Machine Learning in Agricultural Systems

CLAAS Use Cases and Insights

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Agenda

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Introduction

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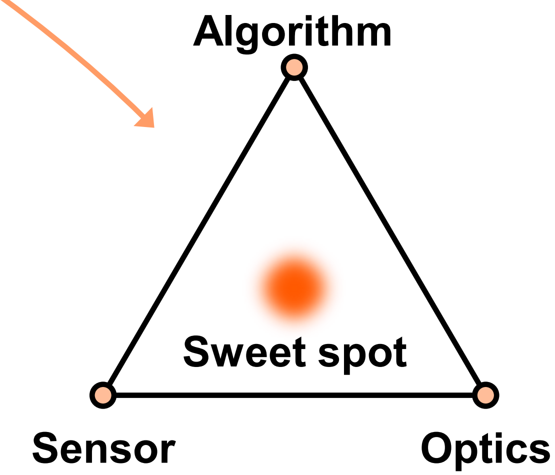
2021 - Today **Head of Camera Sensors**
CLAAS E-Systems GmbH

2020 - 2021 **R&D Manager - Customer Function Process Automation**
CLAAS E-Systems GmbH

2016 - 2020 **Area Product Owner – ADAS & Automated Driving**
BMW AG

2015 - 2016 **Team Lead – Views & Overlays / Camera Systems**
Magna Electronics Europe GmbH

2005 - 2015 **Developer & Project Manager**
CLAAS E-Systems GmbH



Use Case: Improving silage quality in forage harvesters

Problem summary

- Silage quality unknown during harvest; lab CSPS arrives days later
- Under- or overprocessing hurts digestibility and wastes fuel
- Quality varies within fields; static settings underperform
- High throughput requires continuous, robust sampling and feedback
- Target: CSPS > 70% for optimal energy yield

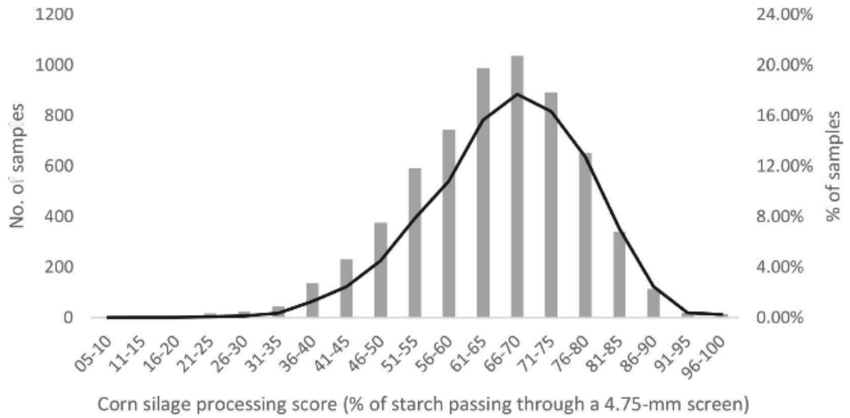
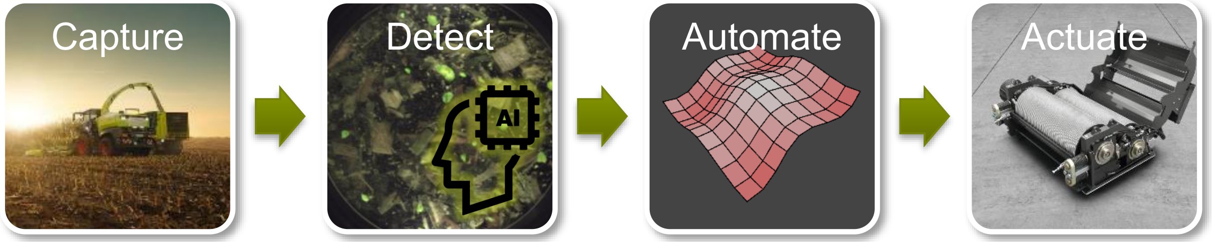


