Optimized Processes and Improved Product Quality with Automatic Image Recognition

Introduction into Computer Vision for quality and conformity control in industrial manufacturing

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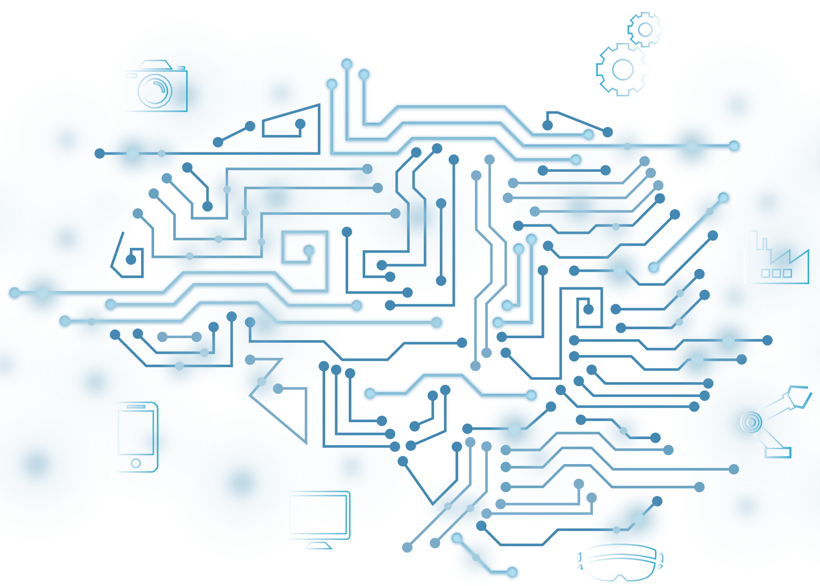

COMPUTER VISION FOR QUALITY AND CONFORMITY CONTROL IN INDUSTRIAL MANUFACTURING

How companies with automatic image recognition optimize their processes and improve product quality.

There are many standardized tasks which are necessary due to different procedures or regulations. But such tasks are monotonous and cognitively exhausting for employees, and therefore error prone. These include visual quality control at the end of the production line or completeness checks. Furthermore, certain product variants must be identified so that a precise response can be made afterwards. Regular and qualified inspections can detect errors early on and proactively improve quality.

Due to their high complexity, such inspection tasks until recently were mainly reserved for humans. By virtue of their cognition, humans are able to react flexibly to different types of errors. However, it is difficult for people to concentrate on such inspection tasks over a longer period, and therefore the detection rate decreases significantly after some time. An alternative is rule-based software systems which can detect specific defects in a stable and secure way. The disadvantage of such systems is their susceptibility to even small deviations in the shape or position of the defect.
They are not able to react to such changes.

Due to the emergence and use of machine learning methods, a more suitable solution for visual inspection has developed in the past few years. For instance, model training using example images in conjunction with the use of suitable hardware. This concept involves teaching solution strategies to a computer system via a so-called „learning" process by providing many examples of question-answer combinations.

With Computer Vision (CV) the above principle is used to extract abstract patterns with the help of many images, which help to make decisions or support the decision-making process. For example, a model trained with photos of welding seams can automatically detect different types of defects, such as inclusions or cracks.

The field of computer vision is currently developing at a rapid pace and is now being used in many different areas of application. This makes it increasingly difficult to maintain a comprehensive overview without losing sight of potential application fields. This Whitepaper is intended to support interested readers in translating the topic from theory into practice with concrete applications, and to show conceivable examples.

» *The strongest growth potential through the use of machine learning is seen in the manufacturing sector at 2.3% p.a.* «

Institute for Innovation and Technology (2018)

AREAS OF APPLICATION

With the current state of the art technology it is possible to relieve people of monotonously repetitive, standardized tasks. This means that in applications with a constant process and with few, well documented variants, machines can assist people doing these tasks. Moreover the images do not always have to come from conventional cameras. Visual data from special measuring devices, infrared cameras or x-rays can also be evaluated using CV.

Potential applications can be grouped into four areas:

- Quality Control
- Completeness Check
- Object Detection
- Location Detection

In automated quality inspection, images of the commodity are taken and compared with a target state.
Via this procedure, it is often possible to determine the exact type of defect. Direct integration of this practice into the production process enables
early detection of defects and offers the prospect of avoiding rejects by reacting quickly.

