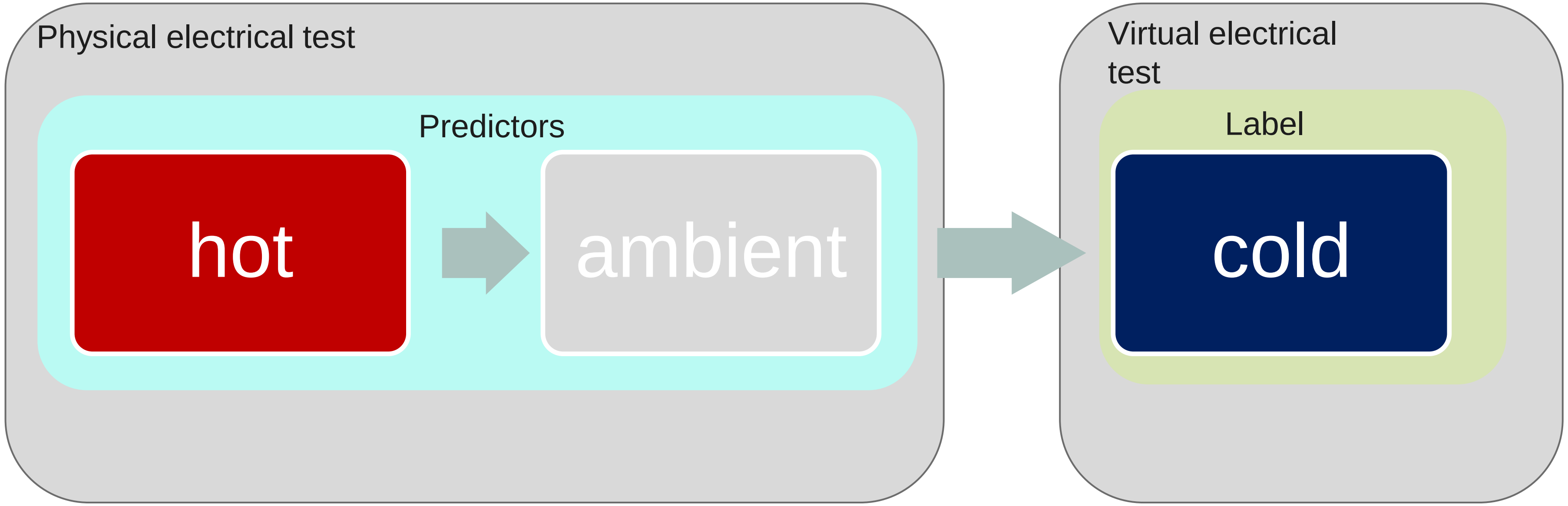
Predicting Cold Temperature Electrical Tests in Semiconductor Manufacturing Using AI

Dr. Jan Papadoudis

Use-case: Replace electrical “cold test” by AI

- Currently products are usually tested under 3 different temperature conditions (hot, ambient, cold)
  - “Cold test” is challenging and expensive

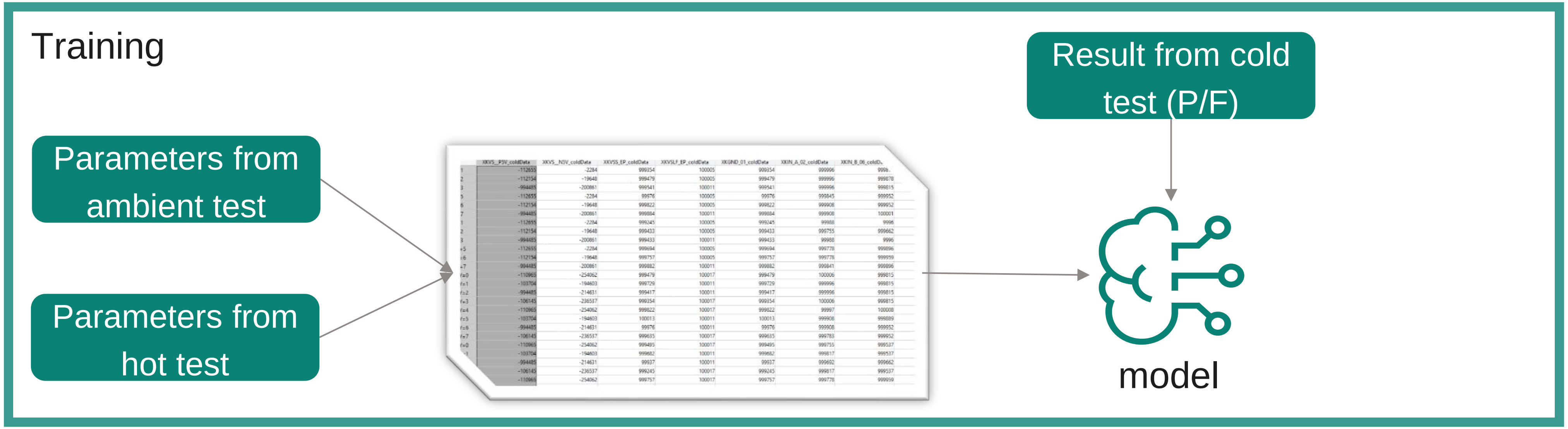
- Aim: Remove cold test and use prediction of AI instead.