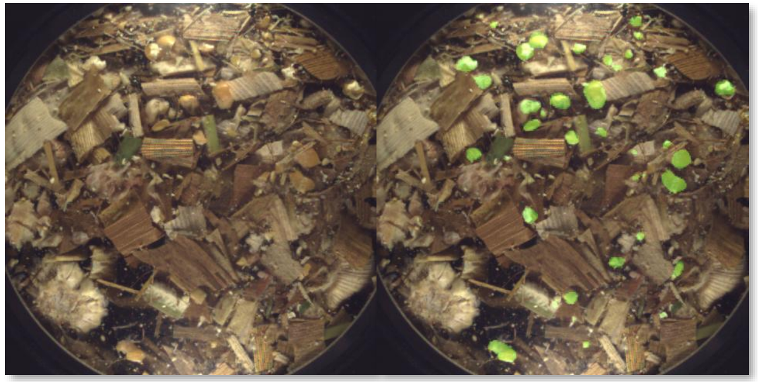
Diagram borrowed from *The Professional Animal Scientist*, Volume 34, Issue 3, 293 - 298

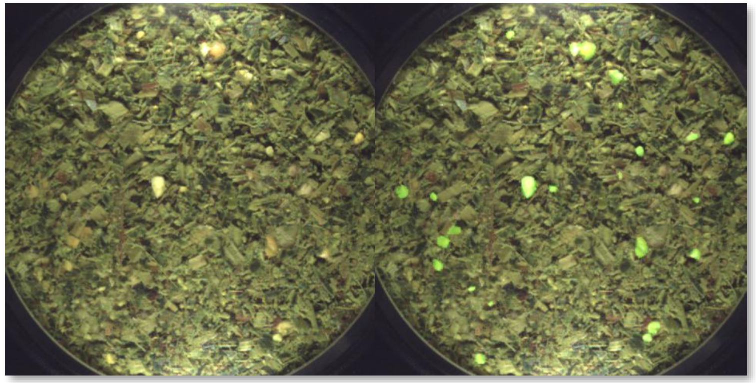
Use Case: Improving silage quality in forage harvesters

Solution

- Online visual inspection using high-speed camera on spout
- Estimation of CSPS using AI[1] [2] on embedded edge device
- Calibrated against lab CSPS on representative samples
- Results feed into CEMOS for actuator adjustment
- Outcome: Consistent silage quality, reduced fuel and wear





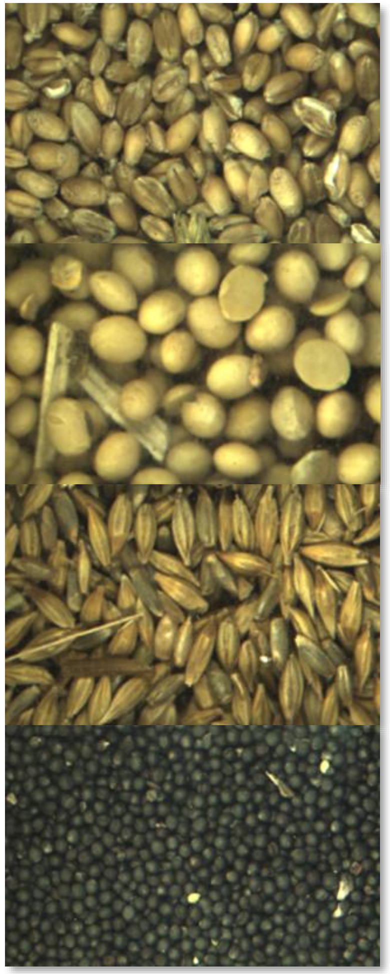


[1] Rasmussen, Christoffer. B. (2021). *Computer Vision-based Monitoring of Harvest Quality*. Aalborg Universitetsforlag. [2] Belau, Sven C. (2023). *Qualitätserfassung von Mais-Häckselgut mit Deep Learning Imaging*. Technische Universität Berlin.

