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Open Platform for Realizing Zero Defects in Cyber Physical Manufacturing

Successful Deployment of Deep Learning Image-based NDI in the real world

The recent advances in machine learning, particularly in computer vision, represent an enormous opportunity to automate the visual inspection processes of the manufacturing industry. The potential benefits include reduced costs-per-inspection, avoiding operator discrepancies, improved traceability, and early defect detection. However, to fully extract the potential and ensure long-term success, it is crucial to consider the entire lifecycle of the NDI computer vision system and how it fits into the existing manufacturing processes.

The lifecycle of a vision-based NDI roughly comprehends three phases: data collection, model development, and maintenance. The approach to each phase highly depends on the working context. For instance, while within academic contexts, most of the efforts are put into the model development phase using existent large-scale datasets, when considering a real-world deployment, the other two phases drastically increase their relevance.

In this article, we will overview the most important aspects to consider in each phase from the point of view of a real-world deployment in a manufacturing industry.

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Data Collection

Data is the raw material of any machine learning system. Data collection and correspondent labelling are the most costly and time-consuming tasks during computer vision systems development. In this regard, the abundance of easily accessible data on the Internet has considerably eased this task. This availability is one of the major factors that enabled the recent advances in machine learning.

In the context of automated vision-based NDI, the availability of large-scale Internet datasets is more limited. Thus, collecting a large amount of specific domain defect data is indispensable.

Here we enumerate some strategies to overcome these handicaps:

- Place the computer vision system strategically to collect product images without disrupting the production line.
- Take advantage of the existing inspection processes performed to ease the annotation task.
- Make efforts to automate the data collection as much as possible to have an abundant flow of training data.
- Use generative models to generate additional synthetic data.

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Model Development

As mentioned, the model development phase is crucial. However, when deploying a Machine Learning technology for a specific application like an automated vision-based NDI, the focus is more on adapting existing model architectures than developing novel model architectures from scratch.

For this purpose, we can use several strategies:

- Fine-tuning general-purpose detection models using domain-specific data can reduce the data requirements during model development.
- Combine different machine learning methods using an ensemble approach.
- Approaches like anomaly detection can benefit from the more abundant type of data: non-defective product images.

Maintanance

Once the model development phase is completed, like any other machine, the defect detection system will need maintenance to ensure its performance does not degrade over time. For this specific case, some of the following aspects can be useful:

- Changes in the image acquisition setup (i.e. illumination variations, new products, or hardware placement) will usually require some model adaptation to maintain performance.
- Automated vision-based NDI does not fully substitute manual inspection. Some occasional manual inspections would be needed to verify that the system maintains its performance over time.

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