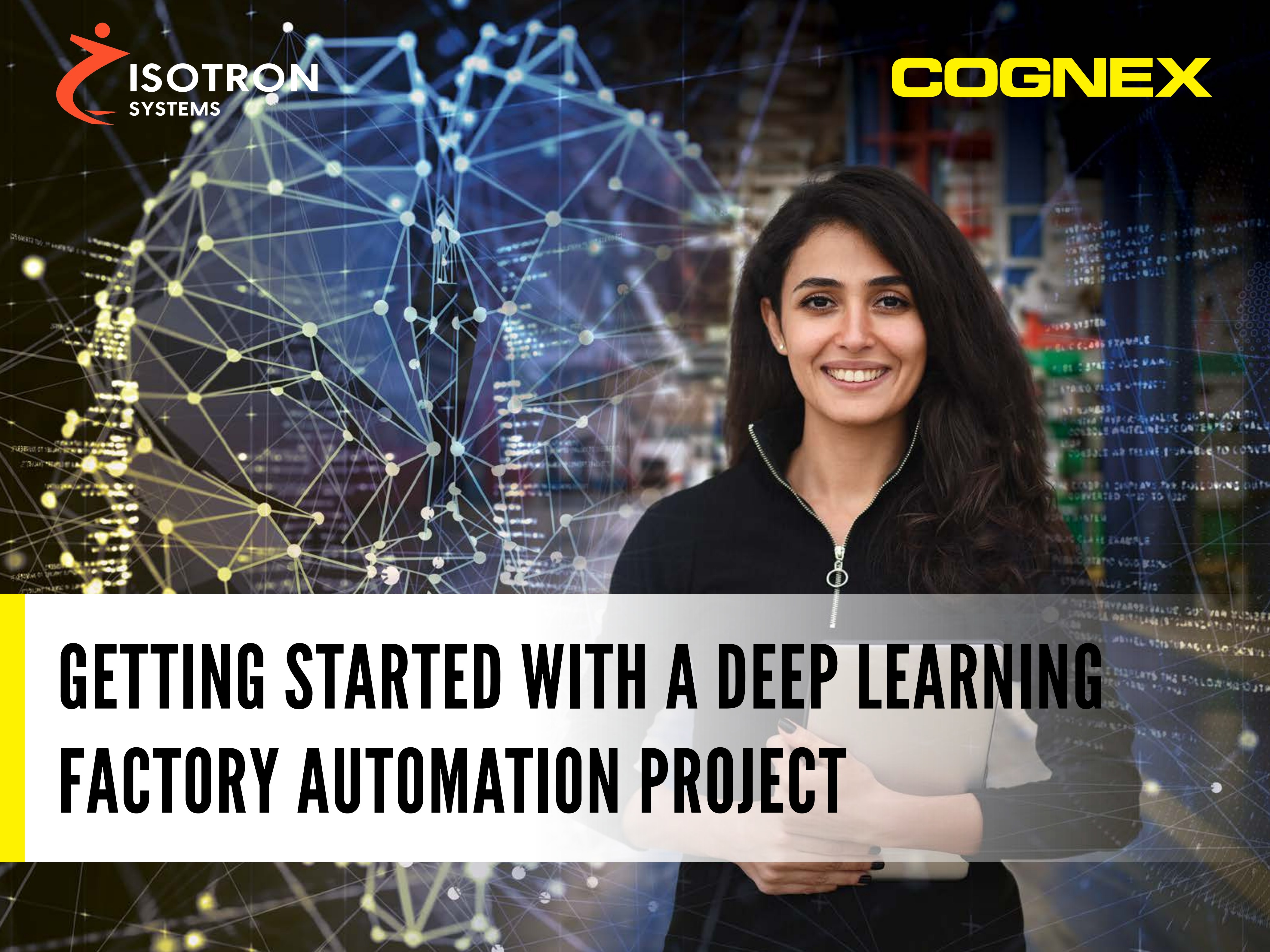

ISOTRON SYSTEMS

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# GETTING STARTED WITH A DEEP LEARNING FACTORY AUTOMATION PROJECT

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Deep learning image analysis is opening factory automation opportunities across a wide range of industries. From inspecting surface defects to sorting variable parts, checking final assemblies, grading product quality, or reading challenging text, deep learning-enabled vision systems can handle numerous new applications.


