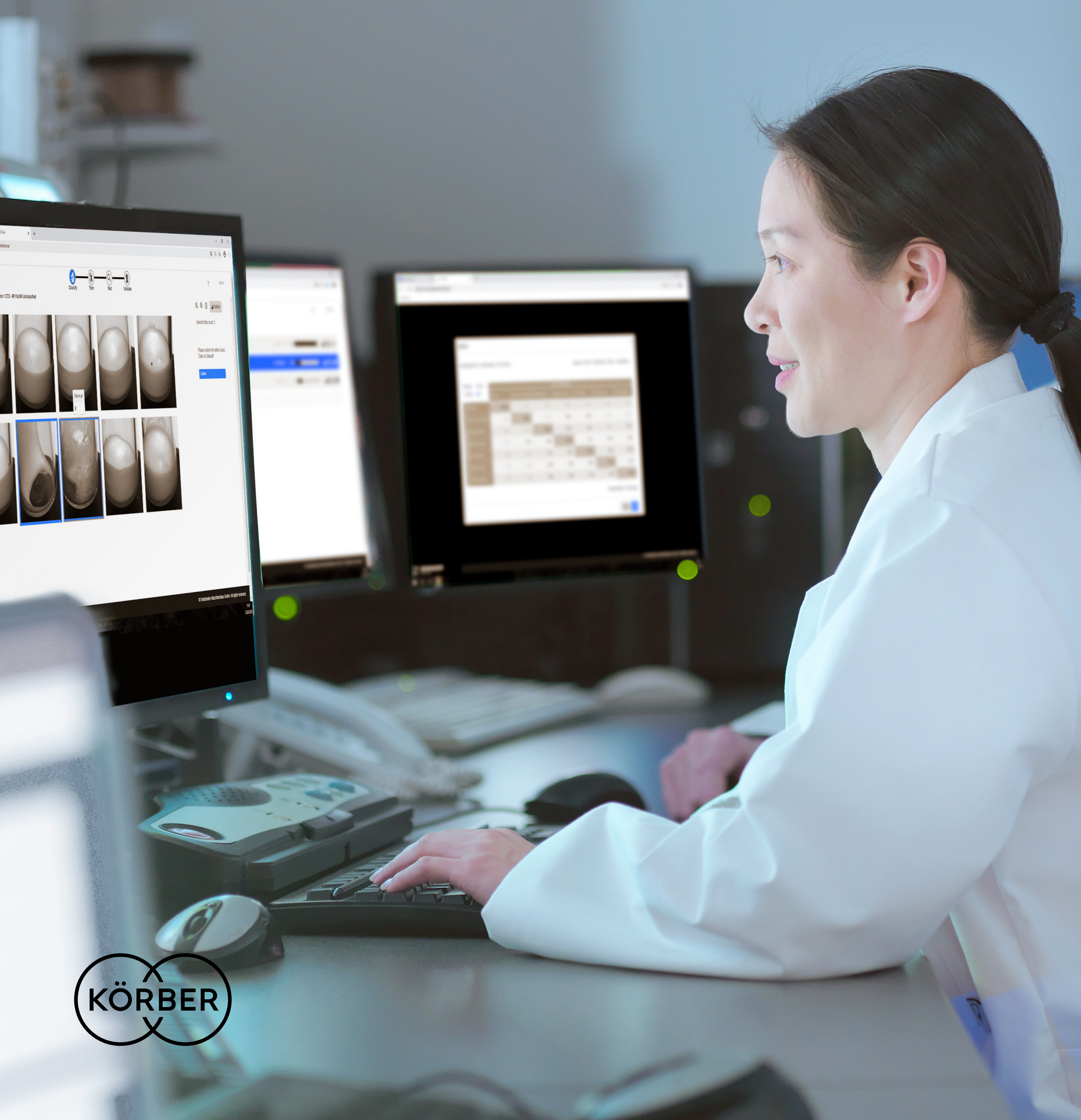
Case Study

Deep Learning

Eliminate your false ejects with EJECT-X



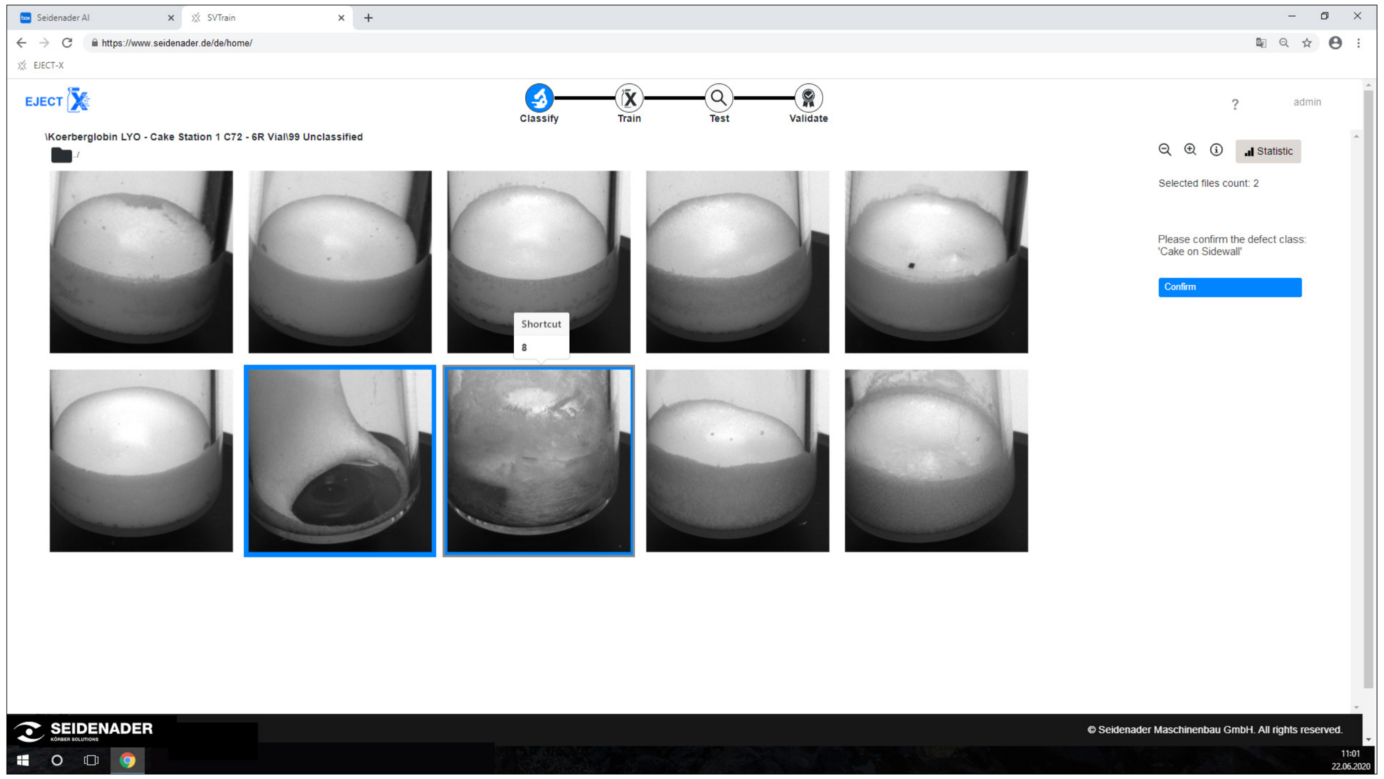
KÖRBER

Reduce up to 99.9% of your false ejects by teaching your inspection machine to learn

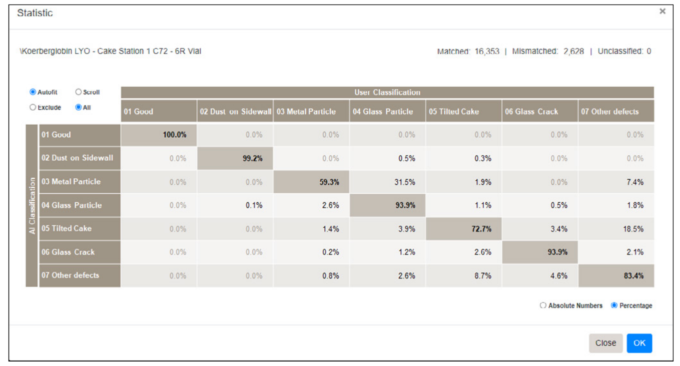
Inspecting expensive biopharmaceuticals often results in ejects of flawless product. False eject rates of **up to 15% cost** the global pharma industry millions of dollars per year. Vision systems with fixed thresholds often misclassify air bubbles as particles. Nontransparent suspensions and varying lyophilized cakes cause misinterpretations of supposed defects.

