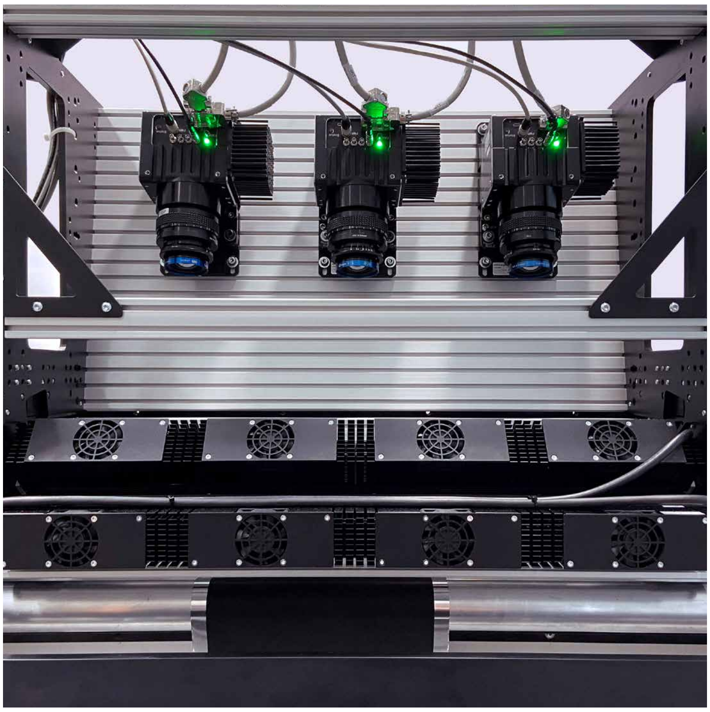
chromasens
IMAGING FOR PROFESSIONALS

BATTERY ELECTRODE FOIL INSPECTION

WITH THE USE OF DIFFERENT ILLUMINATION TYPES AND GEOMETRIES

CASE STUDY



Quality matters

In lithium-ion battery production, the inspection of anode and cathode foil plays an important role in ensuring the quality and performance of batteries and the continuous optimization of production processes. To ensure the production quality of the final product, the electrode needs to be inspected at different stages, including the production of the bare metal alloy foil, after the coating and after the calendering process.

Early detection and sorting out of faulty battery foils before they enter the subsequent process steps leads to cost savings and more sustainable production. In addition, defective parts not only pose a cost risk but can also compromise the safety and performance of the final products. In summary the challenges of the electrode inspection are the high speed of the web material (up to 300m/min) in combination with the requirement of a quite high optical resolution (20Qm/Px) to detect even small defects.

The implementation of image processing systems, such as the Chromasens Line Scan Vision Platform (LVP), combined with deep learning algorithms for anomaly detection, holds the potential to enhance quality control in this context. For this purpose, different data sets of the battery foils are acquired with the LVP (*Figure 4*). The use of the Chromasens **allPIXA evo 8k CXP** line scan camera enables the detection of smallest irregularities of the electrode surface at high production throughput. The approach to solve the challenges mentioned above can be summarized as follows:

- **High-Resolution Image acquisition:** The Chromasens **allPIXA evo 8k CXP** line scan camera offers a high resolution image (8192 Pixel) as well as a fast image acquisition of up to 100 kHz line rate.
- **Python-based Image Preprocessing:** To pre-process the acquired images, they were cut into patches of size (256, 256) and combined images were created from the images of different illumination geometries. Libraries such as OpenCV were used for this.
- **Dataset Creation for Model Training:** To train and test deep learning models, data sets with good and faulty examples are required. Various data sets are generated for this purpose with different lighting geometries for anode and cathode foil.
- **Anomaly Detection with Deep Learning algorithms:** Machine learning methods such as Autoencoders and other Convolutional Neural Networks (CNNs) combined with different classifiers trained with the acquired images enables identification of defects, such as dust or scratches. The Python libraries TensorFlow and Keras were used for this.

