

# Examples of ML and AI in manufacturing: Formulating digital twin and automated visual inspection

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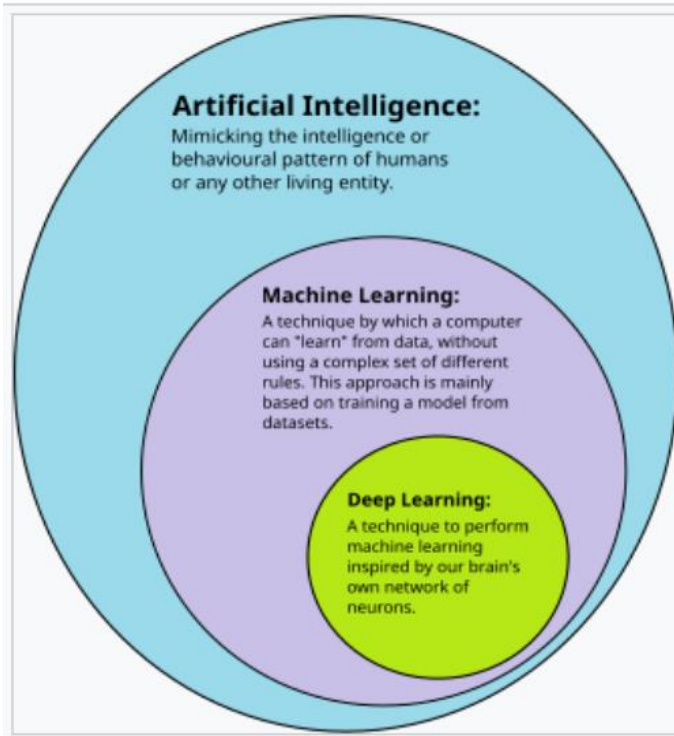
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# Overview

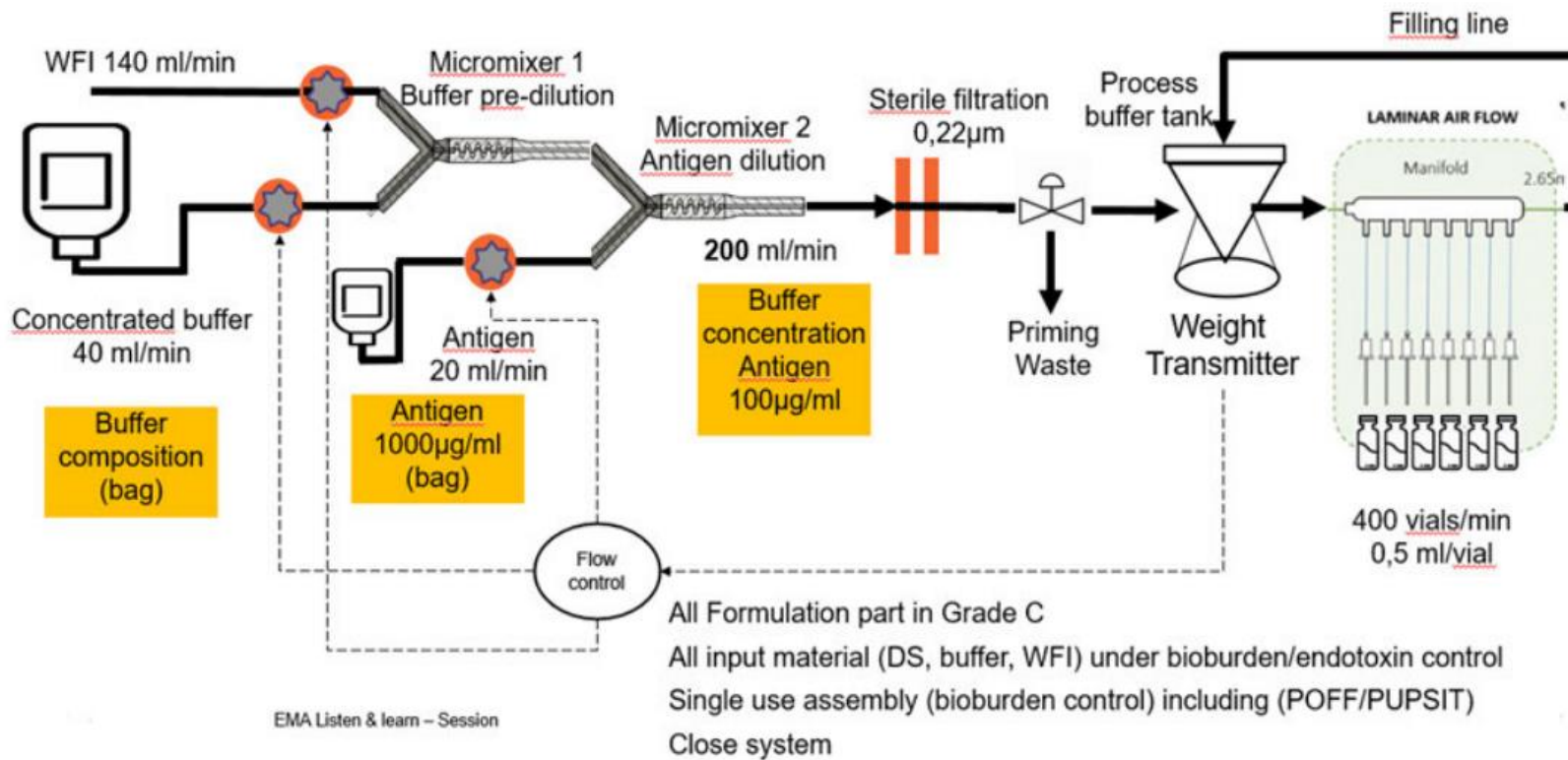
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- Examples of the use of machine learning and AI
  - Machine Learning: Control of continuous formufilling as part of digital twin
  - Deep Learning: Automated Visual Inspection
- General Reflections on how to industrialise in a GMP environment