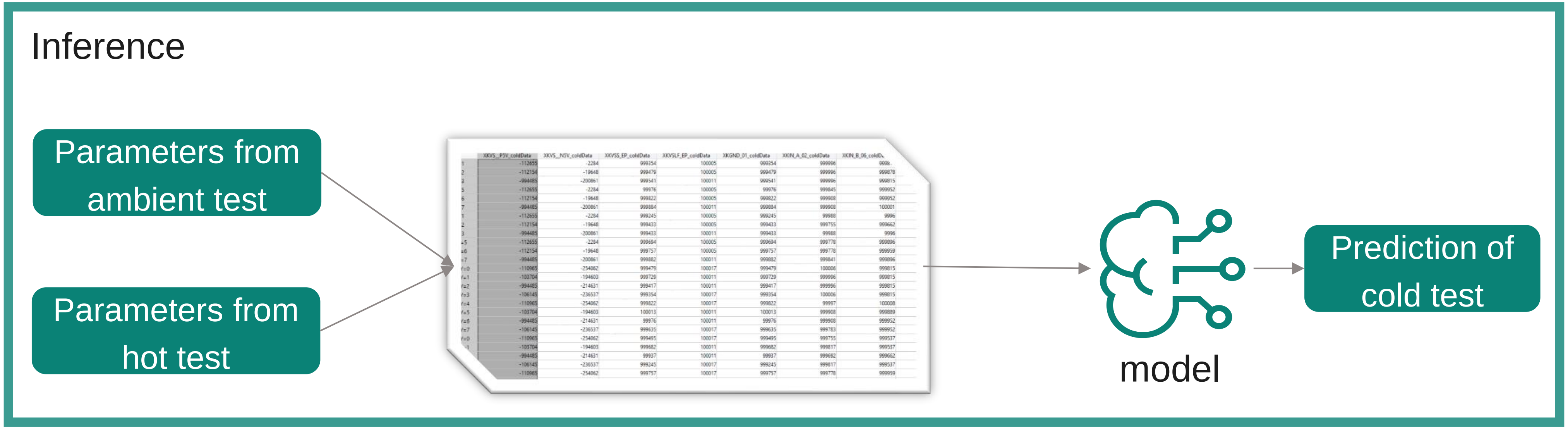


Zero escapees allowed!

The parameters from hot and ambient test are used to predict the result of the electrical cold test

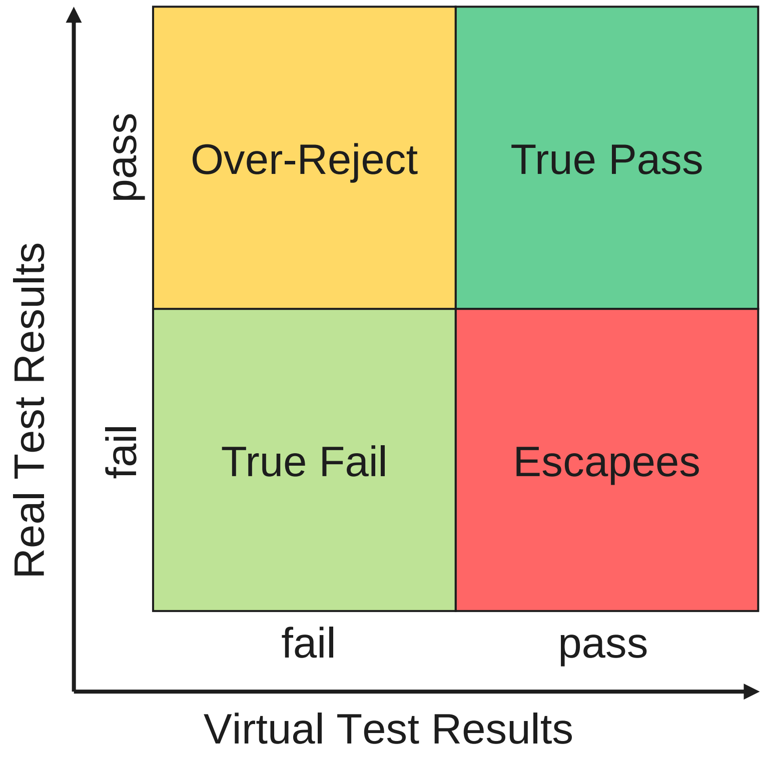
A binary classification is trained on the test parameters





- The model is trained on the results from the cold test
- Only Pass/Fail information is used
- The model is a **binary classification**