Completeness checks and commissioning are carried out in two steps. Firstly, all objects in the image are detected and then added together or forwarded to the commissioning system.

Computer Vision systems also make it possible to measure objects (size & position) and determine their position and/or orientation. In this way, faulty positions can be detected in time and information relevant for further processing can be passed along to machines that are placed downstream.

METHOD OF OPERATION

Once a use case has been identified, implementation begins in a Computer Vision project. The process can be roughly divided into four steps: data collection & pre-processing, image labeling, model creation and model deployment.

Figure 1: The Different Steps of a Computer Vision Project

Collection

If a suitable collection of training images are not yet available, a sufficiently large number of appropriate photos must be taken as a first step. Best results are achieved if the photos are taken with the same camera in the deployment location. For simple applications, a few hundred images are enough to achieve good results. It should be noted that approximately the same number of sample images are made available per (defect) class. Afterwards, the number of images can be further adjusted by selection and scaling.

Labeling

During the labeling process, the images are provided with suitable keywords (labels). For this process, also called annotation, two overriding questions arise:

1. Which labels should be used to annotate the images?

2. How granular should these labels be? How relevant is the position and form of the labeled objects?

A suitable selection of labels depends on the project-specific answer to the above questions. A quality control inspection can be carried out with an object class „ok“ and a few defect classes. In contrast, commissioning can involve over 100 different object types. The granularity of a label indicates how detailed the position and outline of an object are described. Roughly speaking, a distinction can be made between global and local labels. The former describes the entire picture, while local labels only refer to a specific area considered as the region of interest. In addition, local annotations can be categorized into bounding boxes (rectangles which surround the object),

Figure 2: Visualization of Different Types o Labeling (Granularity)

polygons, masks, and as well as points. In general, the more precisely an annotation is specified, the more meaningful it is for the machines later. This is especially important if sizes are to be measured or the shape of the object plays a major role. In order to increase the amount of training data, the images can be rotated, mirrored and distorted after labeling. This procedure, described as augmentation, aims to obtain a more robust model that can also reliably detect specialized cases.

Modelling

When enough images have been annotated, modelling can begin. The training of a model requires a great deal of computational effort. In practice, this process takes place mainly in the cloud. The outsourcing of this resource-hungry process, which is initially necessary but usually only required once, to the cloud is rather more economical than purchasing and operating powerful servers for this purpose.

There are different frameworks that support various model architectures. Two of the best-known frameworks are Tensorflow and Pytorch. For each architecture, a balance must be made between accuracy and model complexity. Highly complex models are more accurate, but also require longer time for inference. This correlation should be considered during training, for example, when automating a time-critical process. Before the model is used, it should be subjected to extensive tests, for instance, an analysis of generalizability („robustness“) and a test of borderline scenarios.

Deployment

Successful training returns a model which can now be used for deployment. Depending on the complexity of the model, implementation is already possible on simple hardware or integration into existing control systems. After the camera has been connected and appropriately positioned, inference can start. Inference is the process of classification or recognition of an image by the model. In a generalized classification scenario, the result of the inference is one or more classes to that image. In contrast, within a local object recognition, the exact position and shape of the object is also recognized. Using this data, further metrics can be calculated, such as the size of the object.

Additionally, the model returns a confidence score, which characterizes the accuracy of the prediction. Furthermore, aggregated statistics can be collected over a longer period, which can be used to generate heat maps of error positions or to analyses patterns in the occurrence of defects. In this way, new findings can be obtained that were previously not possible due to the high effort of manual data collection.

Moreover, the continuous visual inspection now also makes it possible to issue automatic and early warnings when suspicious patterns are detected. The reject rate can thus be considerably reduced, and subsequent errors prevented.