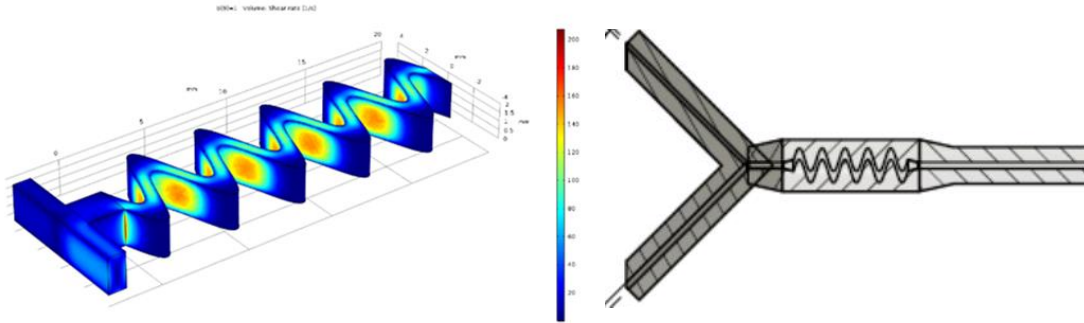
## Continuous Formfilling

# Digital twin control for continuous formulation and filling of a sterile product



- *Hybrid models comprising digital twin derived via empirical studies, CFD simulations, multiple sensor inputs ....*
- *Control of CQAs eg concentration of antigen*