A confusion matrix is used to visualize the performance

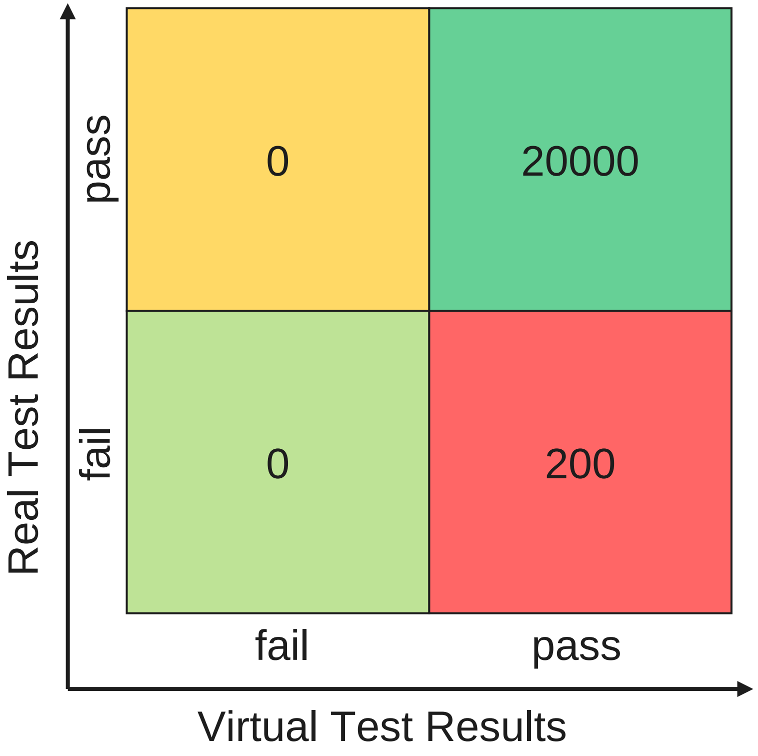


- A confusion matrix can be used to visualize the performance of a classification model
- There are multiple metrics that can be calculated based on such a representation, most commonly

  - **Accuracy:** *(TP + TN) / (TP + TN + FP + FN)*
  - **Precision:** The ability of the classifier to correctly identify positive instances out of all instances it predicted as positive. It is calculated as: *TP / (TP + FP)*
  - **Specificity:** The proportion of actual negative instances correctly identified by the classifier. *TN / (TN + FP)*
  - **Sensitivity/Recall:** The proportion of actual positive instances correctly identified by the classifier. *TP / (TP + FN)*

Data for classes are often imbalanced

- A dataset is imbalanced if for a certain class the samples are significantly lower.
- This can lead to difficulties with
  - Training the model
  - Interpreting metrics

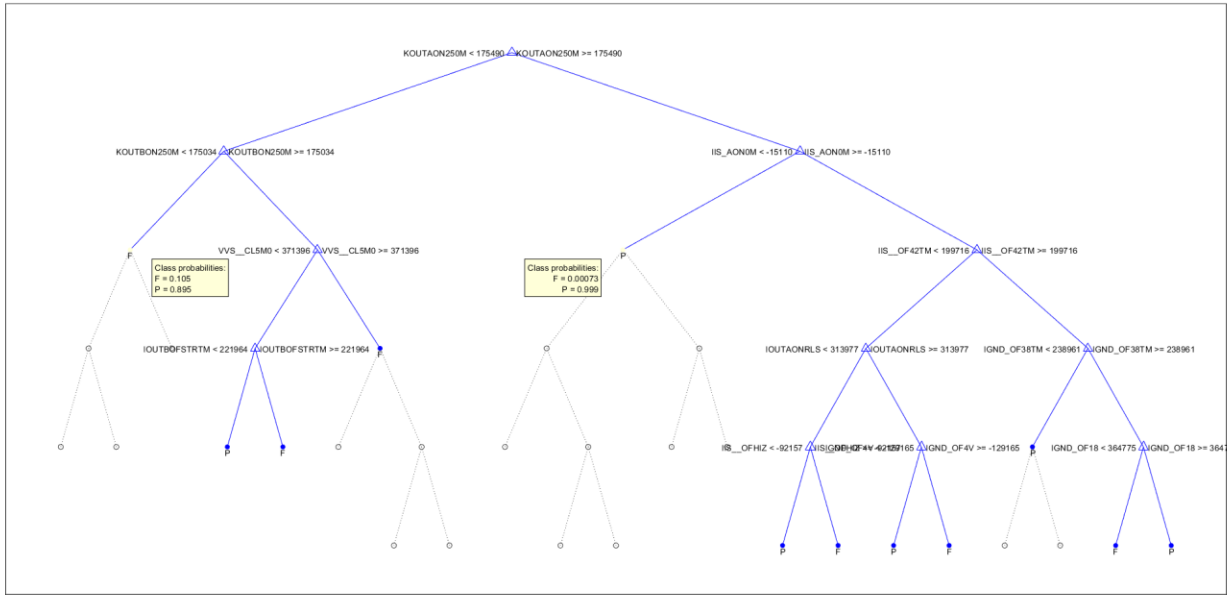


- A classification predicting always pass would already have an accuracy of 99%

→ **Important: Check if data is imbalanced because of an inaccurate representation of the real world**