Detection | Aggregated Statistics | Heat Map

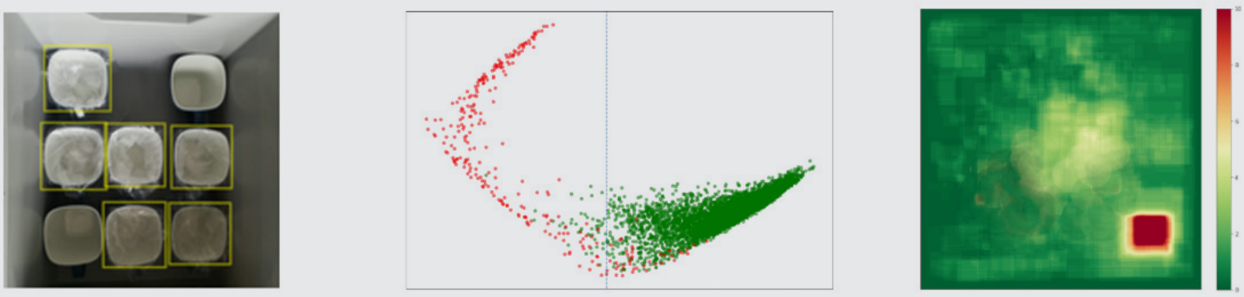

Figure 3: Selected Applications of Computer Vision

LABELING-TOOLS

The most complex and cost-intensive procedure in Computer Vision projects, is the creation of a suitable „ground truth“ data. The manual labeling of large image data sets is a monotonous and time-consuming task. The use of modern and flexible labeling tools can help here. For example, functions to support local annotation can reduce the labeling time to a fifth, which significantly improves overall efficiency. For example, it is possible that pre-trained models already suggest labels which the user must confirm and, if necessary, correct („semiautomated labeling“). It is also possible that image processing methods support the automatic selection of relevant regions. In addition, many state-of-the-art tools already include data management and robust quality assurance. Some providers also offer the possibility of integrating training and deployment directly into the labeling process.

When selecting the appropriate software, special attention should be paid to compatibility with the application. For example, there are two different paradigms for the graphical user interface - tagging and browsing (see Fig. 4). In tagging, the images are individually provided with all relevant labels, which is particularly useful when labeling many different classes. Browsing, on the other hand, allows the user to select all suitable images containing an object of the selected class.