# Modelling Elements within the Formufilling Digital Twin

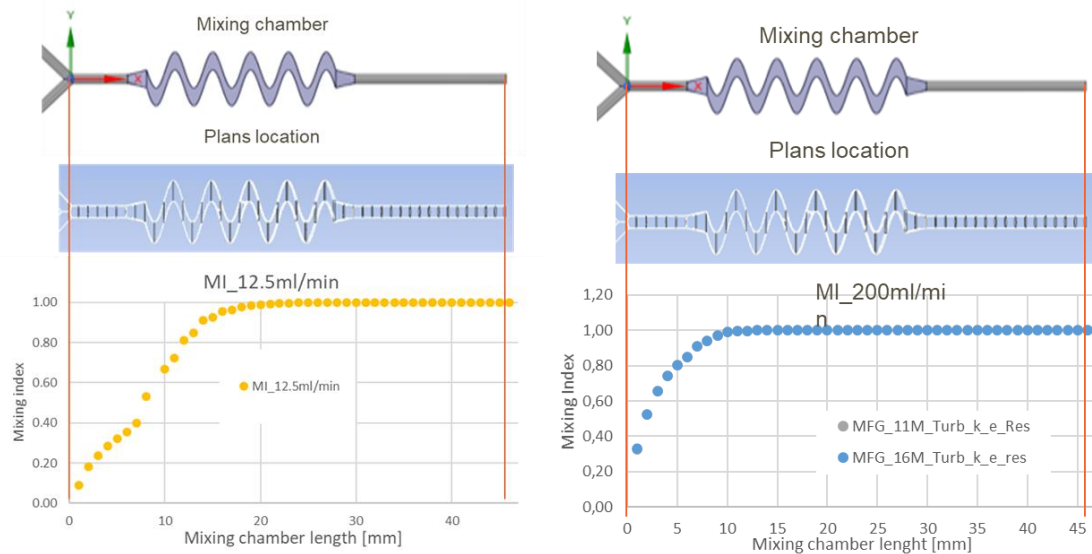


## PAT

- flow-rate meters
- Balance
- Conductivity sensors
- UV detector
- Pressure

## Soft sensors

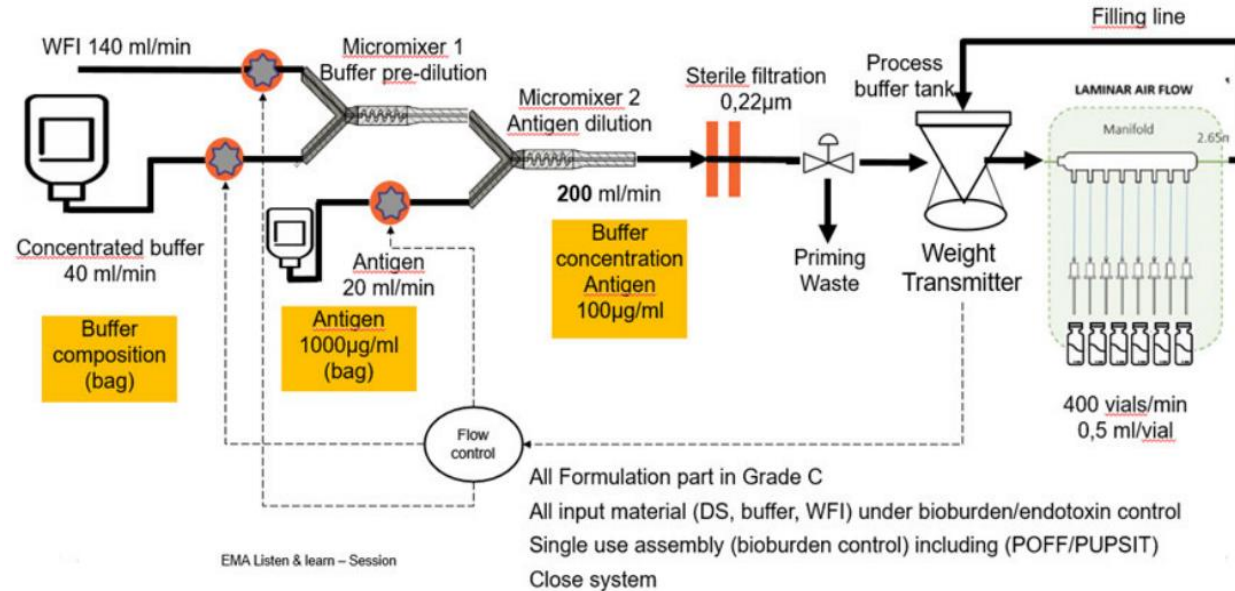
- Antigen concentration prediction
- Flow-rate prediction