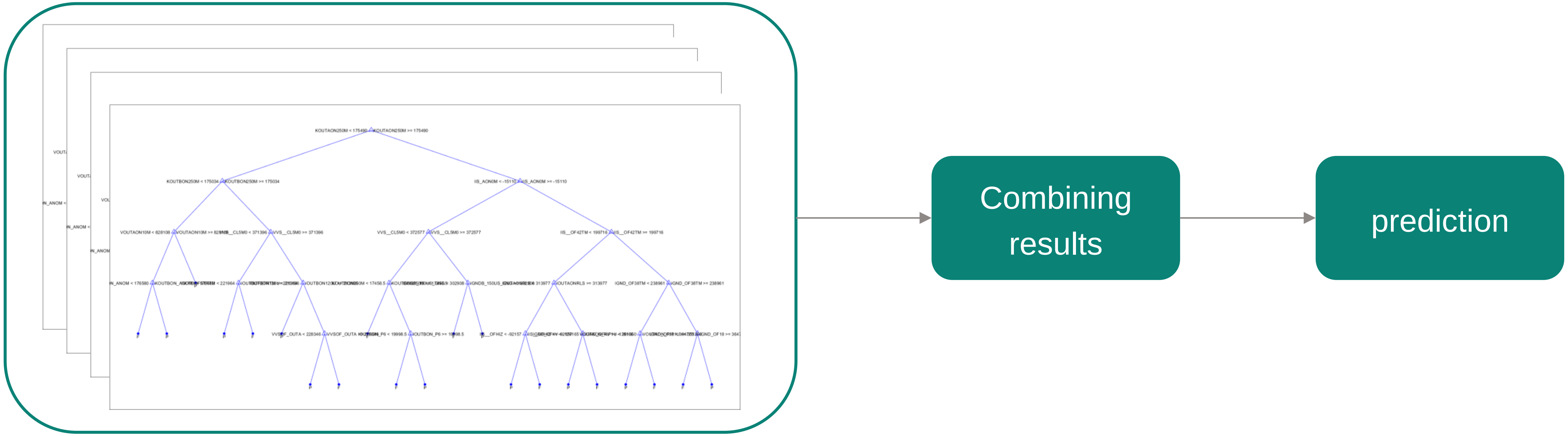
Decision tree is a supervised machine learning algorithm

- A decision tree is a flowchart-like model where each internal node represents a feature or attribute, and each leaf node represents a class label or a regression value.
- Decision trees make predictions by following a series of binary splits based on feature values until reaching the leaf nodes.
- Decision trees determine the best splits by finding features that create the most distinct groups of data points, leading to clear boundaries between classes or regression values.
- Decision trees are interpretable, easy to visualize, and can handle both numerical and categorical features.



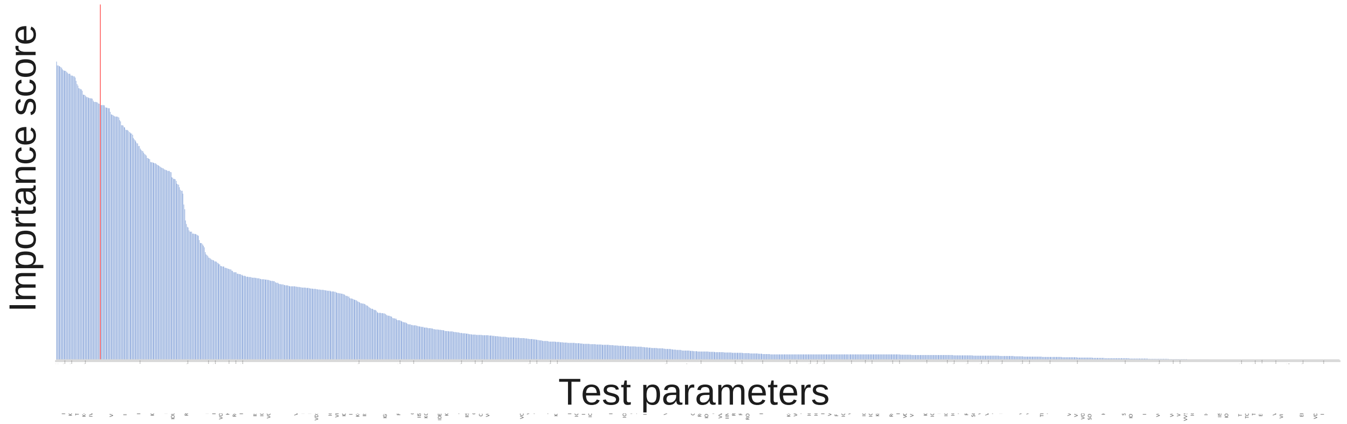
Random forest are ensemble of decision trees