Chromasens Line Scan Vision Platform

The **Chromasens Line Scan Vision Platform (LVP)** offers a modular approach to configure single- or multi camera systems with versatile line light options very easily. That is of great help, since the adoption of the camera resolution, the number of cameras and the lighting geometry must be optimized for every use case. For the electrode foil inspection, the Chromasens **allPIXA evo 8k CXP** camera is the best choice, since it offers high image resolution at the required speed. In addition, the configurable IO concept offers the possibility to perfectly synchronize multiple cameras and the light sources. The precise alignment and the perfect fit of the vision components help a lot to solve challenging vision uses cases, since the image data can be greatly optimized.

A conveyor system (*Figure 1*), equipped with the LVP system (*Figure 4*) is used to acquire the image data sets which are used for further processing. The line scan system is configured as shown in (*Figure 2*) and consists of three Chromasens **allPIXA evo 8k CXP** cameras (1) to cover the field of view at an optical resolution of 20 *Qm/Px*. Chromasens **Corona II LED line light** sources (3) with matching Chromasens **XLC4-1A** lighting controller (4) and an encoder (5) to synchronize the camera acquisition line rate to the conveyor speed.

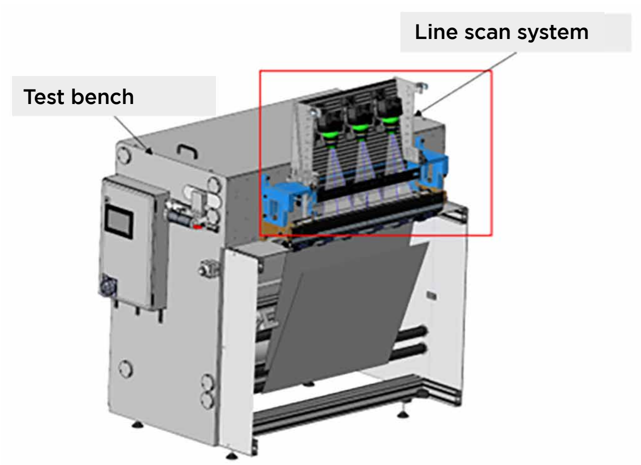


Figure 1: *Conveyor and line scan system for data acquisition*

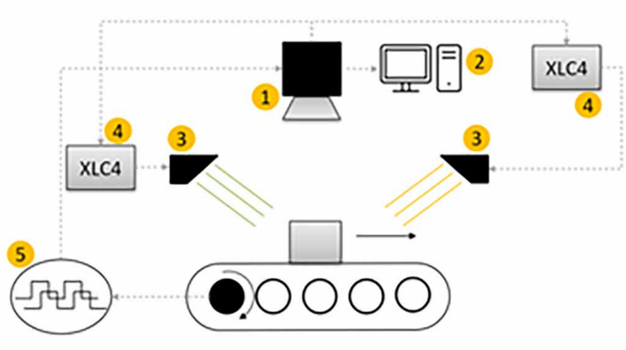


Figure 2: *Setup of a line scan system*

In order to detect all types of anomalies in the electrode foils, different illumination geometries (one bright field and two dark field illuminations) are used (*Figure 3, Figure 4 and Figure 5*).

Bright field is an illumination technique in which reflecting surfaces appear bright, since light source and camera are aligned such that the angle of the incident light equals the angle of observation. In contrast, dark field is an illumination method where the scattered or refracted light from the sample is observed. By combining these techniques, the aim is to detect as many defects on the battery electrode foil as possible.