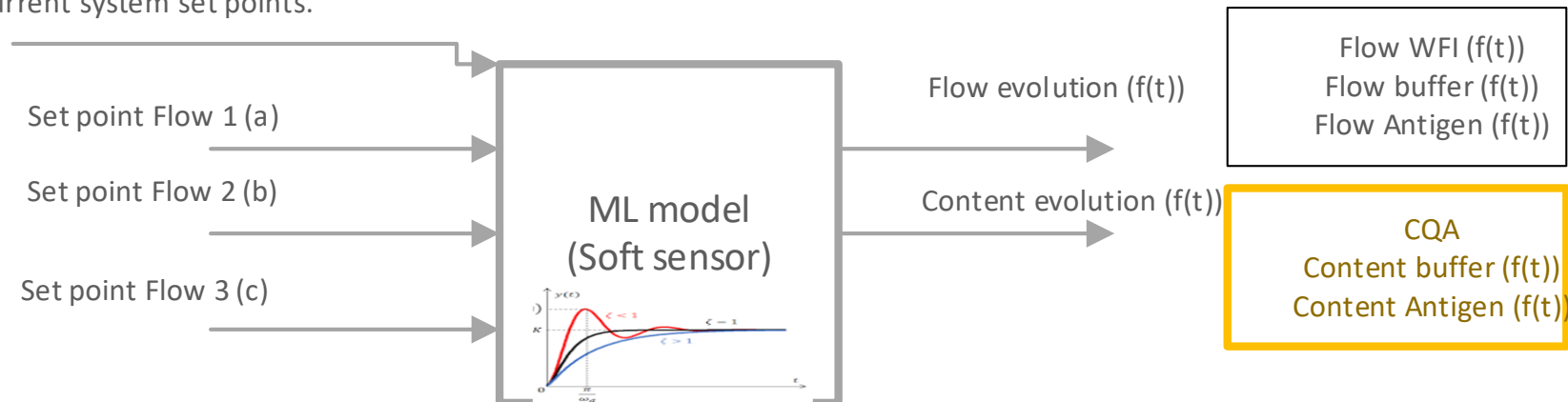
CFD models of mixing

# ML model training and assessment

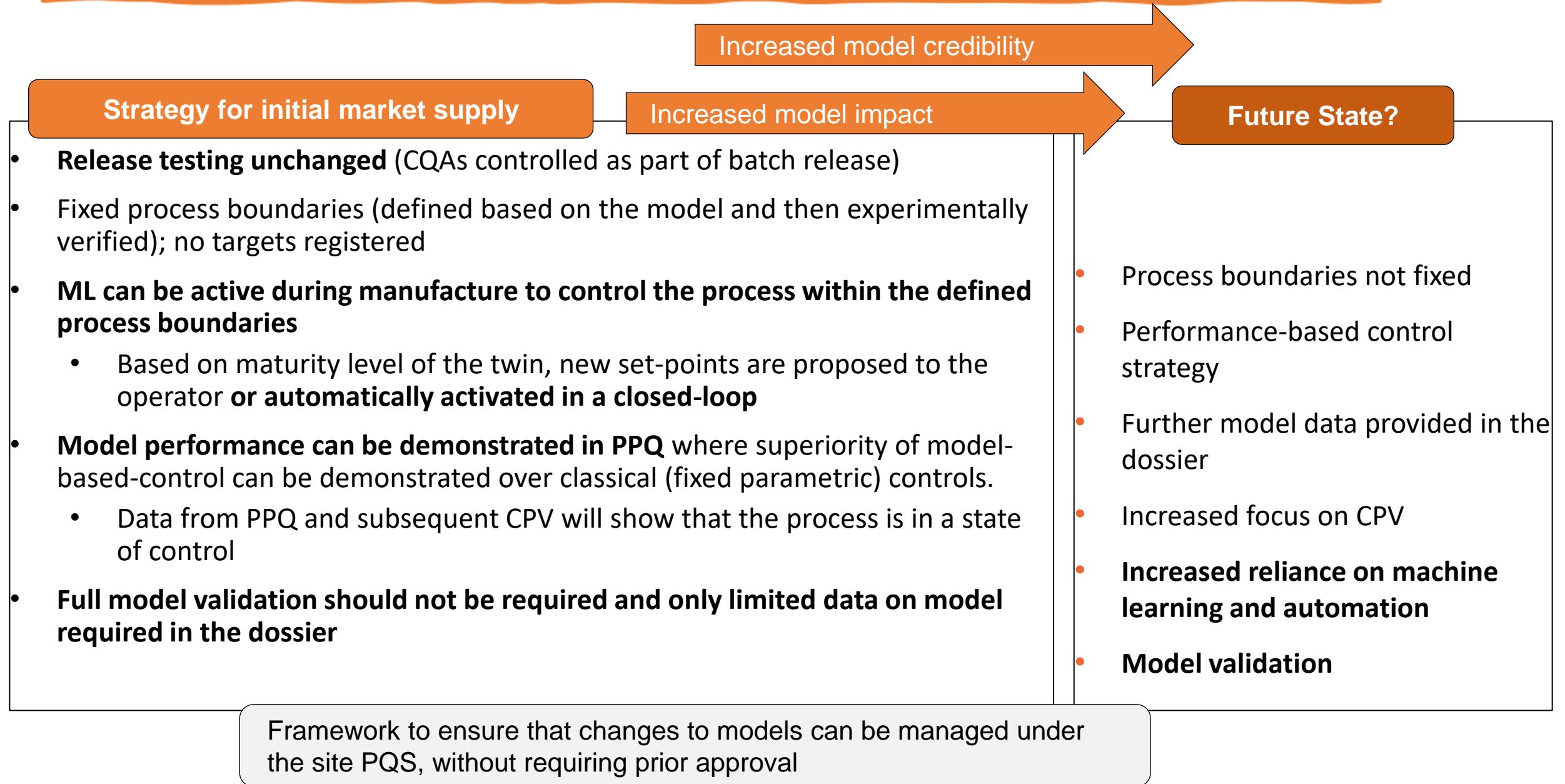
ML model trained and tested via a stressed set of in-silico experiments  
Process performance can be verified as part of PPQ Stage 1



Current system set points.