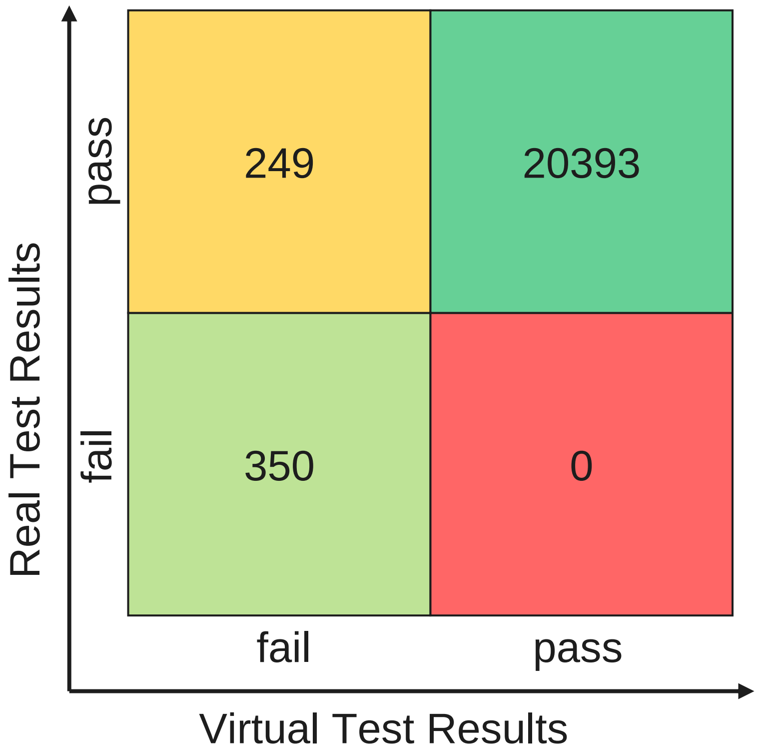
- Random forest is an ensemble learning method that combines multiple decision trees to make predictions.
- It creates a set of decision trees, each trained on a different subset of the data and a random subset of features.
- Random forest is a powerful algorithm that can handle imbalanced datasets effectively.
- It addresses the imbalance issue by aggregating predictions from multiple decision trees
- The random sampling of both, data instances and features, in each tree helps ensure that the minority class is represented in the training process.



First results show the possibility of the approach

- Investigation of important test features for the cold test result.
  - Several parameters do not seem to correlate with the cold test result
- A random forest was trained using techniques to deal with imbalanced dataset
  - First result show promising results but more data is needed