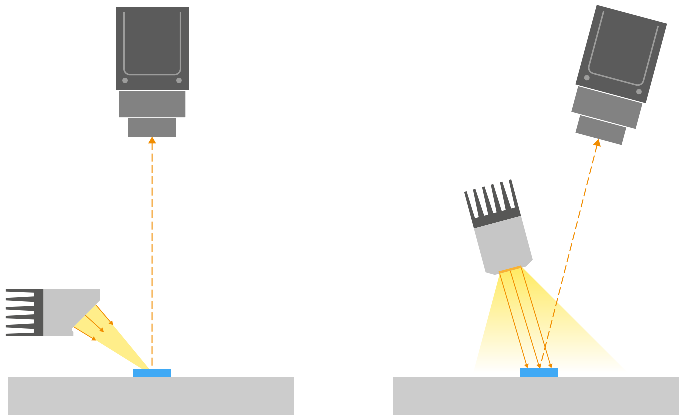


Figure 3: *Geometries of darkfield (left) and brightfield (right) illumination*

The Chromasens LVP offers the possibility to perfectly synchronize the line rate of all cameras and the strobing frequency of the line light sources. Through that approach each line is captured three times, whereas for each line of the three cameras only one light source is switched on. Initially, the front dark field illumination is activated, followed by a single acquired line with bright field illumination, and finally, another line with the back dark field illumination is recorded. This concept allows capturing the surface under different lighting conditions. Through a line shift (deinterlacing), the overlaid individual images are then assembled into three separate images, serving as the basis for subsequent processing steps.

Initially, images of undamaged battery electrode foil are captured to form the basis for later training sets. Subsequently, various anomalies, such as dust, scratches, and moisture, are introduced into the data set to test the image processing pipeline. A test dataset is then compiled from the images of anomalies along with a portion of images from undistorted surfaces. The influence of the three illuminations is illustrated in *Figure 6* and *Figure 7*.