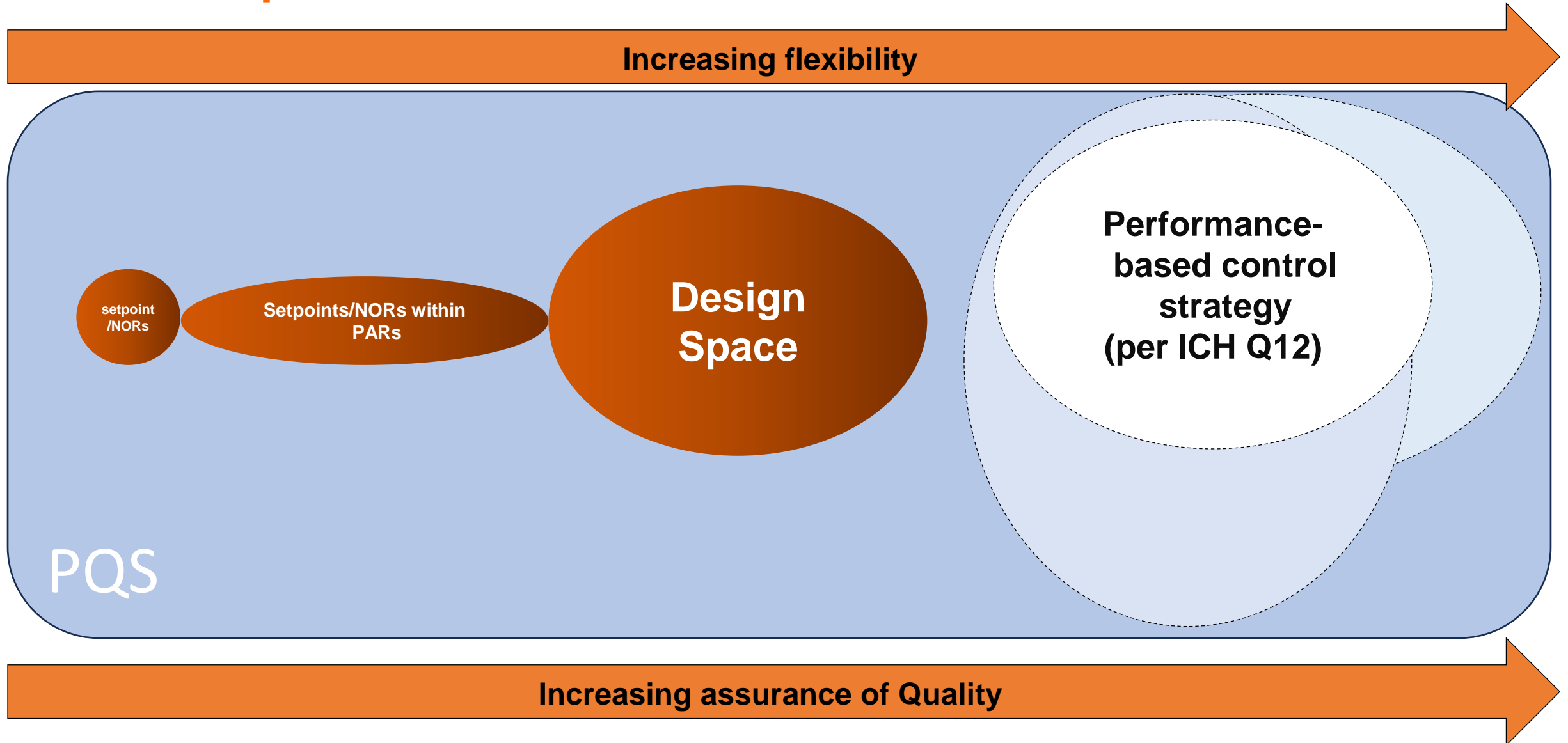


# Model Industrialisation



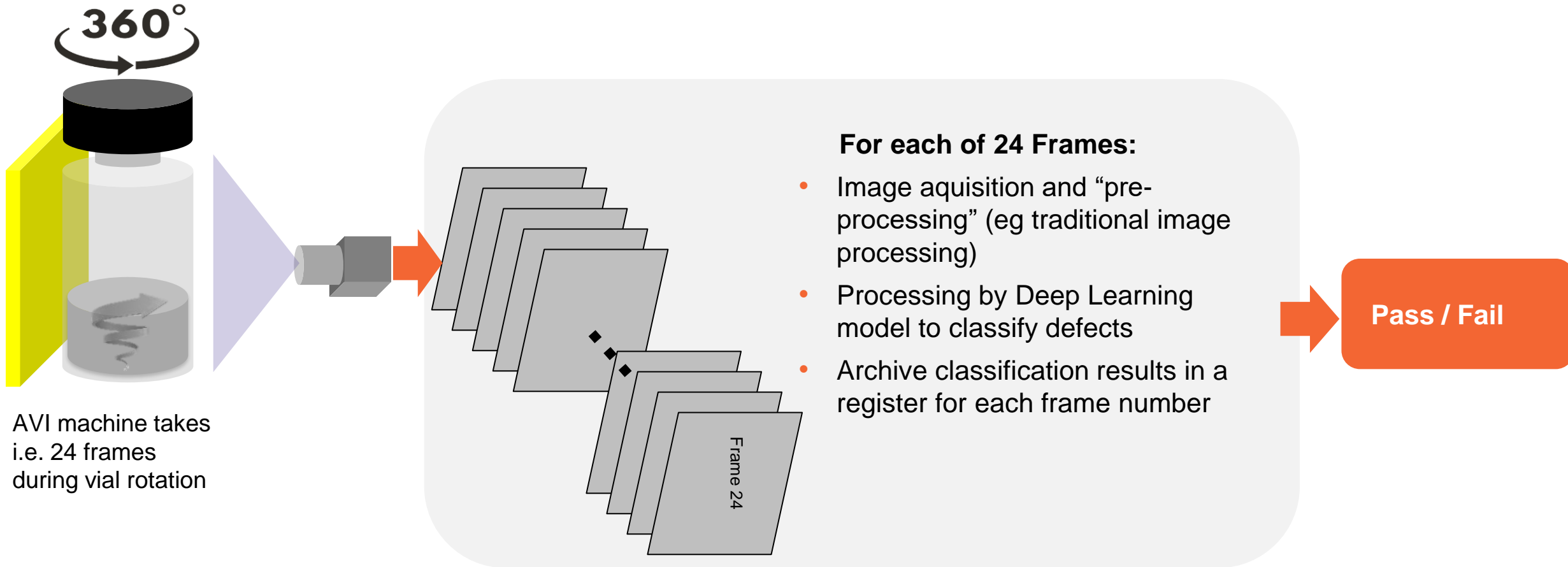


# ML based process controls



# Automated Visual