and repairs, generating additional costs.

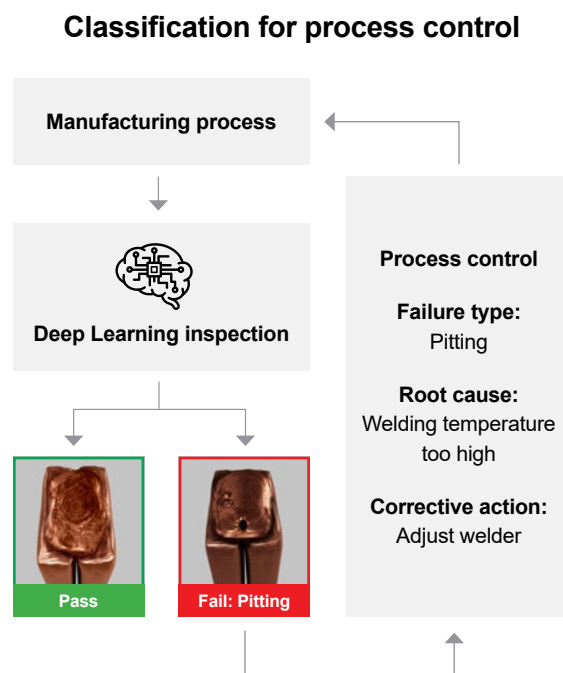
Data generated during deployment helps inform an accurate yield analysis, assessing the overall effectiveness of the deep learning application. The outcome of this assessment enables top management to determine whether the inspections are generating enough quality improvements to justify the investment of time and resources.

## PHASE 4: CLASSIFICATION FOR PROCESS CONTROL

The first three phases of deep learning deployment aim to replicate the most basic work of the human inspector: judging whether a spot weld passes or fails.

Classification for Process Control tells the system what to do next. Welds that pass inspection alert the system to move the parts down the line. Conversely, failures might prompt the production system to deliver the part to a repair area if the scan reveals fixable flaws, while ambiguous flaws might trigger a reroute to human inspectors.

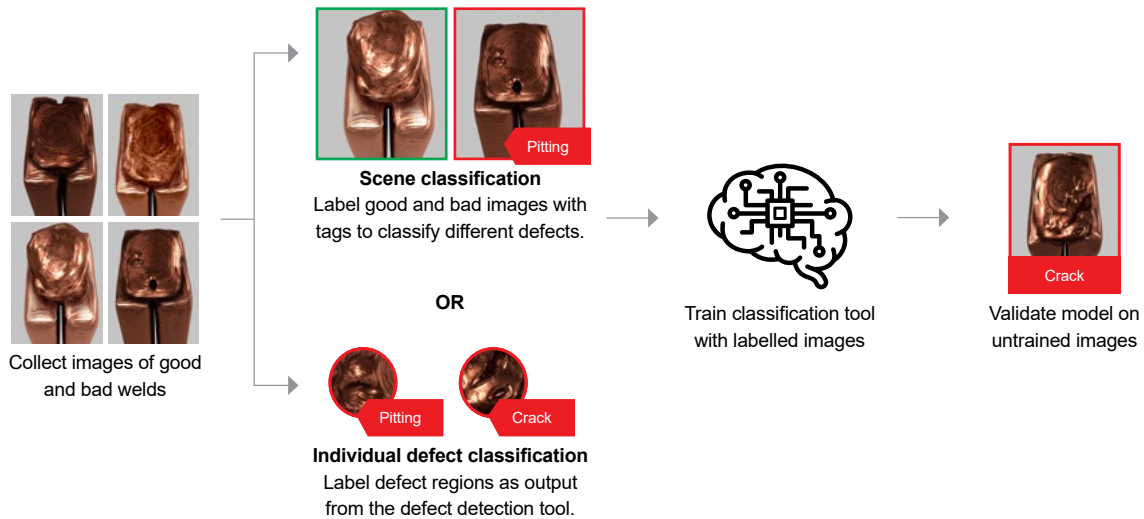
Classification also identifies potential problems in upstream production processes. For instance, a welding machine may be out of alignment, improperly configured, or reaching the end of its productive life.



Classification adds another layer of effort and complexity to a deep learning application because all images in the neural network database must be classified. Additionally, any defects within those images must be selected and labeled.