At Körber, we understand that by reducing false ejects **our customers become more competitive** to secure a leading strategic position in their industry. Learn in this case study about EJECT-X, a Seidenader Solution, how the deep learning software deploys the benefits of human-like decision making to your automatic visual inspection machines and ensures replicable inspection results. Up to **US$ 1 M per year can be saved** with regard to the disposal of good product.

Classify images to train and test the algorithm's performance



You prefer to read the case study later, but want to get in touch with us now? Just 1 click will do.



AI Classification \ User Classification	01 Good	02 Dust on Sidewall	03 Metal Particle	04 Glass Particle	05 Tilted Cake	06 Glass Crack	07 Other defects
01 Good	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
02 Dust on Sidewall	0.0%	99.2%	0.0%	0.5%	0.3%	0.0%	0.0%
03 Metal Particle	0.0%	0.0%	59.3%	31.5%	1.9%	0.0%	7.4%
04 Glass Particle	0.0%	0.1%	2.6%	93.9%	1.1%	0.5%	1.8%
05 Tilted Cake	0.0%	0.0%	1.4%	3.9%	72.7%	3.4%	18.5%
06 Glass Crack	0.0%	0.0%	0.2%	1.2%	2.6%	93.9%	2.1%
07 Other defects	0.0%	0.0%	0.8%	2.6%	8.7%	4.6%	83.4%

EJECT-X can be accessed remotely and no machine stop is required to access the software

A confusion matrix compares the algorithm's results against the operator's classification

Why parenteral inspection is complex and costly false eject rates occur

Vision engineers set up automatic inspection machines with a limited amount of physical defect samples. In many cases the parenteral product is not yet in production and the configuration of the vision system is based on samples produced in a laboratory. Long lists of physical defects which might theoretically appear – e.g. cracks, chips, airlines in the glass – or particles are tested, and vision tools are applied.

Per defect you need at least 5 to 15 samples to ensure reliable detection results with classical vision tools. This setup process is expensive and time-consuming because you must configure up to 18 cameras per machine. Then you have to set up and adjust different vision tools to achieve the required inspection results. Often defects occurring under real manufacturing conditions are not available to set up the inspection machine accordingly.

Despite these tremendous efforts, the global pharma industry still suffers from false eject rates of up to 15%. That's because the pitfalls of parenteral inspections are versatile: The product characteristics challenge classical vision tools and may lead to an increase in falsely ejected products.

As the pharmaceutical industry is highly regulated, fixed thresholds of the vision system are set highly sensitive, resulting in a higher potential of producing false ejects. These false ejects cost the pharma industry assumingly up to US$ 740 M per year.