Traditional, or “rule-based” machine vision performs reliably with consistent and well-manufactured parts and excels in high-precision applications. Those include guidance, identification, gauging, and inspection, all of which can be executed at extremely fast speeds and with great accuracy. This kind of machine vision is great with known variables: is a part present or absent? Exactly how far apart is this object from that one? Where does this robot need to pick this part? These tasks are easy to deploy on the assembly line in a controlled environment. But what happens when things aren’t so clear cut?

Enter deep learning for machine vision. Deep learning uses example-based training and neural networks to analyze defects, locate and classify objects, and read printed markings. By teaching a network what a good image is based on a set of labeled examples, it will be able to tell the difference between a good part and a defective one, considering those expected variations.

However, plant managers rightly hesitate to risk their existing qualified processes in favor of a new technology's potential rewards. If a plant manager brings in new technology and it improves efficiency, that benefits the company. If they bring in new tech and it brings the line down, the negative impacts are numerous.

But successfully implementing deep learning into an automation strategy can yield cost savings, improvements to inefficient internal processes, automate complex inspection applications that are impossible with rule-based vision tools, and help increase throughput.

The following considerations can help factories and manufacturers who are new to deep learning avoid costly missteps and lost time, while generating organizational buy-in for the technology's considerable upside. If done properly, the first successful project can lead to a more ambitious and strategic rollout.

Here are five areas to consider before deploying your first deep learning pilot project.

## 1 Setting proper expectations

## 2 Understand its return on investment

## 3 Resource planning and needs

## 4 Start small with a pilot project

## 5 Undergo a phased project approach

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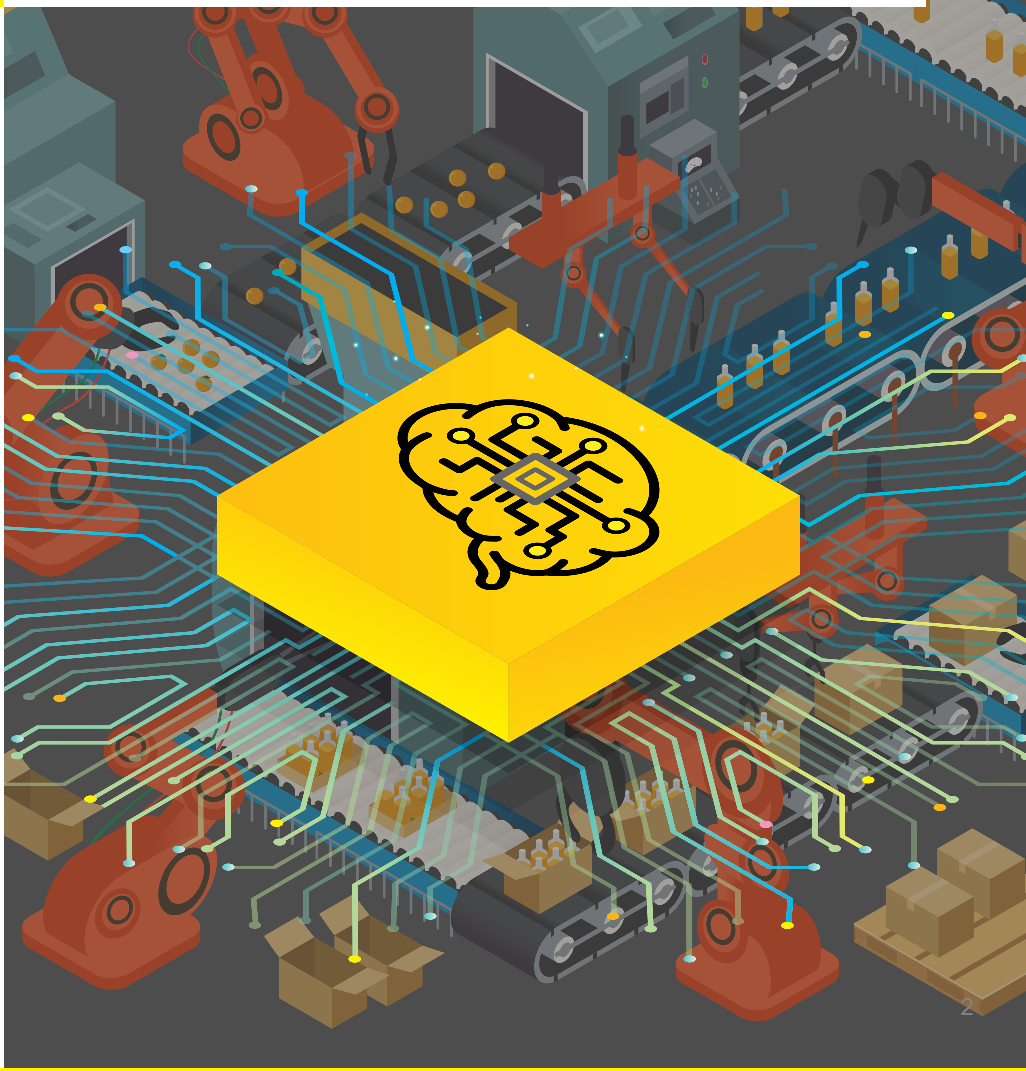