Use Case: Improving grain quality in combine harvesters

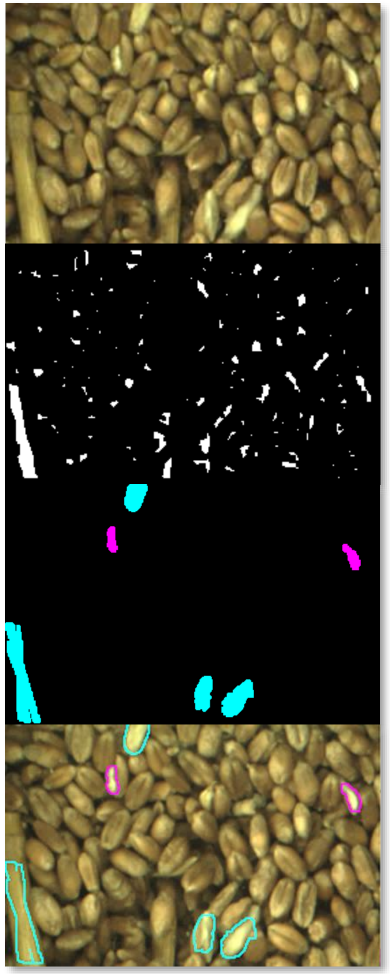
Problem summary

- Online measurement enables automatic adjustments of machine settings to achieve desired harvest quality
- Some fruit types vary greatly in shape, size, and texture, limiting general approaches
- Classical computer vision has plateaued; further gains are difficult and costly
- Per-fruit/per-impurity algorithms are time-consuming to develop
- Trade-off between generality and specificity



Fruit specific algorithms

Variation across single crop

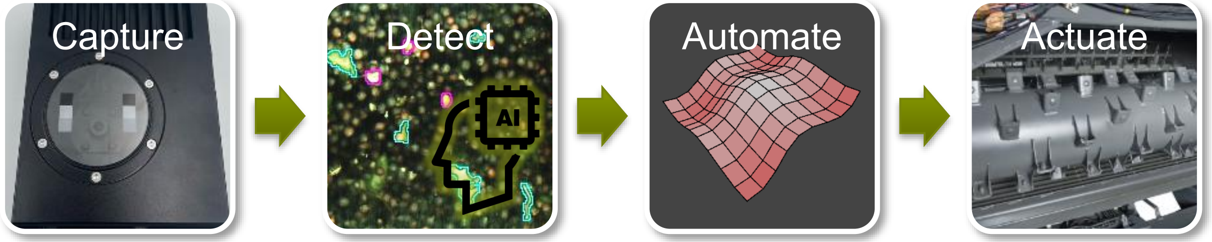


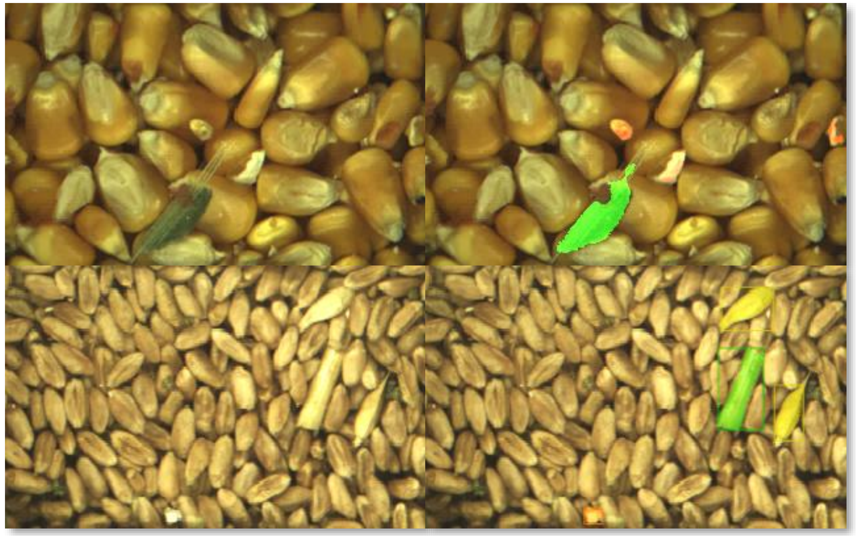
Stepwise approach of classical algorithms