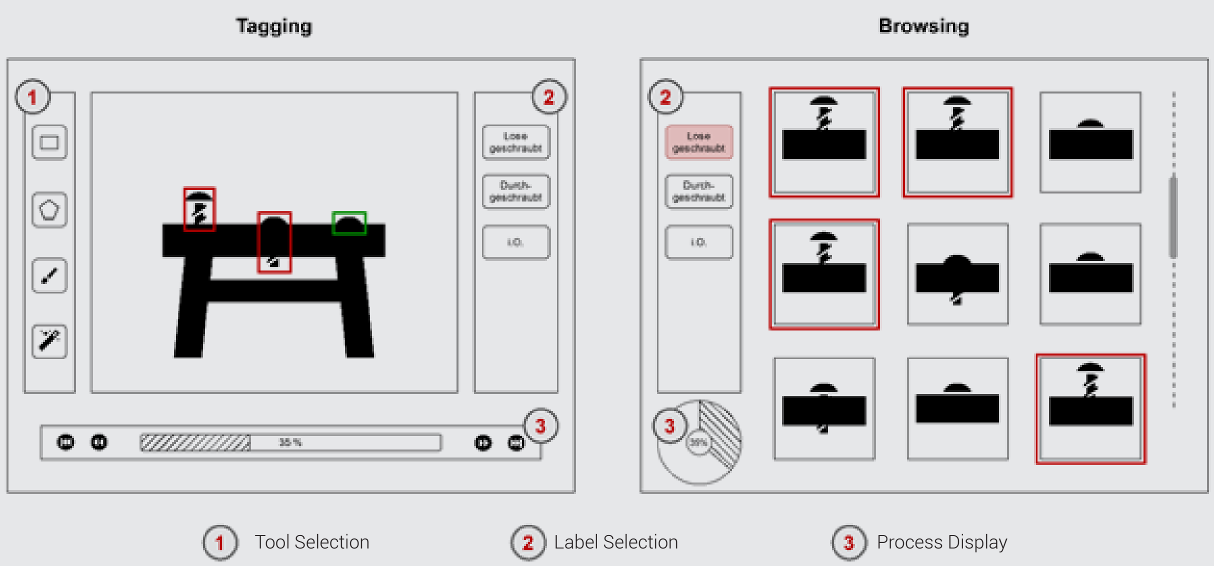

Figure 4: Visualization of the two User Interface Designs Tagging & Browsing

A Comparison of Current Labeling Tools

Currently, the market offers a variety of different labeling tools, which can basically be differentiated between stand-alone tools and platforms. An essential selection criterion for a labeling tool is therefore whether an integrated overall solution (labeling, training, deployment) is being sought or whether the entire process itself is to be implemented. The advantage of platforms is that they generally offer more support for labeling and integrate the model training into the process. This step is otherwise particularly time-consuming, as the training data often must be pre-processed before it is accepted by a framework.

In the following table, Robotron Realtime Computer Vision (RCV) is compared with a selection of currently available labeling platforms. The comparison criteria were specifically selected for use in an industrial context.

Tool	ROBOTRON RCV	GOOGLE CLOUD	AWS SAGEMAKER	LABELBOX
Material	Images, Videos	Images, Videos	Images, Videos	Images, Videos
Granularity	BBoxes, Polygons, Segments	BBoxes	BBoxes, Polygons, Segments	BBoxes, Polygons, Segments, Lines, Points
User Interface	Tagging	Tagging	Tagging, Browsing	Tagging
Model training	✓	✓	✓	✓
Semi-automatic Labeling	✓	✓	✓	✓
Magic Pixel	✓	✗	✓	✓
Collaboration	✓	✓	✓	✓
Reviewing	✓	✗	✓	✓
Data augmentation	✓	✓	✓	✓
Dockerized	✓	✗	✗	✗
Presentation	✓	✗	✗	✗
Location	Germany	USA	USA	USA
Website	robotron.de	cloud.google.com	aws.amazon.com	labelbox.com

The selected platforms offer a comparable basis of standard functions. They can process both images and videos, and all except Google offer several label types (granularity). The tools also share tagging as a standard user interface and allow for integrated model training. This is particularly useful if machine learning expertise is not to be established or maintained and instead should be based on standardized parameters.

Almost all tools also support labeling through an upstream automated annotation (semi-automatic labeling) or through the quick selection of the entire object region (magic pixel). Labeling with several employees (collaboration) and the subsequent control (reviewing) by an expert is also supported by means of user administration and rights management. The extension of training data through mirroring and other transformations is part of the basic functionalities of the platforms (Data Augmentation). In most cases, it can be conveniently initiated by an automated script after labeling.