Trying to classify image sets during the first three deployment phases adds many variables, therefore it is more practical to classify for process control after deployment. In general, deep learning applications are best developed in stages—starting small, optimizing a few processes, and iterating from there.

### Process flow for scene and individual defect classifications



## SETTING THE STAGE FOR DEEP LEARNING SUCCESS

Deploying deep learning to automate spot weld inspections is an exacting, complex process with a wide range of variables unique to each manufacturer. Even in the best of circumstances, there is ample opportunity for errors.

Minimizing missteps starts with an understanding of the four pillars of deep learning application development—prototyping, production deployment, factory validation, and classification for process control. Learning these principles reduces the risk of costly errors and increases the likelihood of a strong return on investment.



# COGNEX DEEP LEARNING SOLUTIONS



## In-Sight ViDi

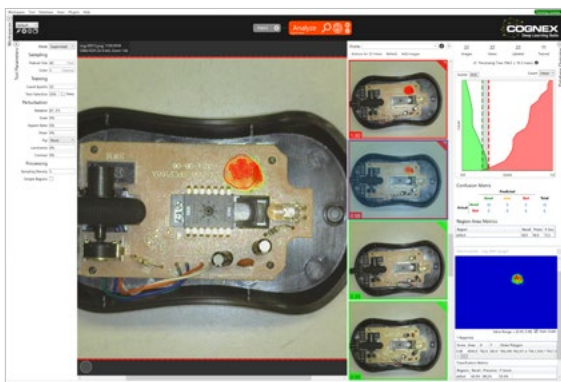
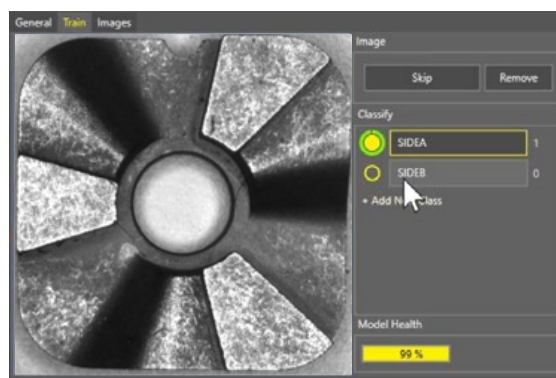
### Simplify complex applications

In-Sight® ViDi™ deep learning tools are deployed on the In-Sight D900 smart camera without the need for a PC. The tools are trained using the familiar and easy-to-use In-Sight software platform, which simplifies application development, expedites factory integration, and delivers the power of deep learning to non-vision experts.

## ViDi EL

### Deploy reliable automation in minutes

Using a pre-trained set of powerful deep learning algorithms, ViDi EL tools automate complex tasks, like advanced segmentation and multi-class classification, quickly and reliably. The tools can be trained in minutes, using a few as five to ten images, with no coding required. This, plus an intuitive graphical user interface and a fast, easy workflow, make ViDi EL tools accessible to a range of skill levels.



## VisionPro Deep Learning

### Easily solve tasks—no programming needed

For more challenging inspections, VisionPro® Deep Learning software combines a comprehensive machine vision tool library with advanced deep learning tools inside a common deployment framework. It streamlines development of highly variable vision applications and allows engineers to build flexible, highly customized solutions tailored to their specific requirements, all without the need for complex programming.

# BUILD YOUR VISION

## 2D VISION SYSTEMS

Cognex machine vision systems are unmatched in their ability to inspect, identify and guide parts. They are easy to deploy and provide reliable, repeatable performance for the most challenging applications.

[www.cognex.com/machine-vision](http://www.cognex.com/machine-vision)



## 3D VISION SYSTEMS

Cognex In-Sight laser profilers and 3D vision systems provide ultimate ease of use, power and flexibility to achieve reliable and accurate measurement results for the most challenging 3D applications.

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## VISION SOFTWARE

Cognex vision software provides industry leading vision technologies, from traditional machine vision to deep learning-based image analysis, to meet any development needs.

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## BARCODE READERS

Cognex industrial barcode readers and mobile terminals with patented algorithms provide the highest read rates for 1D, 2D and DPM codes regardless of the barcode symbology, size, quality, printing method or surface.

[www.cognex.com/barcodereaders](http://www.cognex.com/barcodereaders)



# COGNEX

Companies around the world rely on Cognex vision and barcode reading solutions to optimize quality, drive down costs and control traceability.

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