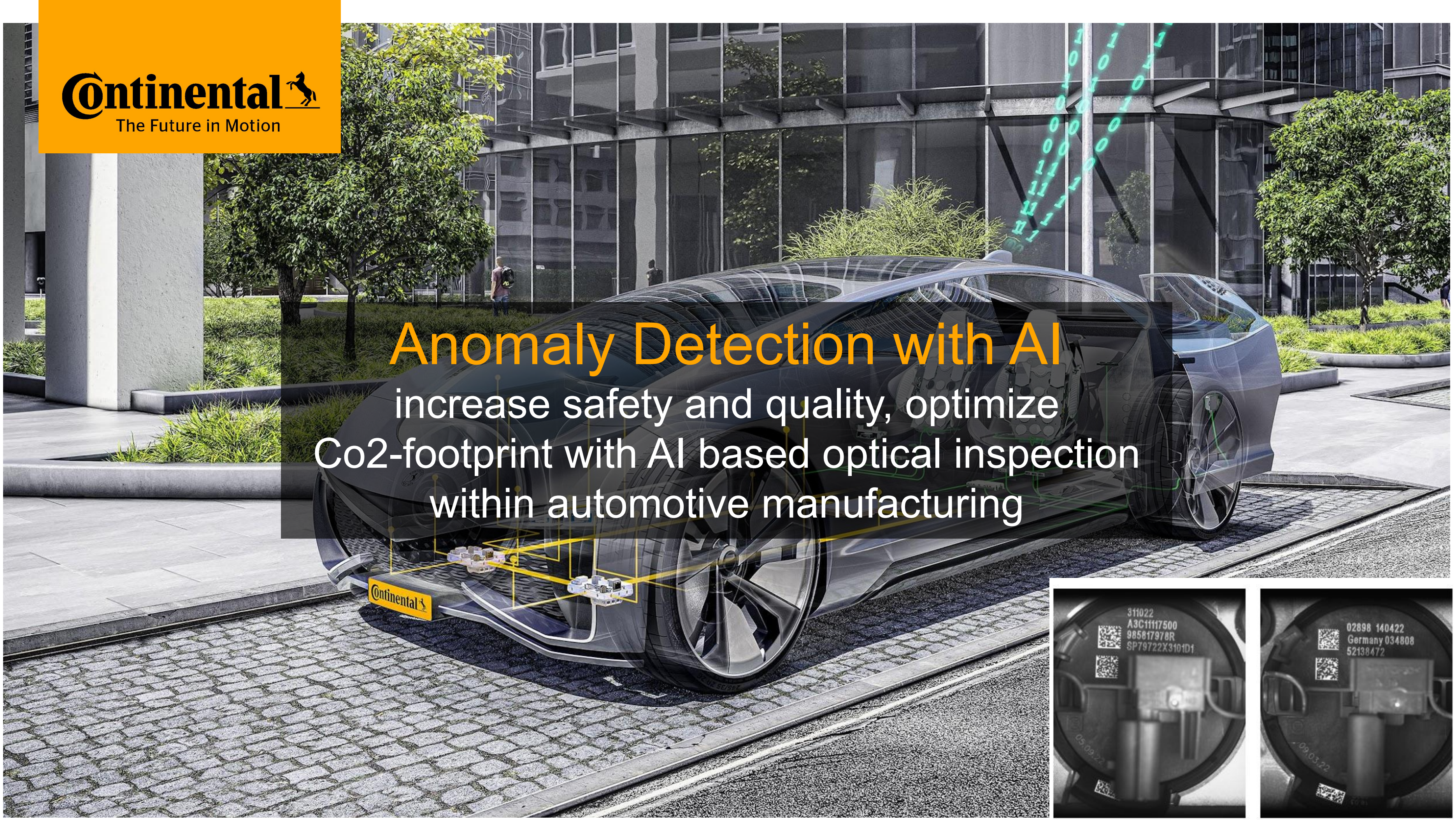
Continental
The Future in Motion
Anomaly Detection with AI
increase safety and quality, optimize Co2-footprint with AI based optical inspection within automotive manufacturing
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Project Title: Anomaly detection for optical quality inspection in automotive manufacturing

Description:

Optical quality inspection is a crucial step in the manufacturing process which ensures that the products meet the required standards of quality. Traditional quality inspection methods rely on human inspection, which can be subjective and prone to errors.

The early detection of defects can reduce the cost of rework and waste, as defects can be addressed before they become significant issues. By detecting and addressing defects early in the manufacturing process, manufacturers can improve the overall quality of their products. This, in turn, can lead to increased customer satisfaction and loyalty, as customers are more likely to purchase products that meet their expectations of quality.

With advancements in AI technology, the use of machine learning for optical quality inspection has become increasingly popular in the manufacturing industry. Anomaly detection is the process of identifying data points that deviate from the expected or normal pattern. Compared to classic ML approaches with supervised learning, where examples of good parts, as well as a lot of examples of all error classes are necessary to train a classifier, the focus in anomaly detection is to train a model primarily on examples of good parts on detecting deviations from the norm. This approach has several advantages:

- in typical manufacturing settings, images of good parts are easily available, since most of the parts being produced do not contain errors
- if a new production line is launched, it is not yet clear which kinds of errors might occur within the production process. New types of errors should also be detected, which cannot be assured by supervised classification models that rely heavily on having examples of error available for the training.
- The amount of data labeling and cleaning is limited since images of good parts are easier to identify.

A potential challenge that needs to be tackled with the provided dataset is, that there are labels and barcodes printed on the products. This print varies from part to part, which creates a base level of variance within the class of good parts that must not be interpreted as a deviation and that the anomaly detection model needs to learn to understand and ignore.

The central task of the project is the training of an anomaly detection model, that is primarily trained on images of good parts only, while being able to recognize faulty images. The focus here lies on finding close to all faulty images, while keeping the amount of false calls (images of good parts that are falsely labeled as anomalies) as small as possible.

Side constraints for the model that can also be taken into consideration for bonus points are

- the model needs to be fast enough to be included into the cycle time of the actual construction line (below 1 second inference time per sample would be optimal)
- the footprint of the model should be as minimal as possible (necessary CPU cores & memory requirements)

The data provided contains 100k samples of good parts that can be used for training the model. Also provided are samples of bad parts, which can be used for validating the model or calibration of sensitivity thresholds.
A private test set will be made available at the end, against which the models can then be tested for their final performance. This test set will also contain new and unknown error classes that are not contained inside the provided validation set.