Inspection

# Automated Visual Inspection Deep Learning Case Study



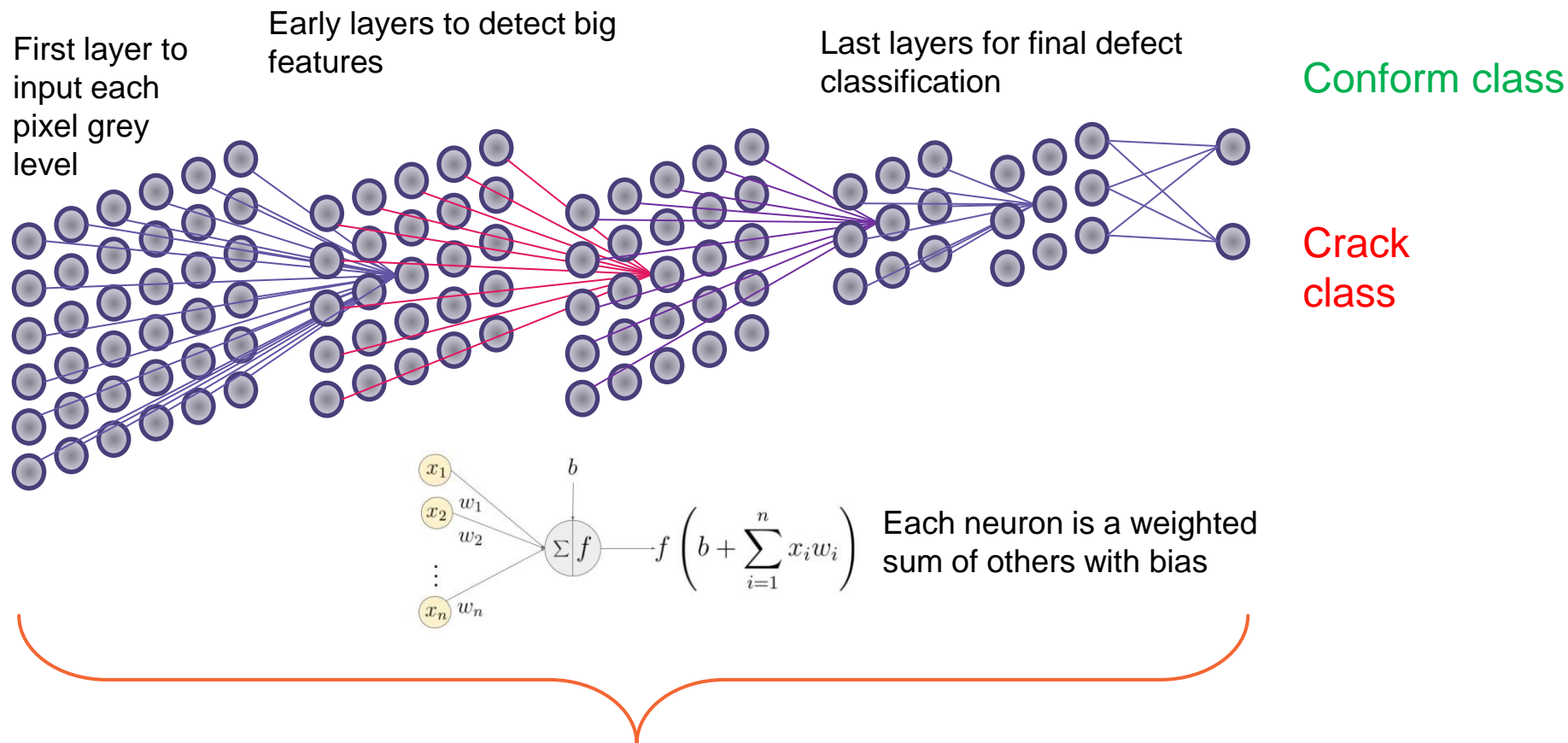
# Automated Visual Inspection Deep Learning Case Study