# 1 SETTING PROPER EXPECTATIONS

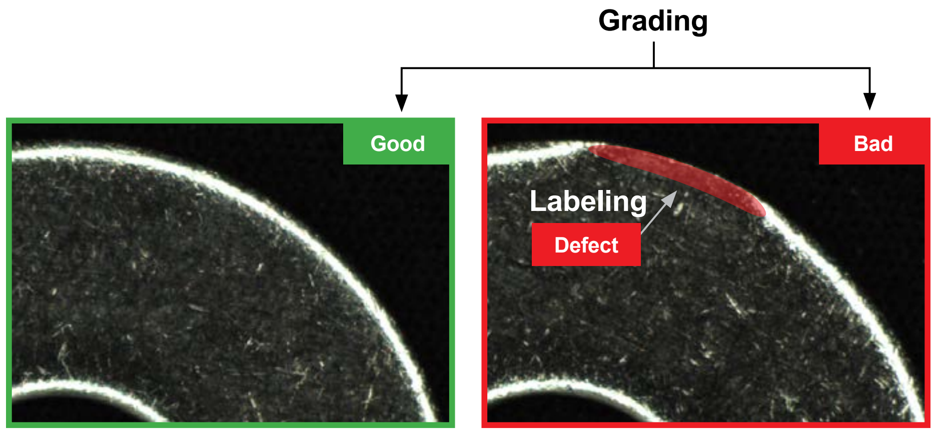
Deep learning leverages neural networks to train an application from a library of images, to identify, for example, what's a good part versus a bad part. Deep learning projects can combine the benefits of human-like judgement with the scale and dependency of a programmable machine vision application.

As with any new technology, however, there are considerations and trade-offs that come with it. While deep learning machine vision promises to solve many complex factory applications, it's not by any means a panacea or silver bullet.

That's why setting proper expectations for what deep learning can do is important to any project; knowing upfront some of the trade-offs is key.

A well-trained deep learning application requires a comprehensive set of training images that represent a range of defects and/or acceptable part variations to perform well in production. Those images also need to be acquired under manufacturing lighting and part presentation conditions. This is essential for any deep learning project to become successful.


Additionally, once images have been collected, they will need to be properly graded and labeled. In other words, a quality expert needs to be involved in any project from the get-go.




In this example, grading refers to the overall "good / bad" decision for each part, while "labeling" is the marking of specific defect pixels in the image.

## Finally, once development of the system has been completed it will need to be tested before entering production.

Sometimes, deep learning systems perform well in the lab but struggle when deployed in the production environment. Oftentimes, user frustration stems from the underappreciated differences between deep learning solutions and the more familiar rule-based machine vision systems.

Qualifying a deep learning vision solution is an iterative process that requires the system to be installed on a production line. And, unlike traditional machine vision systems, training and validation of the images for deep learning must be done during the development phase—it can't wait until factory acceptance testing. Deep learning requires a great number of samples to train with, which could require time to capture the representative set of images needed to train a well performing deep learning tool.

# 2 UNDERSTAND ITS RETURN ON INVESTMENT

What is deep learning going to do for me? That's probably the most pertinent question any company or plant manager could ask. What that question really means is what the return on investment will be. Deep learning systems aren't inexpensive, so there needs to be a tangible benefit for undertaking such an effort.

A realistic project payback is normally met by either reducing costs while maintaining similar yields to the current approach or significantly improving yields while keeping costs the same. Throughput is also a factor in ROI, especially when comparing against manual processes.

Another way to think about ROI is from a direct and indirect perspective.

**Direct ROI** is straightforward since you're just comparing the cost of the deep learning solution to the current approach. This includes everything from software and hardware costs to development time and costs, as well as image collection costs, labor costs, and training, for example.