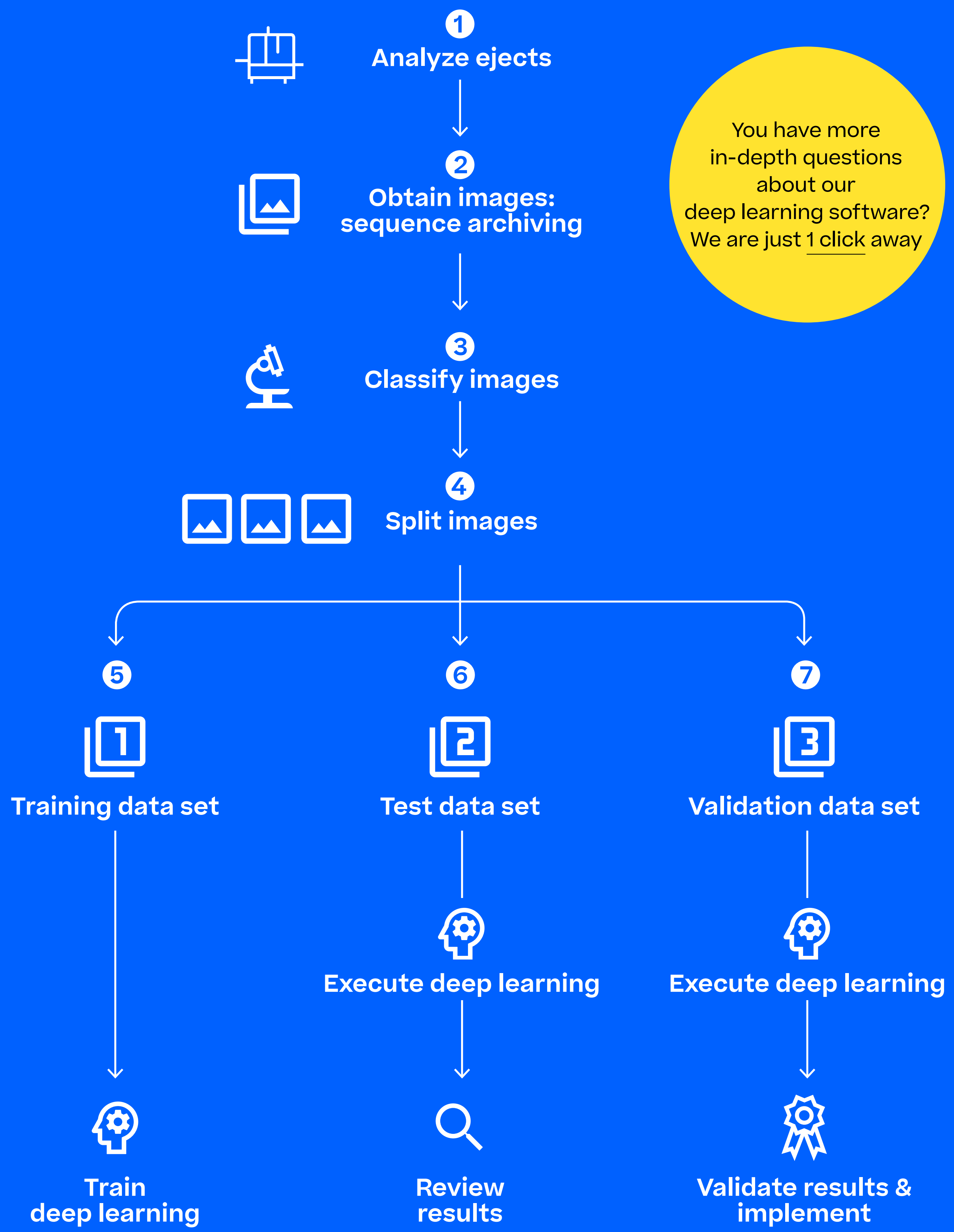
At Körber, we have found a much better way, with the ultimate chance of eliminating your false ejects altogether.

How you design replicable validation processes & reduce false eject rates by up to 99.9%

If you feed a self-learning algorithm with data, your parenteral inspection will automatically become more accurate with increasing amount of image data provided.

Workflow

A guided workflow ensures a replicable process that is easy to validate and manageable during implementation



This is how the new deep learning software Seidenader EJECT-X works:

Step 1

Analyze ejects

Before getting started, check your previous batch records for high eject rates. Also locate responsible camera stations requiring a new vision configuration due to false ejects. By focusing on “high-eject” camera stations first, you keep the project scope manageable and receive quick improvements.

Step 2

Obtain images from the inspection machine

Images are being automatically stored in sub-folders in order to track back every image to its camera station, physical container and defect. The renaming of files is an automated process to enrich the data with additional information, e.g. the batch number or defect information.

Step 3

Classify images

In the next step, you have to classify the images into the different defect classes in order to train the neuronal network with this information. If physical defects are pre-sorted, you can speed up the classification process by confirming images rather than selecting from various defect classes. This initial effort lays the groundwork for the efficiency of the self-learning algorithm.

If images are randomly stored from production, each defect class has to be selected per image. After the classification of approximately a quarter of the data is done, there is also the possibility to use the algorithm to pre-classify the data. With this approach the described ‘confirm method’ can be used to speed up the process.

Step 4

Split image data

Now you split the categorized pictures into three different data sets:

1.
The **‘training data set’** trains the neuronal network.

2.
The **‘test data set’** tests the results of the trained algorithm and helps to improve the performance of the deep learning system by optimizing the data.

3.
The ‘**validation data set’** will not be touched or optimized. It will be used to ensure results of the algorithm are replicable and have not accidentally been optimized for the ‘test data set’. A benchmark of results against the test data will support to digitally validate the algorithm’s performance.

It is very important that images of one particular physical defect are not separated in e.g. the training and the test data set. Otherwise the testing of the algorithm might be misled as e.g. a crack of exactly that shape has been trained and is obviously a lot easier to be recognized again by the deep learning system.

Step 5

Train deep learning algorithm

The images of the ‘training data set’ are now fed into the deep learning system. The neuronal network uses multiple layers to progressively extract higher level features from the raw image input.

Step 6

Test deep learning algorithm

Now it’s time to benchmark the inspection quality by running the ‘test data set’ through the deep learning system and review the trained algorithm. The AI results of the images are compared to the results classified by the operator in step 3. If the operator’s classified results and the AI results match, the deep learning is ready for validation. In case of a negative test, either mistakes in the classification or a lack of enough image data per defect class are responsible and the test has to be repeated.