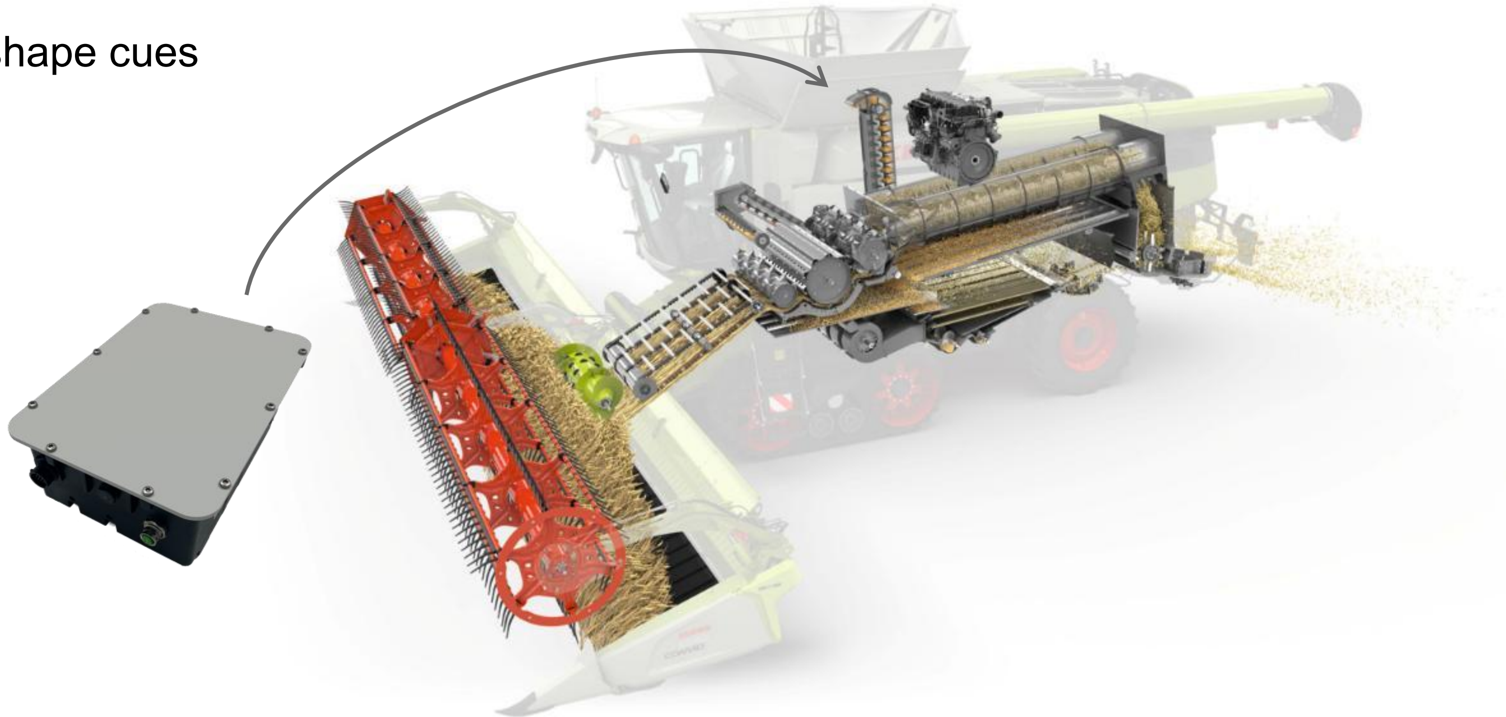
Use Case: Improving grain quality in combine harvesters

Solution

- Hardware acceleration boosted throughput to 25 FPS
- Model architecture reusable across fruit and impurity types
- Finding: Performance depends on annotation quality; domain experts included in cross-validation
- Finding: Even with the fracture face occluded, shape cues are sufficient to identify broken kernels