## Convolutional Neural Network (CNN) for Image Classification

Conform  
images



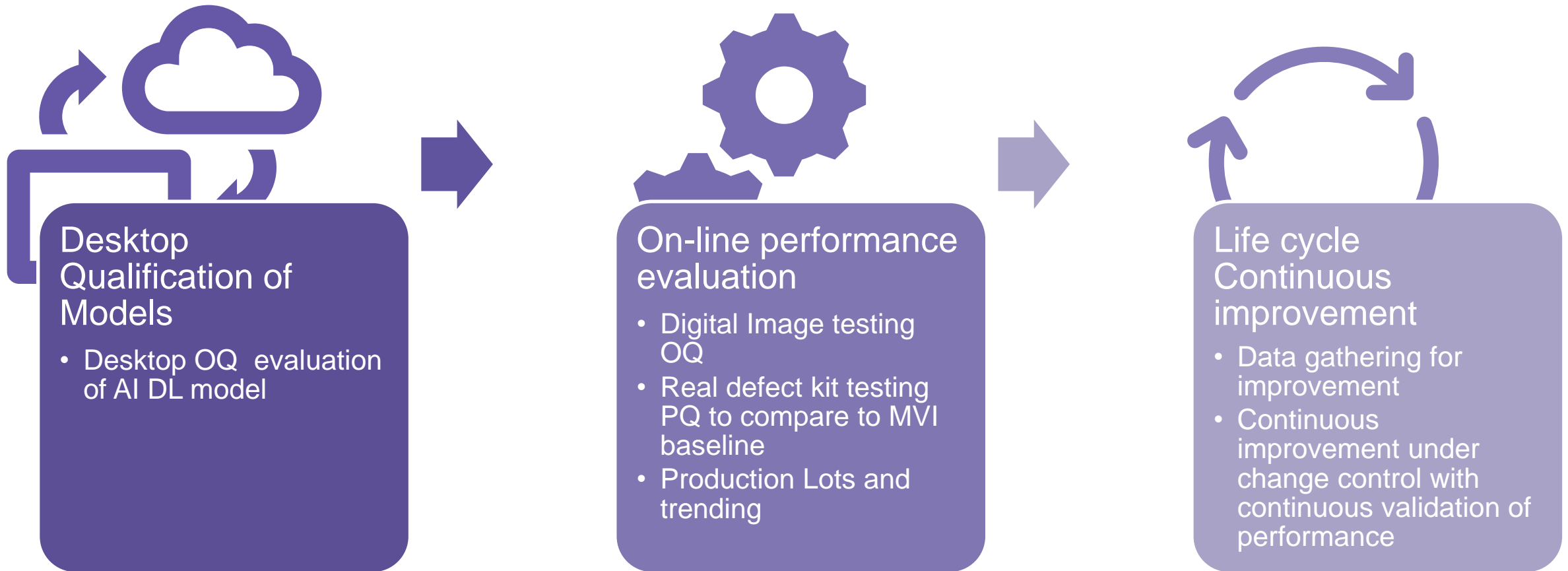
Crack  
images



Many layers, designed to optimize image classification, containing from 3 to 50 million parameters to adjust

# *Automated Visual Inspection Deep Learning Case Study*

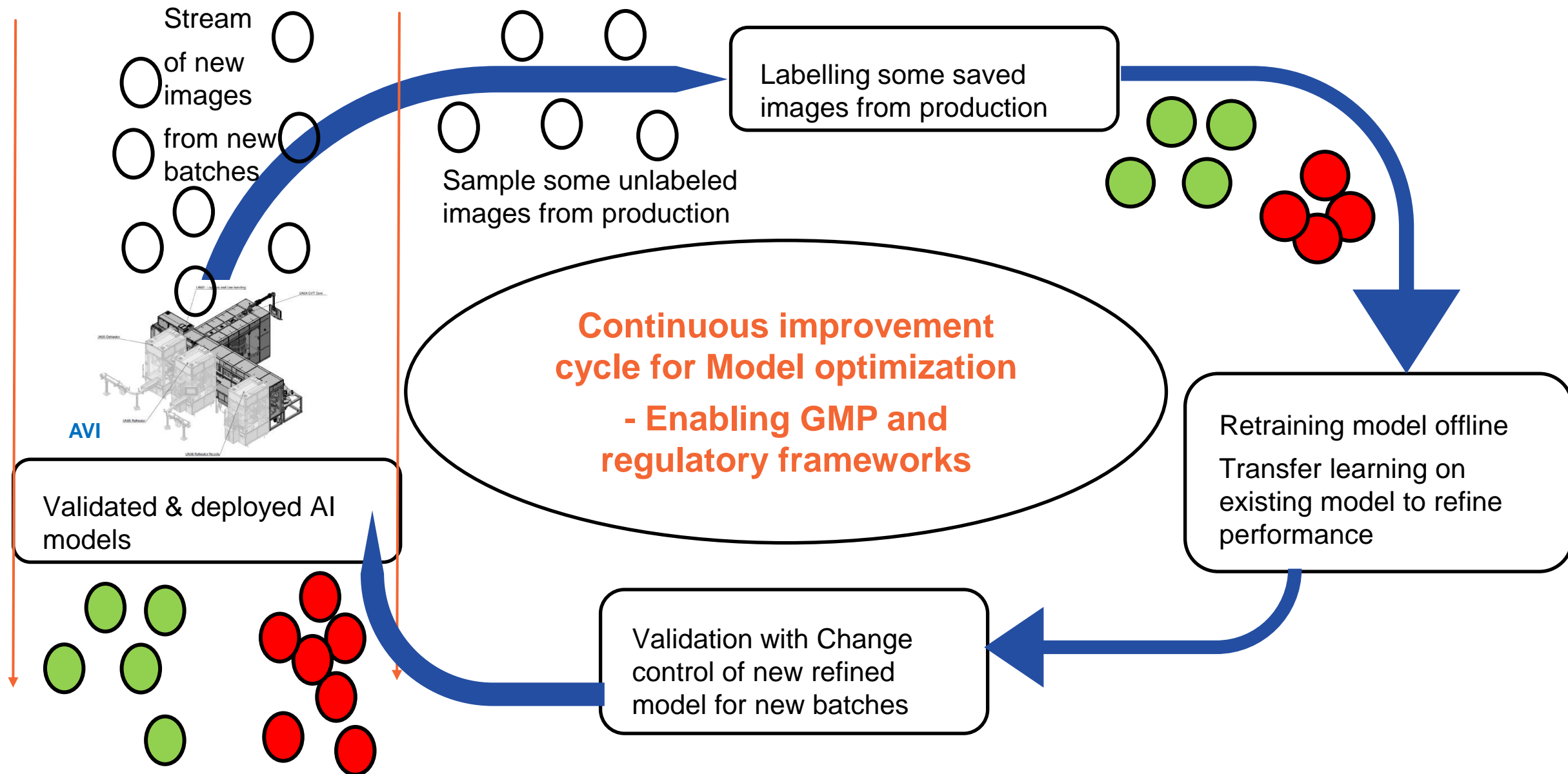
## Validation Strategy for Deep Learning Models in AVI