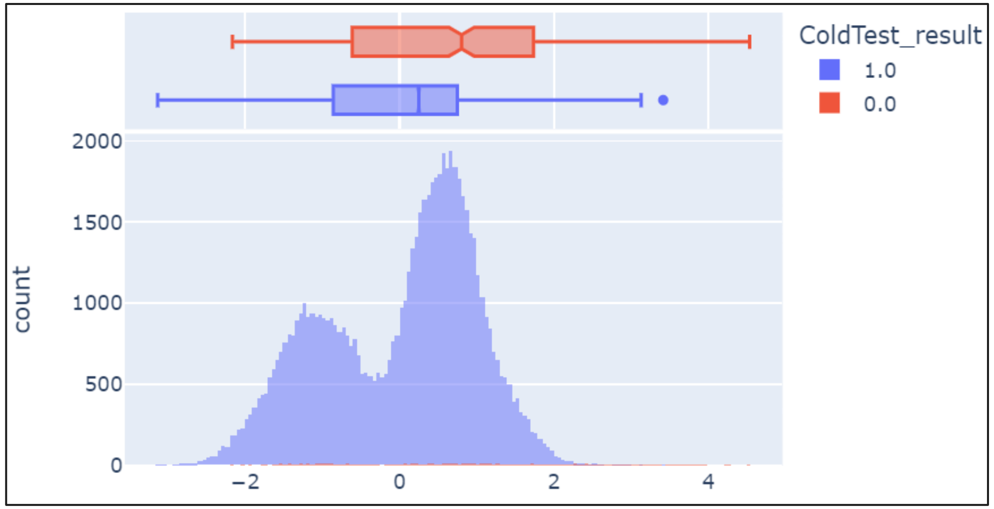


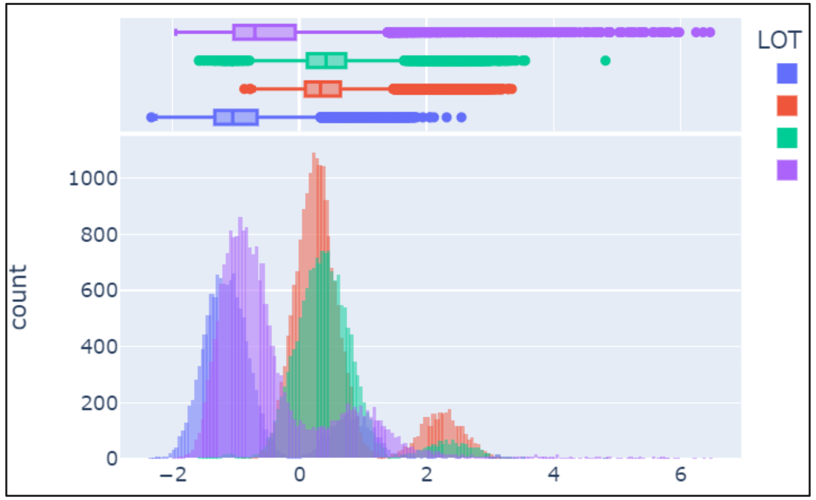


Different lots show high difference in parameters

- Some parameters show good possibility to distinguish between pass and fail in cold test
- Combinations of such parameters give good indication for cold test result

- Different lots have a high variation within a single parameter set
  - Challenge for modelling. Good standardization necessary
- Data from multiple lots necessary to investigate differences





Most errors are very rarely

- There are failure types which are more common than others
- It is mandatory that all types of errors are present in the dataset for model development.

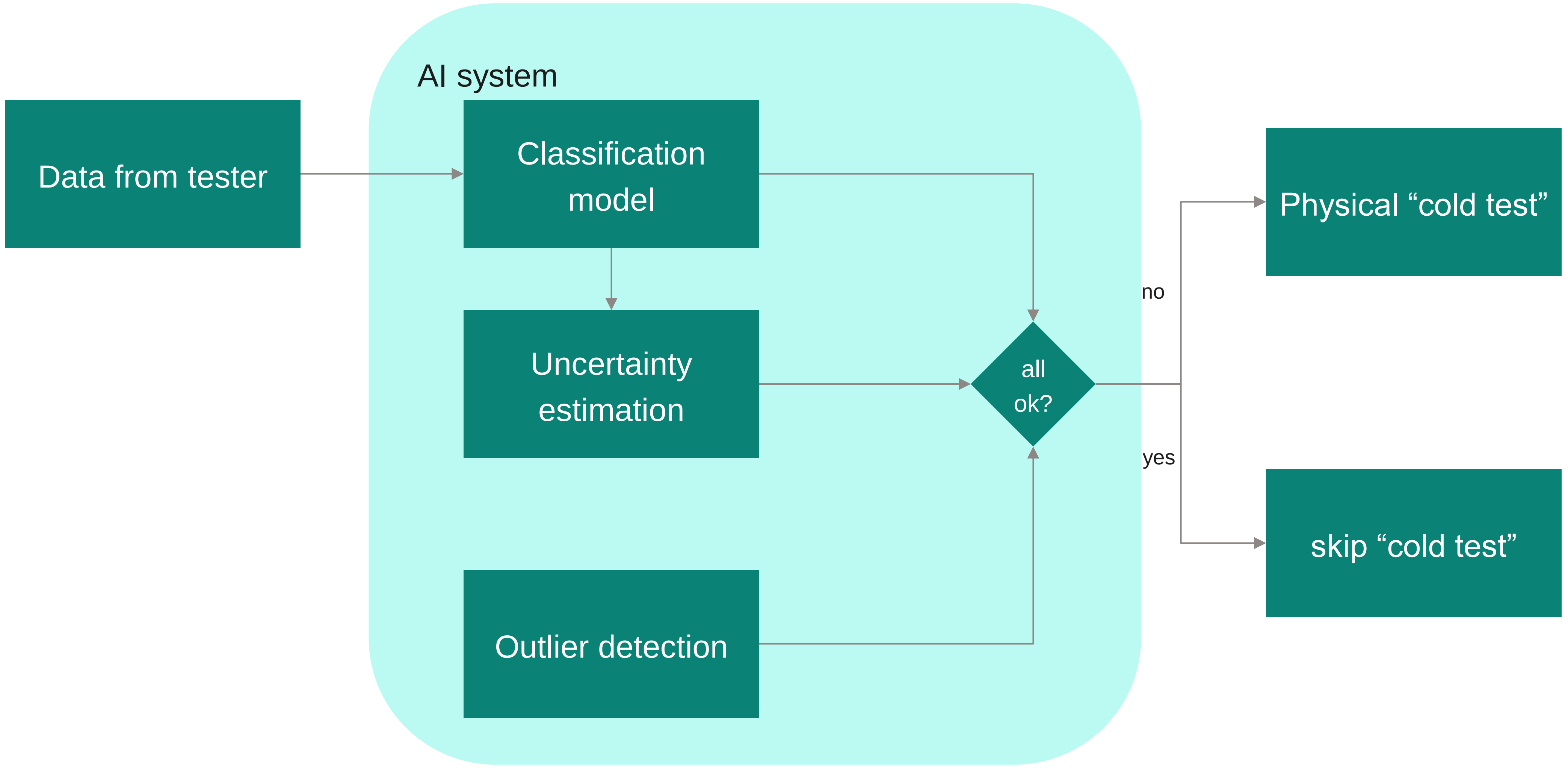
- **In the first dataset only 1/3 of possible failure types were present**