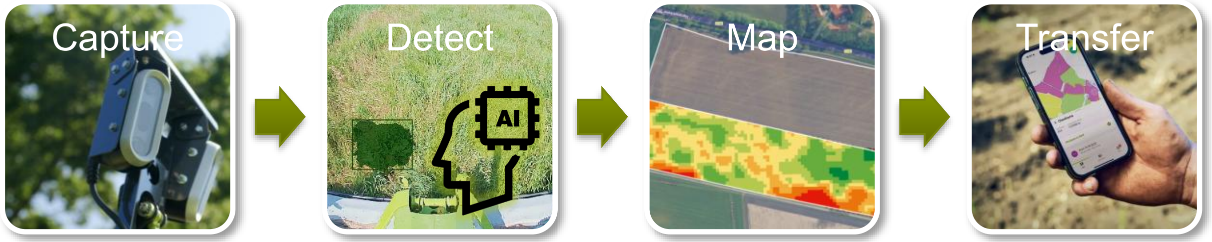


Use Case: Avoiding Rumex in Grasslands

Problem summary

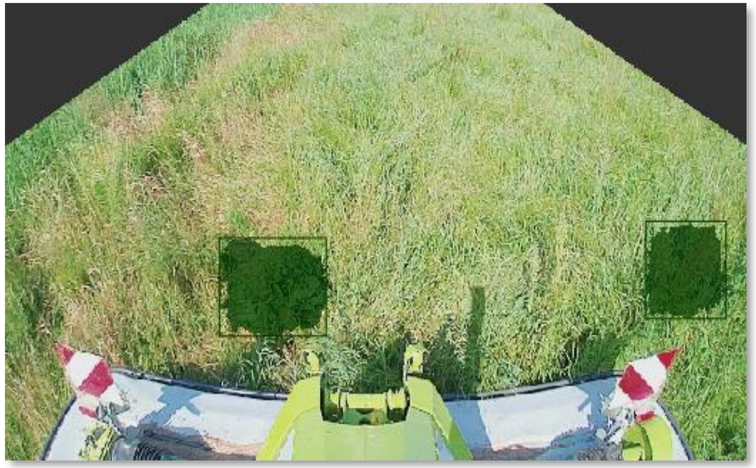
- Rumex obtusifolius spreads generatively (seeds) and vegetatively (roots); patches persist and expand
- Infestations reduce grassland yield and fodder quality by competing for light, nutrients, and space
- Weeds occur in patches; precise localization enables targeted mechanical/chemical control and saves inputs
- Legal constraints limit herbicide use; blanket spraying is not allowed in many grassland contexts

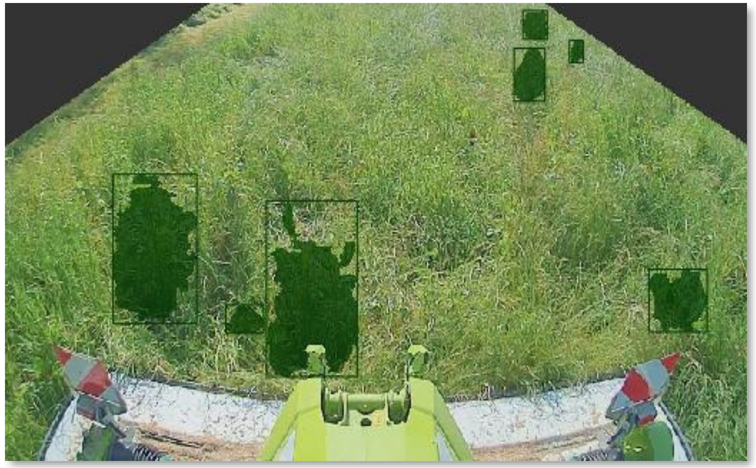
Use Case: Avoiding Rumex in Grasslands



Solution

- Scanning of field with cameras while mowing
- AI-based detection of weed plants
- Mapping of geo-referenced weed locations
- Map transfer to backend for subsequent task planning
- Deployment of map on target platform

