LANDING AI

How to Set Up for Success in Deep Learning Development

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Introduction

Machine vision systems help industries of all types increase productivity, enhance efficiency, and drive revenue by automating disparate inspection processes. Doing so also removes human subjectivity, with results instead based on clearly defined parameters. Certain applications are difficult to quantify, however, and rules-based machine vision algorithms fall short. By introducing deep learning software into a machine vision system, companies can take their inspection systems to the next level, but successful implementation requires significant work both up-front and on an ongoing basis.

Where Rules Fall Short

First and foremost, companies looking to add deep learning capabilities to the production line need a vision system capable of producing high-quality images with which to train the system. Companies with an existing system can move on to the next phase of planning, but **companies without a reliable, proven machine vision system must first establish a method for reliable image capture**.

Whether using an internal expert or a systems integrator, the company must design and specify a machine vision system uniquely suited to its individual inspection needs. This includes but is not limited to cameras, lenses, cables, industrial computers, software, and illumination. Once properly installed, machine vision systems deliver the ability to analyze images and provide results. Common applications include defect detection, gauging, guidance, part tracking, identification, optical character recognition (OCR), and optical character verification (OCV).

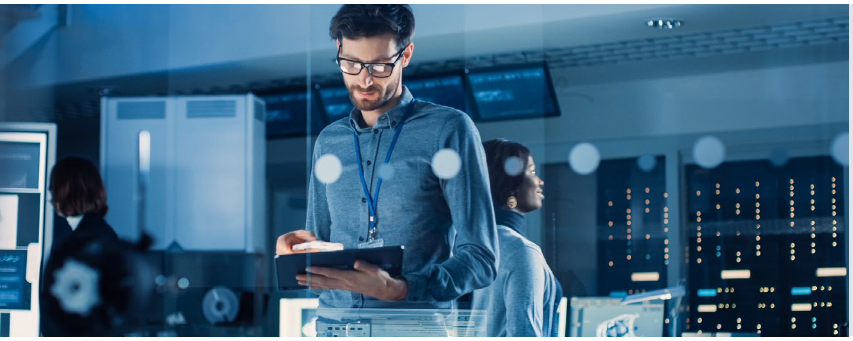
Machine vision systems tend to run into issues when parts, products, or defects become too complex. For example, in wafer inspection, defects can include cracks, scratches, missing components, and edge defects. Traditional rules-based systems will struggle with the range of potential defects on a wafer, but deep learning software trained on a set of high-quality, labeled images can identify defects and anomalies in these images. In short, deep learning software defines defects using a statistical sampling of images rather than mathematical definitions.

Machine vision system common applications:

- Defect detection
- Gauging
- Guidance
- Part tracking
- Identification
- Optical character recognition (OCR)
- Optical character verification (OCV)

Find the Right Platform

Systems integrators and developers are often pressed for time. They don't want to waste time on deep learning software or solutions that don't work. Choosing the right deep learning platform, therefore, is an important step in the process. The integrator/developer should evaluate candidate applications in minutes, not days, for applicability with deep learning.



An effective end-to-end platform standardizes deep learning solutions that reduce development time and scale projects easily to multiple facilities across the globe.

From there, for faster builds, the deep learning software should automatically identify data outliers that adversely impact deep learning solution efficacy. It should also simplify the management of datasets and deep learning model creation, regardless of the number of deployments or locations. Furthermore, deep learning software should easily integrate with traditional independent design environments (IDEs) from major third-party machine vision software vendors. Most hybrid machine vision/deep learning applications require a mix of traditional, rules-based tools — such as blob analysis and edge detection — and deep learning–based classification for overall system improvements.

A Data-Centric Approach

Deep learning software is only as good as the data with which it is trained. **If 10% of data in a deep learning system is mislabeled, manufacturers need 1.88 times as much new data to achieve a certain level of accuracy. If 30% of data is mislabeled, manufacturers need 8.4 times as much new data compared to a situation with clean data**.