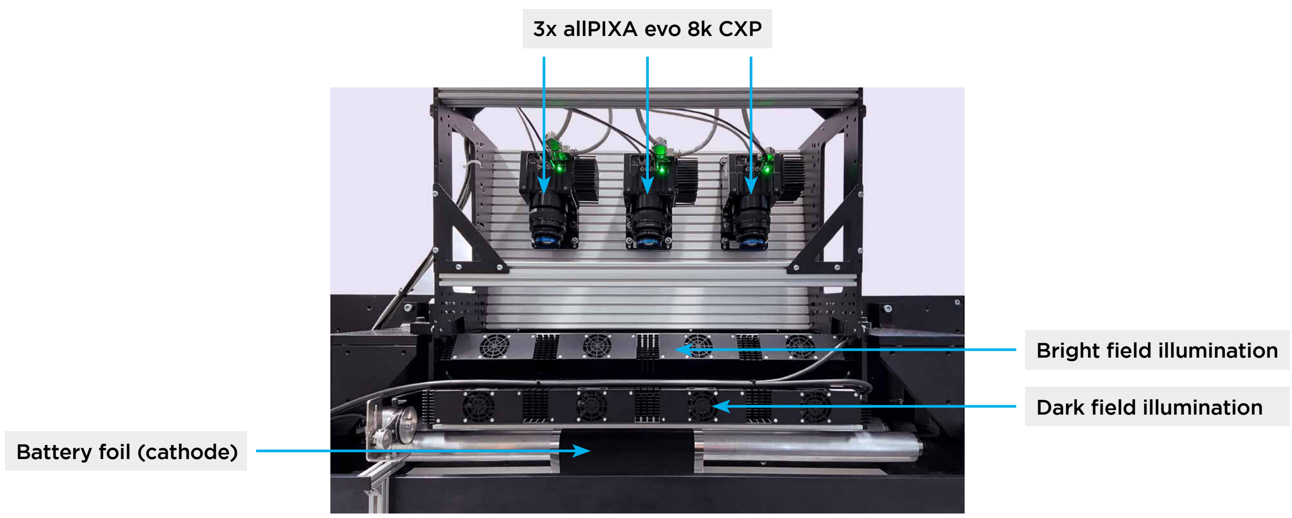


Figure 4: *Line Scan Vision Platform*

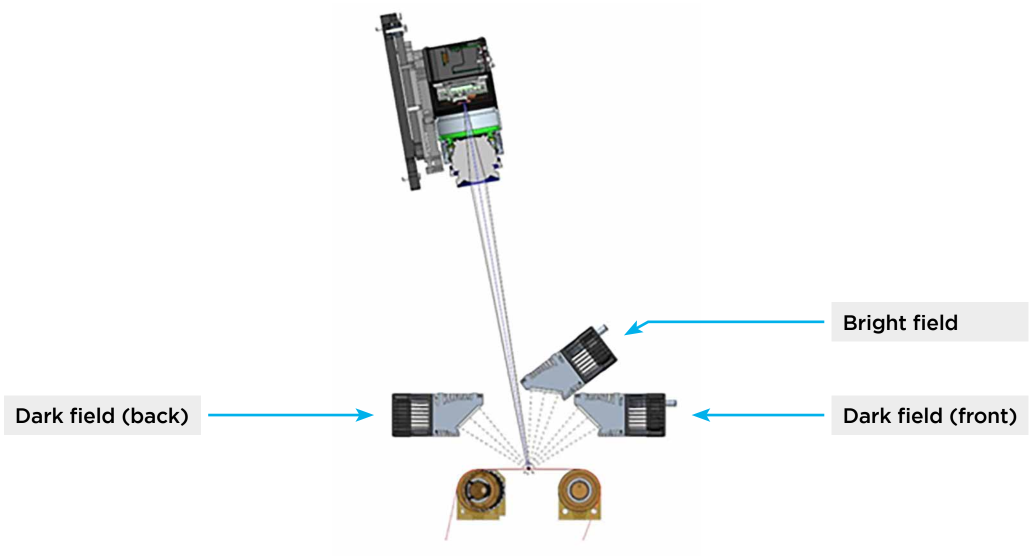


Figure 5: *Different illumination types and geometries are used to make different types of anomalies visible.*

Image Preprocessing

The preprocessing approach also relies on the assumption that defects are more noticeable under different illuminations. By overlaying images from various illuminations, the goal is to identify a diverse range of anomalies within a single image. This study examines this assumption by comparing a fused dataset of illuminations with datasets from individual illuminations.

Dark field (front) **Bright field** **Dark field (back)**

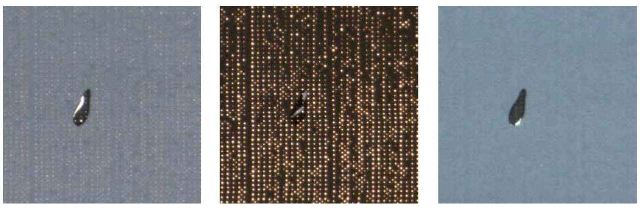


Figure 6: *Influence of illuminations on moisture contamination on* ***anode.***

Dark field (front) **Bright field** **Dark field (back)**

Figure 7: *Influence of illuminations on scratch on* ***cathode.***

Anomaly detection with unsupervised deep learning approaches

Different unsupervised or semi-supervised deep learning methods were compared for anomaly detection. Reconstruction based approaches (Autoencoders) and pre-trained neural networks combined with different classifiers were used for this purpose. A detailed implementation is out of the scope of this document[1]. As part of the evaluation, different experiments are carried out to assess the performance of the developed models. All models are tested for anode and cathode, with the different data sets of the three lighting geometries (dark field back, bright field, dark field front) for anode and cathode, as well as the combined images.

Finally, the inference time of the implemented approaches on the GPU NVIDIA GeForce RTX 3090 is compared. In addition, the influence of the dimension reduction of the extracted features on the *AUCROC* (Area Under the Receiver Operating Characteristic Curve) and the inference time was investigated. The data sets used for these experiments consist of 300 normal training images, 200 normal test images and 200 test images with anomalies (defects). The size of the anomalies corresponds to an area of roughly 0.5 - 1mm^2.