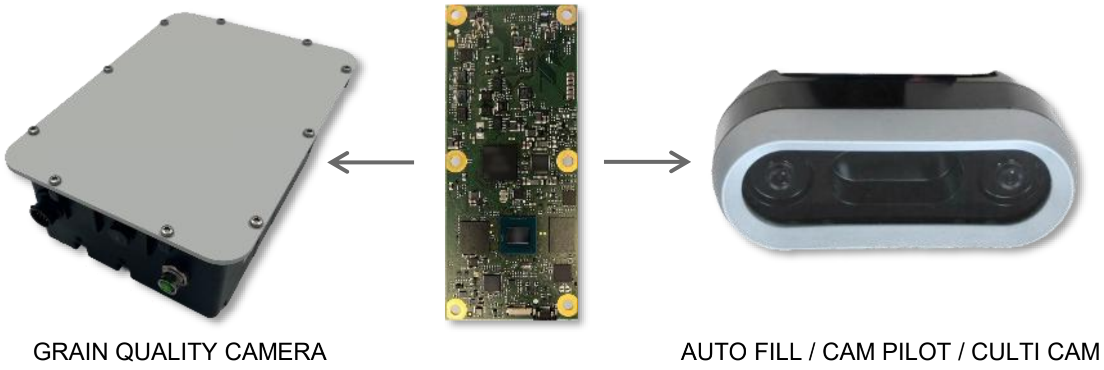




Building Blocks & Reusability

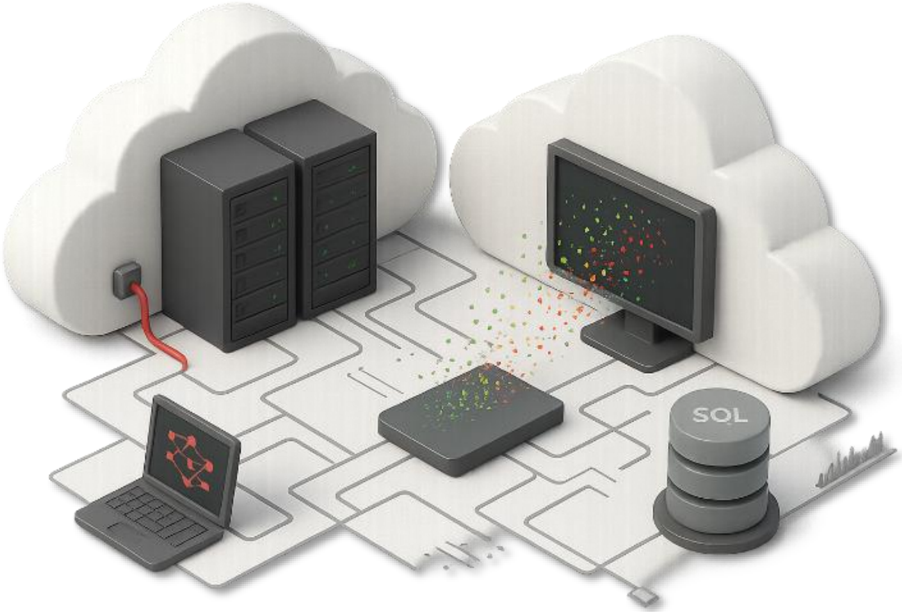
Platform

- Edge device with integrated NPU for online inference
- Up to 3 camera sensor inputs depending on configuration
- Multiple optics and sensor configurations possible
- Integrated into all Camera Sensors products



Infrastructure

- Data import pipelines with automated anonymization steps
- Cloud-based or local training pipelines depending on use case
- Quantization-aware training and target deployment
- Advanced data exploration and annotation tools allow more complex workflows; cross-validation of annotations
- Standard model libraries and toolkits for new use cases



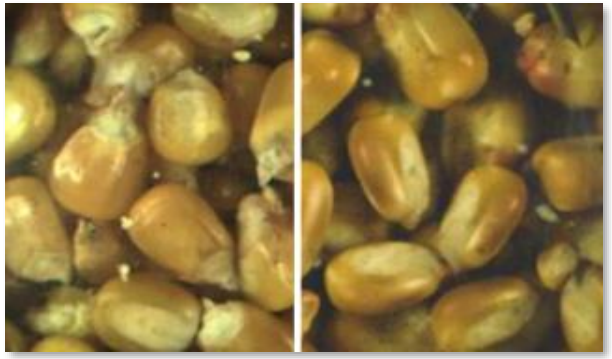
Challenges

Data acquisition

- Botanical variance
- Environmental variance
- Synthetic data

Natural variation

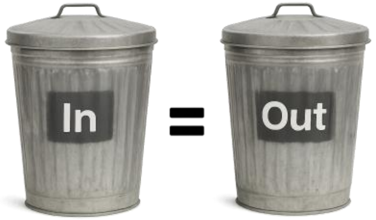
Maturity stages



Real versus synthetic data

Annotation Quality

- Model performance very much dependent on annotation quality
- Different strategies depending on use case; some require expert knowledge



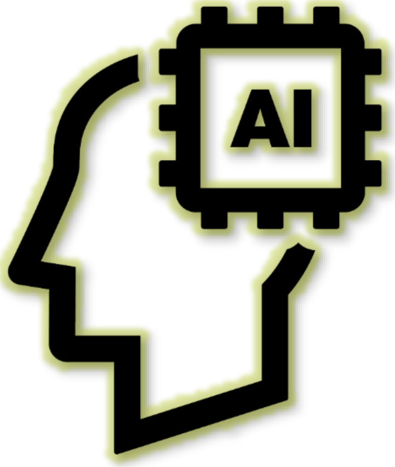
Ways of working

- High degree of front-loading; main effort lies within first 3 steps

Use Case Specification → Data Acquisition & Exploration → Data Annotation → Model Development → Validation → Integration

Conclusion

Machine Learning in Agriculture



- Represents a steep learning curve but delivers a transformative technological leap
- Unlocks significant potential in visual classification, quantification, and automation
- Transforms traditional workflows and operational practices
- Accelerates development cycles once relevant data is accessible
- Revitalizes projects and ideas previously considered too complex to solve
- Offers yield optimization and cost saving potential for the end customer

Thank you for listening...