Hard drive failure prediction:

Continual learning motivation:

- **Adapting to changes in failure pattern**: as hard drive distribution (company bought new HDD) or operational environments changes (number of drive racks increases, temperature changes), new failure mode or pattern may emerge.
- **Rare Events:** Some rare defects can happen infrequently and may not represented in initial dataset. As rare failure can be obtained in new dataset, model can incrementally learn to detect them.

Continual learning scenario:

- A new dataset becomes available each quarter—for example, Q1-2024 covers data from January 1, 2024, to April 30, 2024. From this dataset, we select the drives that have failed and extract their data from the last **N** days before the failure occurred. This extracted data is then used to create a new training dataset for our model.
- Input: Model name (coded into number), corresponding raw or normalized smart number in between N days, changes of smart value in last x,y,z,.. days (optional).
- Output: a number that represents predicted days left till defect.

Wafer surface detection:

Continual learning motivation:

- **Process Changes:** Manufacturing processes evolve due to equipment upgrades, changes in materials, or new fabrication techniques. These changes can introduce new types of defects not present in the original training data.
- **Aging Equipment:** Wear and tear on equipment over time can result in new defects.
- **Good Adaptation:** Enable company to train and adapt their own models (each labor and their set of equipment will produce different distribution of defection types and also, they can have different types of labels base on their needs). As not all defect events not available in initial learning, further training can help model to recognize them.

Continual learning scenario:

- As new data becomes available (monthly or quarterly), we may identify new groups of labels in our dataset. For example, if we observe an increasing number of "left_down_edge" defect patterns, it is no longer appropriate to categorize them

under "random defect patterns." Therefore, we introduce a new class called "left_down_edge" to accurately label these defects.
- **Input**: Pixel map (0 is for non-wafer area,1 is for non-failure wafer area 2 is for failure wafer area)
- **Output:** Failure pattern labels.

Relay degradation detection:

Continual learning motivation:

- **Relays Changes:** Relays changes due to equipment upgrades, they may operate under different loads, voltages, temperatures, and environmental conditions. These changes can introduce new degradation patterns not present in the initial training data.
- **Concept Drift in Data:** Example: Seasonal changes cause significant temperature variations, affecting the physical properties of relay components. Or the electrical load can change due to various factors, changing the stress on relays.

Continual learning scenario:

- As new data becomes available, we can gather information from failed relays to create a new training dataset for our model.
- **Input**: Relay type (coded into number), contact resistance / switching current (or only the opening / closing time extracted from switching current, when changes in current occurs)
- Input data subjected to be changes and not similar to HDD data, in event we assume that there are a lot of missing data in one relay lifecycle.
- **Output:** predicted cycles left till defect.