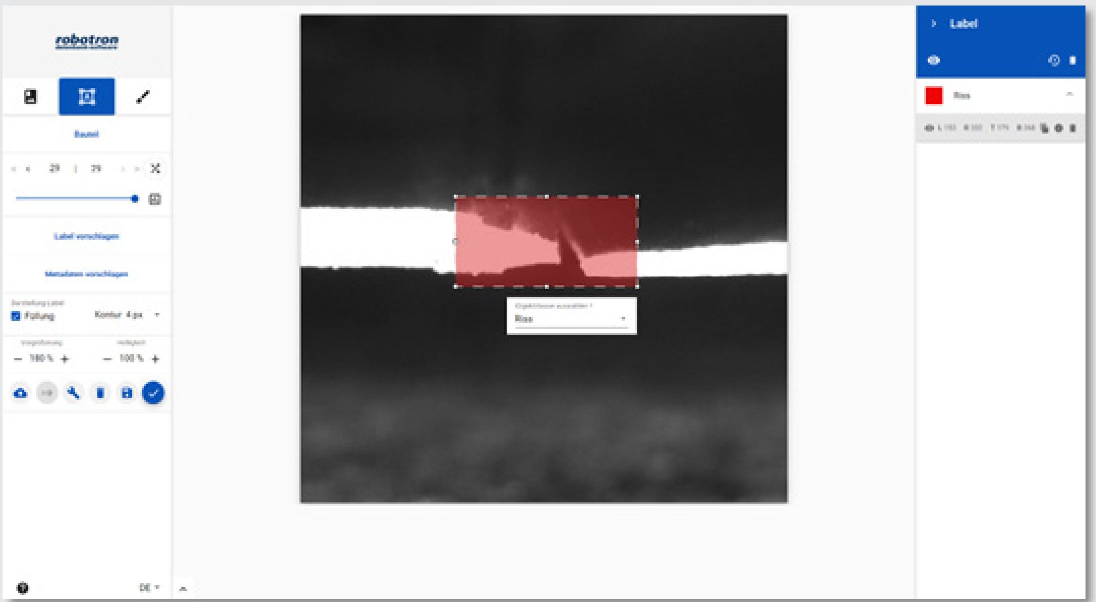

Figure 5: The Robotron RCV Labeling Tool during the Annotation of Cracks

There are major differences between the platforms in the criteria of location and control as well as in the adaptability to individual requirements. Google and Amazon each offer solutions that can only be used together with their own environment (Google Cloud, AWS). As a result, the data must be kept in the cloud, and therefore the choice of frameworks and label types is limited. On the other hand, the Robotron RCV tool also enables local deployment through its docker architecture and can always ensure the confidentiality of the data through its encapsulation. In addition, its modular design also allows a mix of local deployment and implementation in the cloud.

After the model deployment is completed, an additional module should be available to evaluate the inferences and display the results clearly. Most platforms offer only an interface that returns exclusively the raw data of the inference (mostly as JSON). Robotron has developed the VOR Dashboard (see Fig. 6) for visualisation purposes, which presents the raw data as well as the results on the image in a graphical interface. The VOR Dashboard is especially designed for the application in an industrial context by providing a simple test logic, wherein a comparison of ACTUAL is provided as TARGET state and visual feedback.

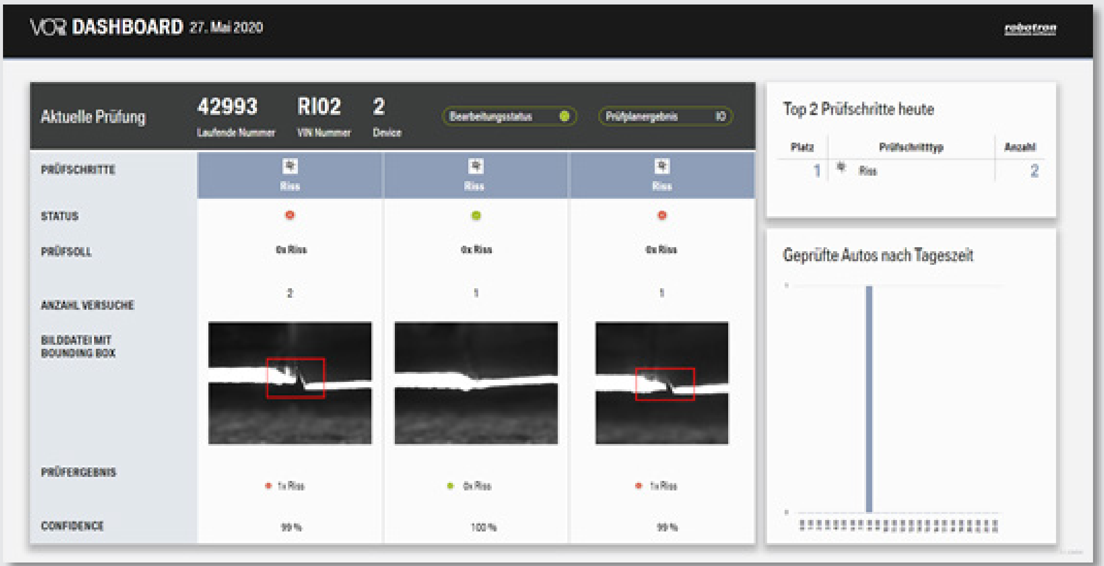

Figure 6: The Robotron VOR Dashboard assists in the test by matching the ACTUAL with the TARGET state

Once the model has been trained and set up on site, it will continuously provide data in the concrete application case without the need for an employee. In addition, the model can be developed further at any time and, for example, adapted to a new or changed process environment by updating it with new images.

CONCLUSION

Computer Vision is a technology with rapid growth and enormous potential for industrial production. There are currently some seasoned and functional solutions for the application of automated image recognition which are used in industry.

With the right software solution, the use of Computer Vision is suitable for all companies that want to optimise their processes and improve product quality.