Exact approach will depend on how AVI is deployed

# *Lifecycle of Deep Learning Model*

## Active Learning Loop to speed up continuous improvement with real defects



# *Automated Visual Inspection Deep Learning Case Study*

## **Considerations for industrialization**

Deep Learning can significantly improve visual inspection processes

- Use of Deep Learning may require new competencies and infrastructure
- Validation, lifecycle management should be based on quality risk management principles and characterization of risk
- Comparison of risks from human and automated visual inspection is a key consideration
  - Training, periodic review, documentation, acceptable false positive rate...
- AVI can fit within existing GMP and data integrity frameworks –need for manufacturers, regulators and QPs to understand the framework

# What regulatory framework is needed for Digital Innovation?

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## No Regulation

Ultimate flexibility

Lack of clarity

No harmonisation



## Strict regulation

Clarity

Lack of flexibility

Can be Harmonised



## Goldilocks regulation?

Flexibility

Clarity

Harmonisation





Back-Ups

22 February 2024  
EMA/90634/2024

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## Preliminary QIG Considerations regarding Pharmaceutical Process Models

### Q2. What data is expected in the dossier in terms of model description and scope?

The level of detail regarding the model development and its description in the regulatory submission is dependent on the intended use of the model, its role in the control strategy, and the risk to material quality. This forms the basis for defining the degree of justification, and the extent of description, in an application. Requirements are defined as a function of the model risk (see Table 1 in question Q3).

*“risk to material quality”* is a function of the control strategy

*“detailed description”* in “S2/P3” would be a significant concern - detailed established conditions should not be required for medium risk

### Q3. What data is expected to be included in the dossier in terms of model validation?

Risk	Example	Dossier location	Dossier requirements (see also question Q2)
Low	<p>Process development, e.g. used to develop process understanding.</p> <p>Process optimisation (w/o change to registered process details).</p> <p>Mechanistic model used to speed up bioprocess scale-up/down.</p> <p>Digital Twin in shadow mode.</p> <p>Support batch release decisions based on QA predictions.</p>	Dossier sections S.2.6/P.2.3 and S.2/P.3, as appropriate.	<p>High level description of the model intent, type of model and how it is used.</p> <p>Manufacturing process validation data as described in the process validation guidelines.<sup>4,5</sup></p>
Medium	<p>Process design (change to unit operation principle or setting of in-process control limits).</p> <p>RTD model in combination with in-line NIR process control.</p> <p>Support batch release decisions based on CQA predictions but not in combination with PAT and release testing.</p>	Dossier sections S.2.6/P.2.3 and S.2/P.3, as appropriate.	<p>Detailed description of the model intent, type of model, how model is used and model operation.</p> <p>model assumptions, type of data used and model validation summary.</p> <p>Manufacturing process validation data as described in the process validation guidelines.<sup>4,5</sup></p>
High	<p>RTD model w/o other related in-process measurement.</p> <p>Real-time release testing (reduced release testing).</p>	Dossier sections S.2.6/P.2.3, S.2/P.3 and S.4/P.5, as appropriate.	<p>As for medium risk above, plus model validation report (training/ validation/ test datasets, prediction metrics acceptance criteria, model validity space, etc.).</p>

*“validation summary”* a concern - appropriate verification is justifiable