Literature search

1) Peladarinos et al., *“Enhancing Smart Agriculture by Implementing Digital Twins”* (2023) – Comprehensive review of digital twin applications in agriculture

Link: https://www.mdpi.com/1424-8220/23/16/7128

- How Digital Twin (DT) technology is transforming smart agriculture.
- How virtual replicas of farms—integrating data from sensors, IoT devices, weather forecasts, and satellite imagery—can simulate real-world conditions to optimize irrigation, fertilization, and pest control.
- The potential of DTs to enhance productivity and sustainability, while also addressing challenges like data integration, privacy, and the need for high-quality simulations.
- The future directions for advancing Agriculture 4.0 through more robust and intelligent DT systems.

2) Zhang et al., *“A Comprehensive Review of Digital Twins Technology in Agriculture”* (2025) – Covers DT architecture and predictive maintenance use-cases.

Link: https://www.mdpi.com/2077-0472/15/9/903

- How Digital Twin (DT) technology is being used in agriculture to improve productivity, sustainability, and decision-making.
- Explains the structure and types of DT systems, and explores their applications in crop management, pest control, livestock monitoring, machinery optimization, and resource planning.
- Challenges such as data collection, integration, and model accuracy.
- Future directions, including combining DTs with advanced AI models to make farming smarter and more adaptive.

3) Agricultural Robotics: A Technical Review Addressing Challenges in Sustainable Crop Production
Link: https://www.mdpi.com/2218-6581/14/2/9#:~:text=The%20regulation%20of%20autonomous%20robots,level%20of%20safety%20equivalent%20to

- Current state of agricultural robotics, detailing how robots are being designed and deployed to automate tasks like soil preparation, planting, weeding, plant protection, and harvesting in both open fields and greenhouses.
- Robots offer clear benefits for productivity and environmental sustainability, the authors highlight high acquisition costs and technical hurdles—such as reliable navigation in varied terrains and crop types—that still slow widespread adoption.
- Key research directions aimed at improving the efficiency, adaptability, and affordability of robotic solutions for diverse farming contexts.

4) Smart Farming Revolution: AI, IoT, and Robotics in Precision Agriculture and Soil Conservation
Link:
https://www.researchgate.net/publication/391059105_Smart_Farming_Revolution_AI_IoT_and_Robotics_in_Precision_Agriculture_and_Soil_Conservation#:~:text=695

    - Explains how cutting-edge technologies converge to transform modern agriculture.
    - IoT-enabled sensor networks and wireless platforms that continuously monitor soil moisture, nutrient levels, and microclimate parameters, feeding data into AI models for real-time decision support on variable-rate irrigation, fertilization, and pest control.

5) Žalik & Rizman, *“A Review of Federated Learning in Agriculture”* (2023) – Surveys FL methods and benefits for smart farming.

Link: https://www.mdpi.com/1424-8220/23/23/9566

- Machine learning across decentralized devices without sharing raw data.
- It explores how FL can enhance privacy, efficiency, and collaboration in smart farming by analyzing different FL architectures (centralized vs. decentralized), data partitioning methods (horizontal, vertical, hybrid), and aggregation algorithms.
- Challenges like communication bottlenecks and propose solutions such as model compression and sparsification
- A comprehensive overview of FL’s potential to revolutionize agricultural data management and decision-making.

6) Berkani et al., *“Advances in Federated Learning: Applications and Challenges”* (2023) – Discusses FL challenges like communication overhead and non-IID data

   Link: https://www.mdpi.com/2073-431X/14/4/124

   - FL and its applications in smart buildings.
   - How FL allows devices to collaboratively train machine learning models without sharing sensitive data, improving privacy and efficiency.
   - FL’s use in areas like energy prediction, thermal comfort, healthcare, and anomaly detection, and discuss key technologies such as digital twins, 5G/6G networks, and blockchain.
   - Challenges: communication overhead, data heterogeneity, and security risks, and propose future directions including adaptive learning and hybrid architectures to make smart buildings more intelligent and secure.

7) Dust et al., *“Pattern-Based Verification of ROS 2 Nodes using UPPAAL”* (2022) – Example of using UPPAAL to verify timing in ROS2 systems.

Link: https://www.es.mdu.se/pdf_publications/6797.pdf

- Pattern-based approach for verifying distributed robotic systems built on ROS 2 using the UPPAAL model checker.
- Introduces reusable Timed Automata templates to model callback scheduling, latency, and buffer overflow across different ROS 2 executor versions.

8) A Comprehensive Review on Smart and Sustainable Agriculture Using IoT Technologies
   Link: https://www.researchgate.net/publication/381305392_A_comprehensive_review_on_smart_and_sustainable_agriculture_using_IoT_technologies#:~:text=include%20addressing%20connectivity%20issues%2C%20,and%20privacy%2C%20scaling%20solutions

9) Possibilities to deploy neural networks in MCUs

M. Munster, *“Deploying Neural Networks on Microcontrollers with TinyML”* – Embedded.com article (2022), shows use of STM32/ESP32 for on-device ML

10) Federated learning online course: https://learn.deeplearning.ai/courses/intro-to-federated-learning/lesson/y9bk4/why-federated-learning

Thesis project proposal based on the macro topics:

Simulation Based Predictive Analysis in Smart Farming Using Digital Twins and Federated Learning

- Develop a **simulation-driven smart farming system** focused on predictive monitoring and decision making.
- Begin with **collecting data from simulated** or real sensors (e.g., soil moisture, air temperature, humidity, or water pump anomalies).
- Use this data to train lightweight AI models suitable for deployment on resource-constrained devices (Edge AI).
- Explore the use of **federated learning** (e.g., with the **Flower** framework) to train client models on separate datasets, either randomly generated or collected from real sensors and aggregate them into a global model.
- Integrate the trained global model into a **digital twin** of the farm to simulate behavior, perform predictions, and evaluate system responses to various scenarios.
- Apply **UPPAAL** to formally verify timing and safety properties, such as sensor communication deadlines, processing delays, and control response times.
- Optionally integrate real hardware using available microcontrollers (e.g., STM32, Arduino Uno, ESP32) to collect live data or test edge deployment of trained models.

Platform: Windows

VS code

Install pytorch windows: https://www.youtube.com/watch?v=wCuJncQsXxI

Use conda, Hydra and RAY

Questions

- Which programming language?
- Which software should I use?
- If required, can I access the hardware from the university?
- Edge AI
- How to combine these technologies