We hope to have convinced you of the versatile application possibilities of the Realtime Computer Vision platform. Let our experts advise you on how you can identify your individual application cases for Computer Vision, recognise the potentials and optimise your production processes.

Do you have a problem in your production, or open questions?

Find out more on our website or make an appointment today with one of our consultants.

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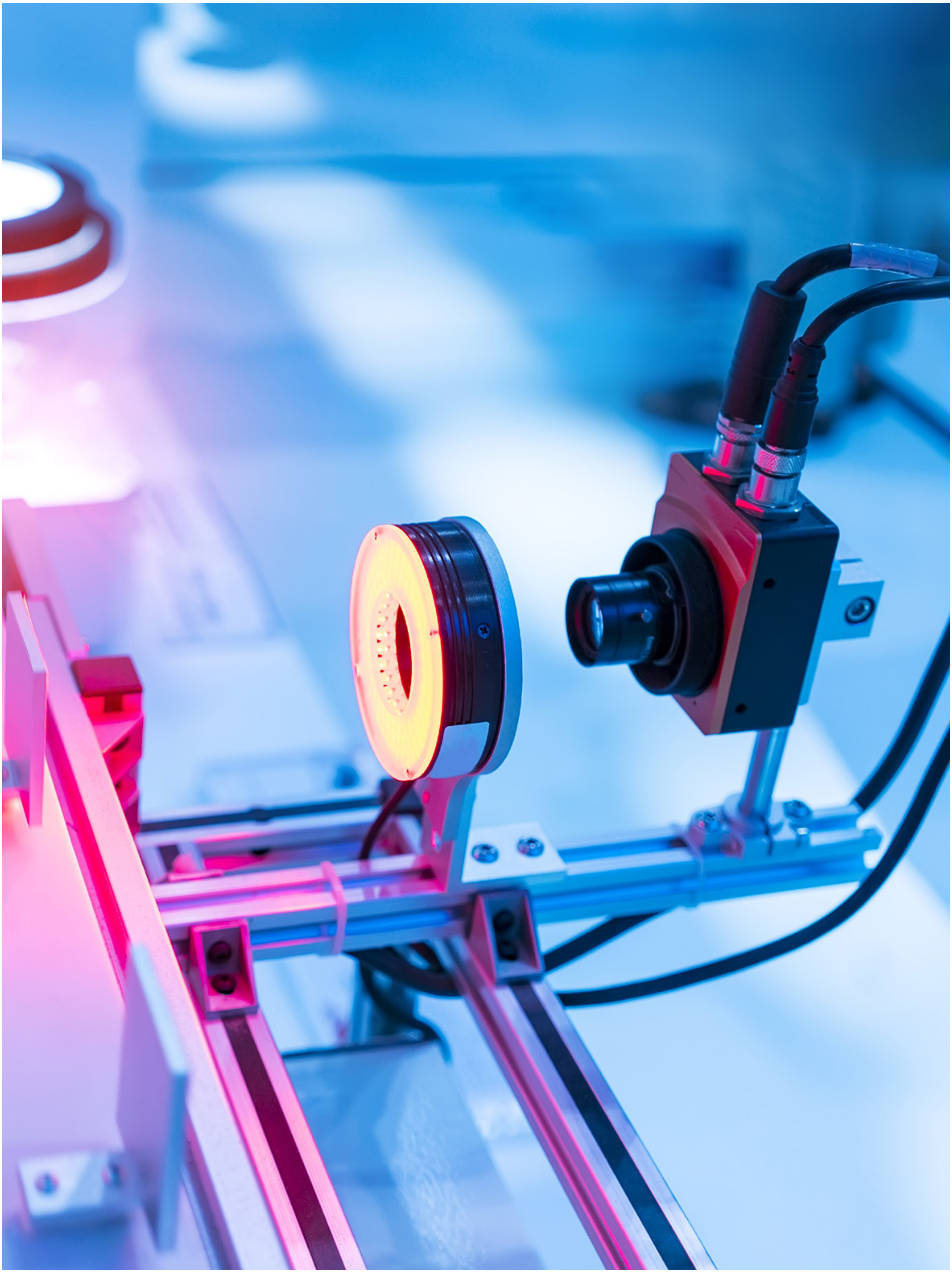

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