**Indirect ROI** measures all the additional benefits beyond simple dollars and cents. Even if a project manager couldn't attribute a precise monetary figure indirect benefits produce, they are important to consider. Traceability, continuous improvement, upstream process control, and analytics are all necessary for the factory automation and digital transformation currently underway.

# 3 RESOURCE PLANNING AND NEEDS

With any deep learning project, there are four core jobs to be done. It's possible for one employee to cover more than one role but being aware of the types of experts needed is helpful to have upfront. For example, while deep learning technology is based on neural networks, in a factory automation setting a neural network expert is not really needed. Instead, a machine vision expert with a basic understanding of deep learning principles would suffice.

Here are the required skill sets needed for a deep learning deployment:

## Vision Developer

The developer implements the deep learning vision analysis solution, as well as optimizes the lighting and image formation.

## Quality Expert

The quality expert analyzes images and grades them, which is the act of determining the ground truth for the part: pass/fail, type of defect, etc. The importance of grading images can't be understated because deep learning's example-based learning approach relies on clear and consistently graded images to train the system.

## Image Labeler

Labeling images is the interactive process of indicating which regions in the image define the defect or features of interest. Labeling is a precise, detail-oriented process that needs to be done accurately and consistently on every image in the training set. As the project accumulates larger image sets, an employee separate from the quality expert may be needed to fill this role.

## Data Collector

The data collector needs to record and organize all the information including images, grades, labels, and metadata. Optimizing a deep learning system involves testing it against these data sets. A data collector may also record the decisions of inspectors if a manual procedure is currently being used in order to associate them with certain image sets.

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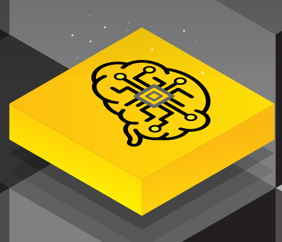
It's also worth nothing—aside from these roles—that any deep learning initiative will require a powerful Windows-based PC with a graphical processing unit (GPU) installed.

# 4 START SMALL WITH A PILOT PROJECT

In the excitement of applying new technology, it can be tempting to start the journey with the hardest, most ambitious challenge on the list. If deep learning can solve this, many automation managers might think, it can solve anything. That, however, will only lead companies down a path of frustration and delays for reasons that have nothing to do with deep learning technology.

The most ambitious challenges may be inherently too complex or unstable; the project may be cancelled if it fails to show rapid progress and ROI; or, worse, even if it eventually is a success it could steer companies to the wrong conclusions.



Instead, it's important to start small. Pick a project with a clear payback that can't easily be solved with traditional rule-based vision, but which isn't so difficult that it never makes it into production. Focus on a core need and develop both a core competency and understanding of what deep learning can and can't do in a factory automation setting.

Deep learning pilot projects should have two primary goals: evaluating its broader utility for a more holistic automation strategy and automating an inspection or verification process that is either not done at all or done manually.

So, what makes a good first project to tackle? That's unique to every company, certainly. Yet, in most manufacturing settings, the two best to start with are typically at the end of the line for final inspection or in-line assembly verification to catch problems between manufacturing steps. These two applications are good for a first pilot project because traditional machine vision applications struggle with the range of potential defects to identify, as well as variations in lighting, perspective, and part appearance. Deep learning is uniquely qualified to solve for these variances. Typically, these types of inspections also have well defined inspection criteria already established; thereby removing the need to create and solidify the quality metrics before implementing an automated solution.

# 5 UNDERGO A PHASED PROJECT APPROACH

Deep learning projects should be approached in four phases. The different project phases are:

## 1. Prototyping

- Understand current process and determine if deep learning is a good candidate to solve it
- Acquire a small database of graded and labeled images
- Build a proof of concept system to test approach

## 2. Image Data Collection

- Integrate the camera and lighting system on the production line
- Begin gathering and organizing image data and manual inspection results
- Establish baseline data
- Optimize and label image sets consistently

## 3. Optimization

- This will be the lengthiest stage: improve the deep learning solution until it meets the performance targets
- Compare deep learning results to baseline and manual results
- Adjust system and retrain as needed

## 4. Validation & Deployment

- Qualify the solution and begin using it in production
- Pass factory acceptance tests and lock configuration
- Integrate into production and expand to additional lines
- Prepare for future changes and establish continuous monitoring and improvement process