- Modelling approach should be backed up with an anomaly detection / confidence value

To ensure that the model catches alle failures an extensive testing and training phase is needed until all errors occurred

Outlier detection to find unknown data

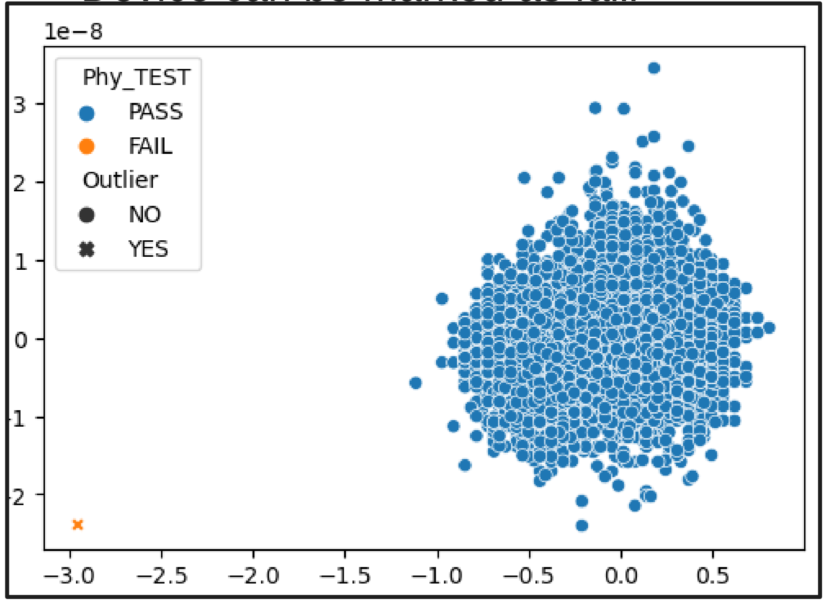
– The initial model is enhanced by an uncertainty estimation and outlier detection to reduce risk of escapee.

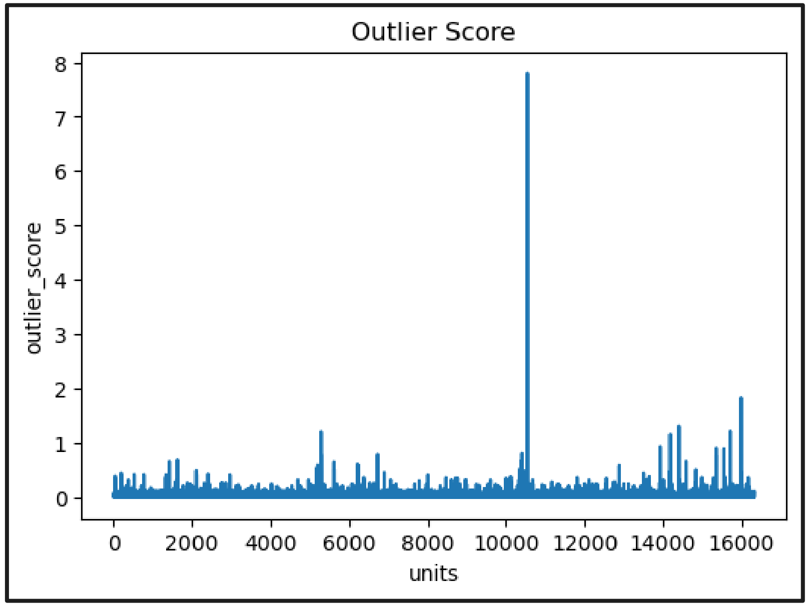


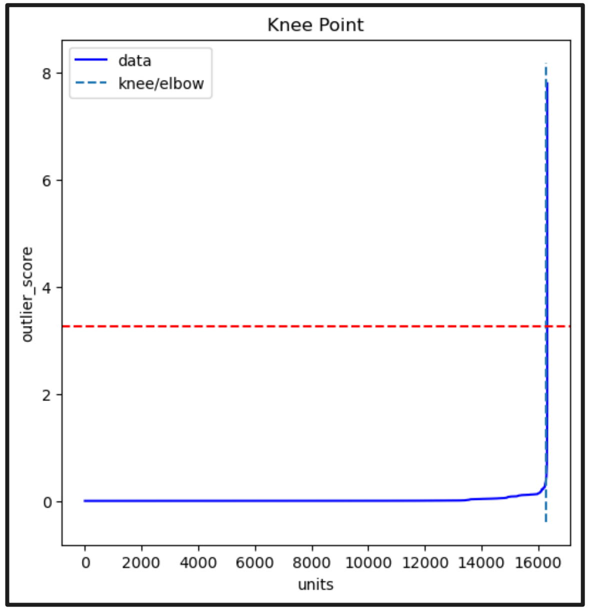
Outlier detection: Based on expert knowledge