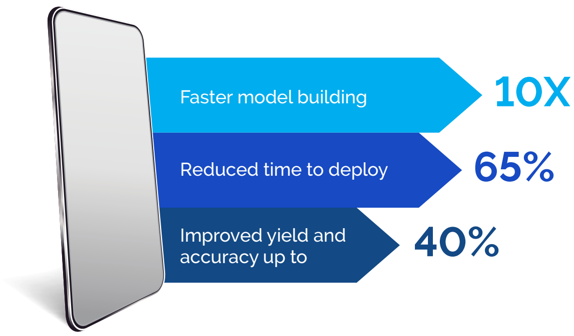
Instead of focusing on the quantity of data used to train a system, companies must shift their focus to the quality of data (taking a data-centric approach rather than a model-centric approach). A data-centric deep learning design platform that is machine learning operations (MLOps) compliant can also save a significant amount of time and energy while allowing a company to optimize the system by feeding it quality data.

Once a machine vision system has been developed, the company must establish a process for data collection, which involves delegating employees to become part of the deep learning team. In practice, this might mean running the production line for a certain period — perhaps a month — and collecting images.

With a Data-centric approach, teams can work in parallel and directly influence the data used for the AI system. By removing unnecessary back and forth among groups and looping in human input at the point where it's needed most, the result is reduced development time.

Members of the team should then label defects in the images and compare the results by creating a shared repository for defects, allowing everyone to reach a consensus on what constitutes a good part versus a part bad. Whenever consensus is reached on a given image set, the data should be added to the model to refine and improve system performance. This shared "defect book" allows designers to deploy an infinite number of models based on this data. It also provides an easy method for collaboration and remote support, as anyone can log in and communicate with image labelers, no matter their location. Teams must continue to gather data and add it to the model, allowing it to continuously improve.

Improvements from adoption of a data-centric approach



The work space should provide internal tools for remote support and communication when discrepancies arise or a consensus is reached, and these tools should be available to everyone in the company — regardless of location — thus allowing the deep learning process to scale.

Succeed with Human Input

When conducting an initial evaluation of potential applications, the team should start by identifying a project that can offer a quick win. A systems integrator or someone with deep learning knowledge should partner with team members with expert knowledge on internal processes to build a deep learning solution that produces positive results within weeks to months.

Additional benefits of data-centric AI include the ability for teams to develop consistent methods for collecting and labeling images and for training, optimizing, and updating the models.

The team must also identify a project that offers a solid return on investment (ROI), which helps justify the expense and lay the groundwork for possible future deployments. To do so, it is important to establish clearly defined and measurable objectives that add value. If possible, choose an application where a current rules-based machine vision system cannot produce adequate results, but deep learning can.

Before deploying a deep learning solution on the production line, the team must evaluate the model against human inspectors, especially if the line is a test for future global rollouts. This is often called the human-in-the-loop (HIL) method. Using an HIL strategy allows teams to leverage both human expertise and deep learning systems. Deep learning systems consistently and effectively execute repetitive tasks that may leave human operators unfocused and fatigued — and thus prone to error.

On the other hand, humans are better at adapting to changing conditions and making judgments on difficult cases. Together, humans and deep learning can create a system that not only provides better results in the short term but also produces additional data that improves system performance over time. HIL strategies should be implemented right away.

The team must also make sure that the project is technically feasible. It must perform a feasibility study at the beginning to increase the likelihood of success and avoid wasted time, effort, and money.

Iterative Process Improvements

Once a system has been specified, designed, and deployed, the deep learning team is tasked with making iterative improvements to the model. For example, when new products or product variations are added, the team must label these images, reach a consensus, and add that data into the model as well. In addition, if changes occur — for example, if lighting conditions change or a camera is replaced — the team should collect this data, label it, add it to the defect book, reach a consensus, and add to the model.

A data-centric AI approach involves building AI systems with quality data — with a focus on ensuring that the data clearly conveys what the AI must learn. Doing so helps teams reach the performance level required and removes unnecessary trial-and-error time spent on improving the model without changing inconsistent data.

Over time, data collected by the system can improve overall manufacturing processes through statistical process control methods. As the deep learning system collects increasingly more data, members of the deep learning team may be able to find root causes of errors in the manufacturing process by reviewing and analyzing images.

Ultimately, deep learning offers manufacturers a method to significantly improve processes, but teams must first enact a thorough plan based on a data-centric and collaborative approach that aims to continuously improve the process.

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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