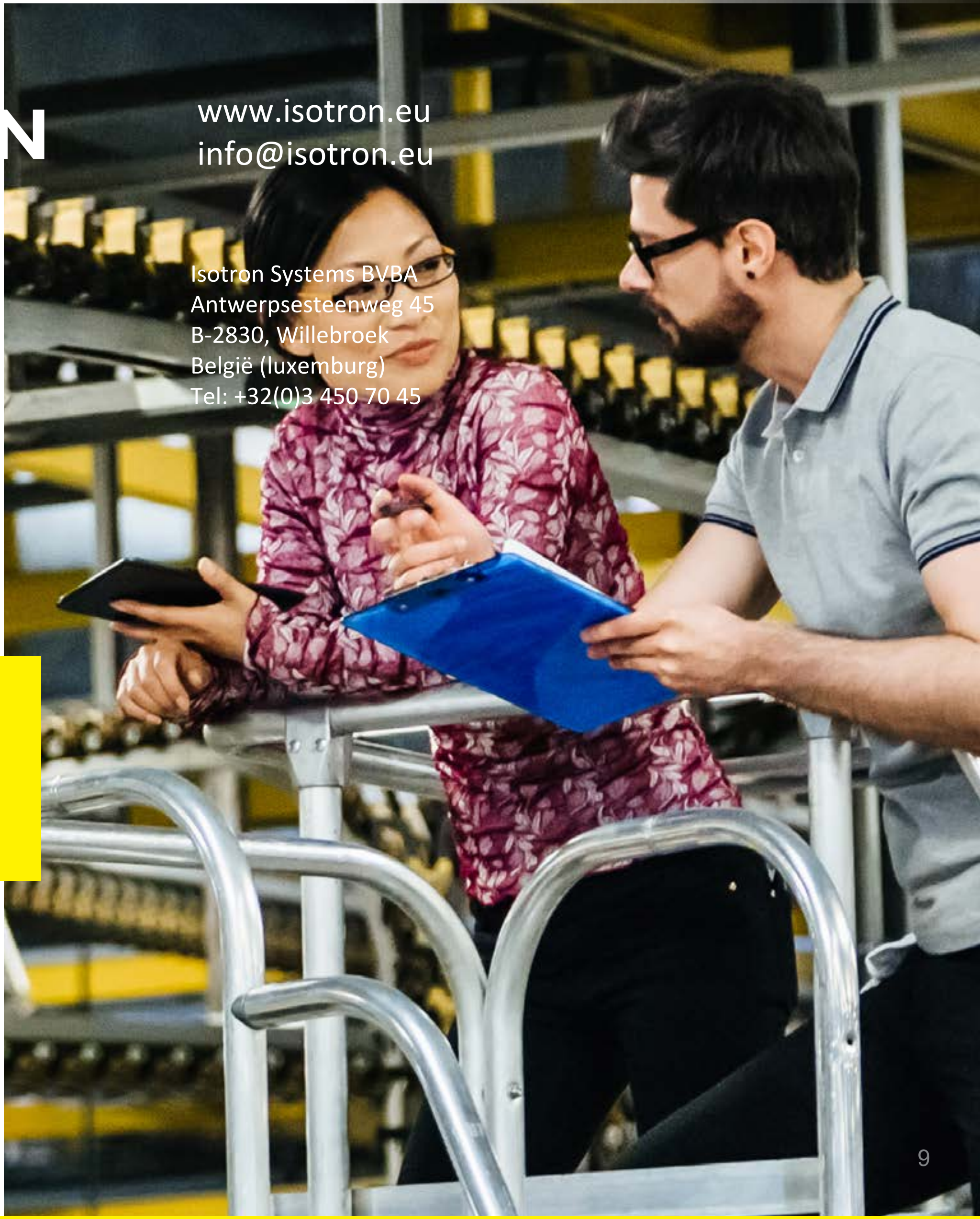
# ACHIEVING SUCCESS WITH DEEP LEARNING

By piloting small manageable projects in a sensible phased approach automation teams can set themselves and their companies up for long-term success with deep learning image analysis. While traditional rule-based machine vision experience provides a solid foundation into deep learning, the two technologies are different enough in both their scope, execution, requirements, and use cases.

But, by starting with realistic expectations, building experience, and learning which applications are better solved with deep learning, manufacturing companies will begin to understand the power that deep learning adds to factory automation strategies.

**To learn more about Cognex deep learning solutions, visit**

**cognex.com/ViDi-deep-learning**



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