- First outlier score:
  - Train isolation forest on training data
  - Find unknown instances during inference to trigger physical test

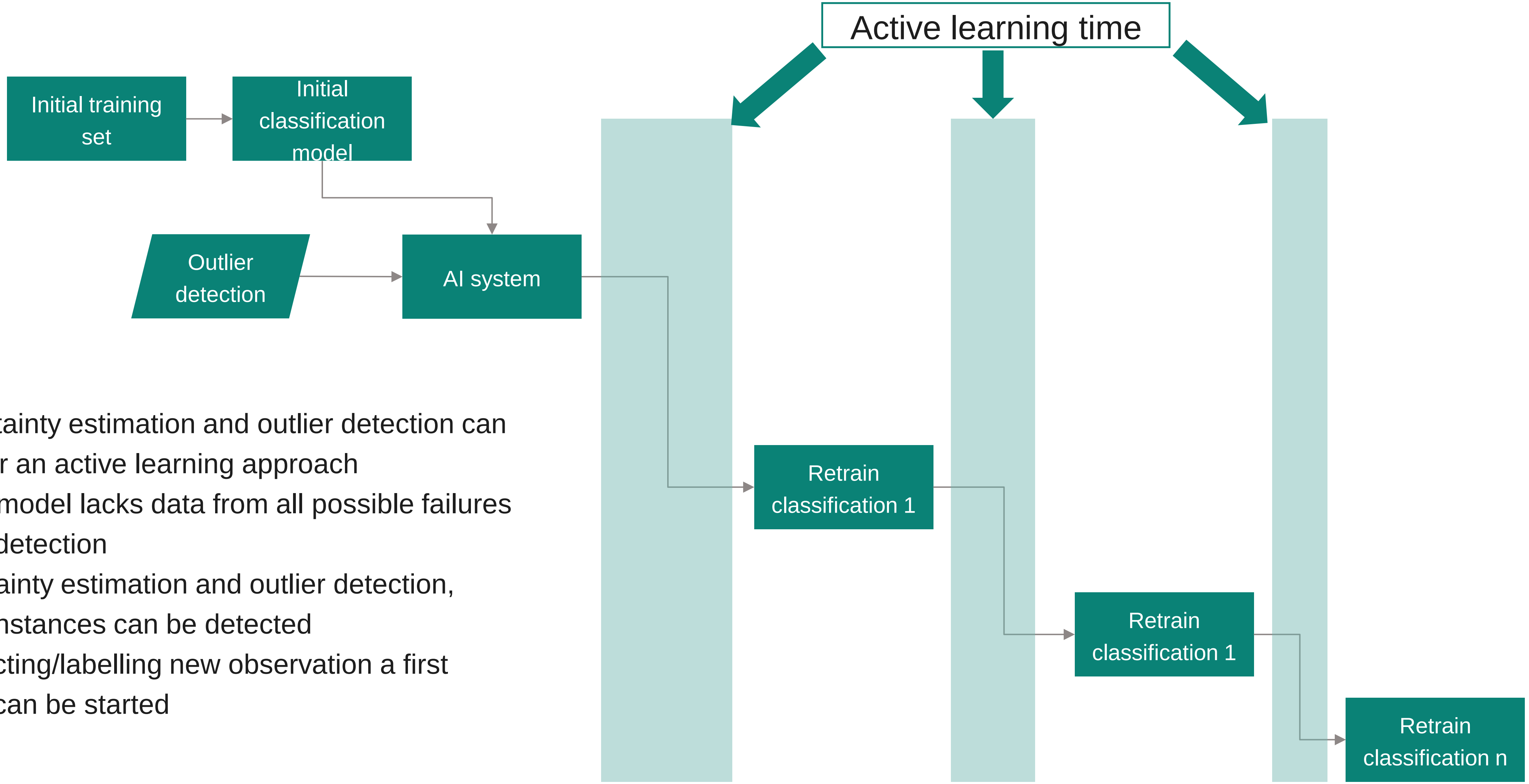
- Second outlier score:
  - It is known that some parameters show high correlation within a lot
  - Dynamic nearest neighbor can detect outlier test
  - Device can be marked as faill







Approach can be integrated in active learning cycles



- The uncertainty estimation and outlier detection can be used for an active learning approach
- The initial model lacks data from all possible failures for robust detection
- Via uncertainty estimation and outlier detection, unknown instances can be detected
- After collecting/labelling new observation a first retraining can be started

Summary

General AI key takeaways

- Data (and its quality) is most crucial for the model's performance
- Imbalanced datasets are common in a real production environment
- It is important to be precise on the use of metrics for validation
  - Accuracy can be misleading

Virtual cold test takeaways

- As a final test before delivery, high demands on the model.
  - 0 escapees allowed
- High variation of parameter range between lots
- Approach shows possibilities to reduce test effort
- Classification + anomaly detection is useful
- Active learning approach integrated for continuous improvement

Next step: Include production data into prediction

Questions & answers

Infineon