Step 7

Validate deep learning algorithm

Finally, you validate the algorithm by running the validation data set through the deep learning system and compare it to the results of the test data set.

These two examples illustrate how you save up to US$ 1 million /year

Without re-inspection on a Seidenader V90+ (semiautomatic inspection machine)

Annual production volume	10,000,000 containers
Production cost per container	US$ 1.50
False-eject rate	5%
Annual saving potential for wrongly discharged products	US$ 750,000

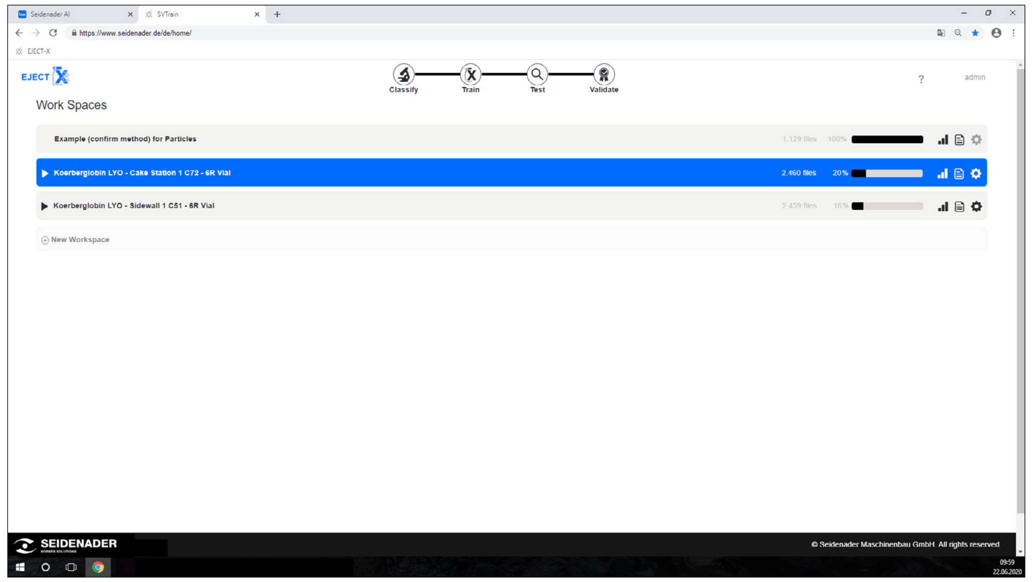
With re-inspection on a Seidenader V90+ (semiautomatic inspection machine)

Annual depreciation of two V90+	US$ 40,000
Number of V90+	2
Number of operators per V90+	3
Number of shifts	2
Annual costs per operator	US$ 75,000
Total annual running costs of two V90s	US$ 940,000

About Körber Pharma Inspection

We develop and build inspection machines for parenteral medicine manufacturers all over the world. Many years of experience in handling pharmaceutical product and in the development of innovative inspection technologies make our systems economical and reliable. With 125 years of operating experience in the high safety and quality requirements of the pharmaceutical industry, we are today one of the world's leading suppliers of inspection solutions.

A general overview of all workspaces with progress bars and sub workspaces is provided



EJECT-X is a modular solution and scaleable by choice

Our Seidenader EJECT-X, based on a deep learning technology, will **perfectly integrate into the vision system** of your inspection machine. It's a modular system: You can focus on 'high-eject' camera stations first and **upgrade them** with deep learning capabilities. So, you can scale it up at your own speed and ensure quick readiness for production. You do not need to exchange or modify any hardware or software of our inspection machines ordered in 2020.

In just one day* you can setup EJECT-X on your vision configuration on Seidenader MS, VI, and SWITCH series. Up to ten-year-old inspection machines can be retrofitted and upgraded with our deep learning software.

* only considering the setup time; not including obtaining the images, classification, training, testing and validation

EJECT-X – eliminate your false ejects with deep learning!

- **Modular & scalable: upgrade camera by camera**
- **100% integration into existing vision system to combine with existing vision tools**
- **Easy-to-use image classification**
- **Guided workflow**
- **ROI in just 1 year**
- **Ready to implement in new inspection machines**
- **125 years of expertise**

You want to know how you can apply EJECT-X to your visual inspection machines? We are happy to discuss this with you in a free consulting call.

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