The studies showed the effectiveness of overlaying different illumination geometries for the cathode, while the anode methods did not benefit from such overlays. The best *AUCROC* values for the anode were only achieved with dark-field backlighting, with the approach using a pre-trained model combined with a classifier achieving an *AUCROC* of 97%. For the cathode, an *AUCROC* of 99% was achieved in the data set of the overlaid images. However, it should be noted that the anomalies tested were not generated in a real production environment. The inference time (time for one prediction) for a patch of size (256x256) were around 0.12s on the GPU NVIDIA GeForce RTX 3090. In efforts to optimize the inference times, the influence of dimensionality reduction on classification performance was also examined. It was found that the dimension reduction leads to a significantly faster prediction speed, but the *AUCROC* decreases. With the data of the superimposed cathode images, for example, inference time of 6×10×3s with an *AUCROC* of 90% can be achieved with a dimensional reduction of the extracted features to 4 dimensions.

[1] Please contact us for more information at **„sales@chromasens.de“**

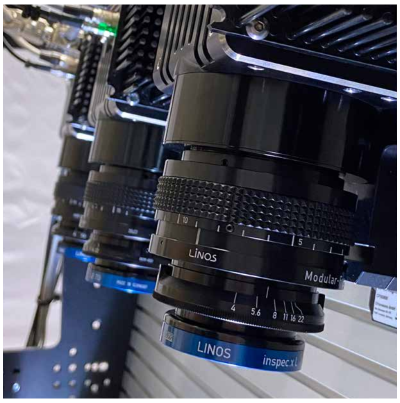
Summary

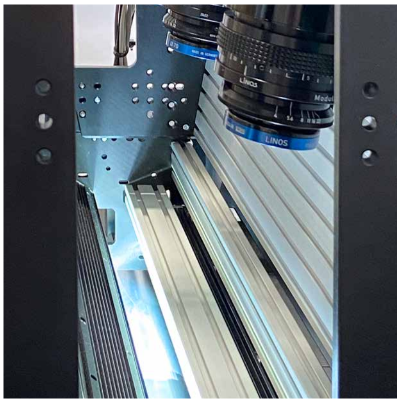
To summarize, this study investigated different unsupervised machine learning approaches for detecting anomalies in battery electrode foils for lithium-ion batteries. The approach using pre-trained networks with classifiers showed better performance compared to auto-encoder methods. We used the **Chromasens Line scan Vision Platform** with different illumination types and geometries, including **bright field** and **dark field illumination**, to capture different aspects of anomalies of battery foils. While overlaying different lighting geometries proved to highlight defects on the cathode, it did not benefit in case of the anode, where the best results were achieved using a single high power **dark field illumination**.

The *AUCROC* results meet the required inspection requirements whereas a major challenge is to meet the real time requirements in combination with the very high data rates. Therefore, classical image processing needs to be combined with machine learning approaches to achieve ideal results.

The extent to which the deep learning models are optimized for recall/tpr (true positive rate) or max.-f1-score (optimum between precision-recall trade off) depends still on the specific requirements of the process since the end-user can determine the follow-up costs and economic effects of the application. If the costs for a missed anomaly are very high, it would be worth optimizing for recall, even if this means accepting a higher number of false positives (false alarms).

In addition, the presented approaches can be applied to other surface and foil inspection applications as for the bare metal foil, the coated electrode foil as well as for the inspection of the separator foil. The camera resolution, illumination geometry as well as the applied algorithms can be independently configured to ideally match the specific requirements.





chromasens
IMAGING FOR PROFESSIONALS

THE LINE SCAN EXPERTS

LINE SCAN CAMERAS

LED LINE SCAN LIGHTING

3D LINE SCAN CAMERAS

CUSTOMIZED OEM SOLUTIONS

Chromasens GmbH
Max-Stromeyer-Straße 116
78467 Konstanz
Germany
sales@chromasens.de

www.chromasens.com

A TKH TECHNOLOGY COMPANY

V1-03.2024