

Autonomous Robotic System for Precision Farming: Enhancing Sustainability and Efficiency in Agriculture

Arjun Veeramony ¹, Vipin Krishna Vijayakumar ², Akhilesh Kakkayamkode ³,
Krithika Premkumar ⁴ und Angel Mary ⁵

Abstract: This project aims to develop an autonomous robotic system for precision farming to enhance agricultural productivity sustainably. The robot will navigate autonomously using a camera, identify plant conditions, and perform actions like weeding and spraying pesticides to maintain crop health. Real-time coordination will allow multiple robots to assume roles such as observer, weeder, and crop protector. Using Multi-agent UML (MUML) techniques and ResNet-18 for image processing, the system ensures precise interventions. UPPAAL for mechatronics modeling guarantees performance and reliability. This innovation reduces manual labor, minimizes chemical use, and supports sustainable farming practices.


Keywords: Mechatronic UML (MUML) , UPPAAL, Autonomous Vehicle (AVs)

1 Motivation

The project is driven by the critical need to enhance agricultural productivity and efficiency in a sustainable manner. As the global population continues to grow, there is an increasing demand for innovative solutions to feed the world while minimizing environmental impact. Precision farming, which involves the use of advanced technologies to optimize crop yields and reduce resource usage, presents a promising approach to address these challenges.

2 Goal

The primary goal of this project is to develop an autonomous robotic system for precision farming that can navigate a designated track, identify various plant conditions, and perform necessary actions to maintain crop health. This involves designing and implementing a robot capable of driving autonomously on a scaled road-track using a camera as its primary sensor. The system must follow solid and dashed lines and recognize unique markers representing different plant conditions. The robot will be equipped to identify healthy plants, diseased plants, and weeds, and based on these identifications, it will perform actions such as weeding and spraying pesticides to ensure crop health maintenance. Additionally, real-time coordination patterns will be developed for the autonomous vehicles to interact within a

⁵ Fachhochschule Dortmund , Department of Computer Science, Dortmund, Germany,
angel.mary014@stud.fh-dortmund.de,  <https://orcid.org/0000-0000-0000-0000>

community, allowing each vehicle to assume multiple roles (e.g., plant observer, weeder, crop protector) and coordinate with other vehicles to optimize the overall scenario.

Furthermore, the project aims to refine the principle solution into a detailed software model using MUML techniques. This includes identifying roles and behaviors, mapping them to agents, specifying overall agent behavior, refining requirements into checkable properties, and verifying the system's correctness to ensure deadlock freedom. By achieving these goals, the project seeks to advance productive, efficient, ecological, and economical farming practices that support global food supply sustainability.

3 System specification with CONSENS

3.1 Usecase Diagram



Abb. 1: Usecase Diagram

The use case diagram in fig 1 outlines the interactions between various actors and their respective roles within a precision farming system. The system involves three main actors: the Observer, Weed Picker, and Protector. Each actor has specific roles and responsibilities aimed at maintaining the health of crops. The Observer is responsible for surveying and monitoring the plants to assess their health. This role includes the fundamental task of observing plants. During observation, if the Observer identifies the presence of weeds, it extends to the use case "Detect Weed". Similarly, if the Observer detects unhealthy plants, the use case extends to "Detect Unhealthy Plant". Once weeds or unhealthy plants are detected, the Observer sends their location to relevant actors via the "Send Location of Weed/Unhealthy Plant" use case. The Weed Picker's role involves plucking weeds from the

identified locations. This process starts with the "Detect Weedüse case, which includes the action of "Pluck Weeds."For the Weed Picker to perform this task, they need to navigate to the specific location where weeds are detected. This is covered under the "Navigate to Locationüse case, which includes receiving the location details sent by the Observer.

The Protector is tasked with treating unhealthy plants. Upon detecting an unhealthy plant, which is an extension of the Öbserve Plantsüse case, the Protector must perform the action described in the SSpray on Plantsüse case. Similar to the Weed Picker, the Protector also relies on the "Navigate to Locationüse case to reach the identified plants needing treatment, based on the location information received from the Observer.

In addition, the Observer also has the use case "Navigate in Track, ensuring that it can effectively move through the track to carry out observations. This comprehensive mapping of roles and responsibilities ensures seamless coordination between observing, detecting, and addressing issues in the crop field. The diagram effectively illustrates the critical role of the Observer in identifying problems, the Weed Picker in managing weeds, and the Protector in treating unhealthy plants, ensuring a holistic approach to precision farming.

3.2 Requirements diagram

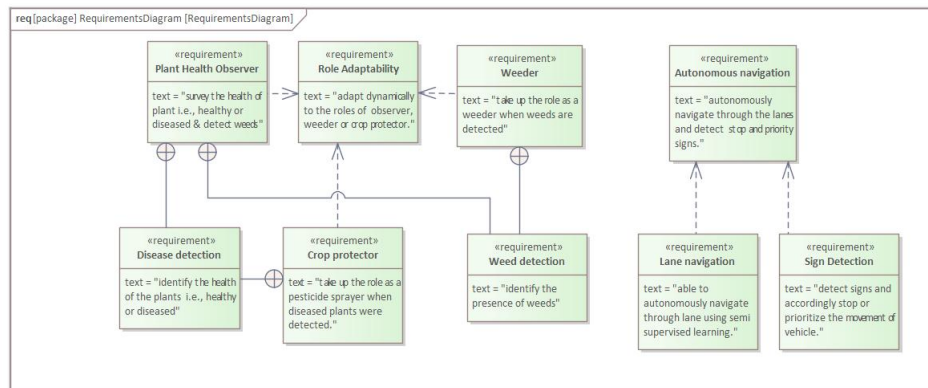


Abb. 2: Requirements Diagram

The requirements diagram in fig 2 outlines the essential specifications involving autonomous vehicles used in precision farming. The core requirement, Plant Health Observer, specifies that the system must be capable of monitoring plant health, identifying whether plants are healthy or diseased, and detecting the presence of weeds. The Role Adaptability requirement emphasizes that the system should dynamically switch roles based on detected conditions, adapting to become an observer, weeder, or crop protector as needed. This adaptability is directly linked to the Weeder and Crop Protector requirements, where the system assumes the role of a weeder when weeds are detected and a crop protector, applying pesticides,

when diseased plants are identified.

Autonomous Navigation ensures that the vehicle can navigate through lanes autonomously, identifying and responding to stop and priority signs. This requirement is supported by Lane Navigation, which involves navigating lanes using semi-supervised learning techniques, and Sign Detection, which focuses on recognizing signs and adjusting the vehicle's actions accordingly. The Disease Detection requirement involves accurately determining the health status of the plants to identify any diseases, directly supporting the plant health observation role. Additionally, the Weed Detection requirement mandates the system to detect weeds, further linking to its role as a weeder.

Overall, this requirements diagram provides a comprehensive overview of the essential functionalities for autonomous vehicles in precision farming. It highlights the system's capabilities to dynamically adapt its roles, navigate autonomously, and detect and respond to various conditions in the field. Each requirement is interconnected, ensuring a cohesive and functional autonomous vehicle system that effectively supports precision farming.

3.3 Block Diagram of the system

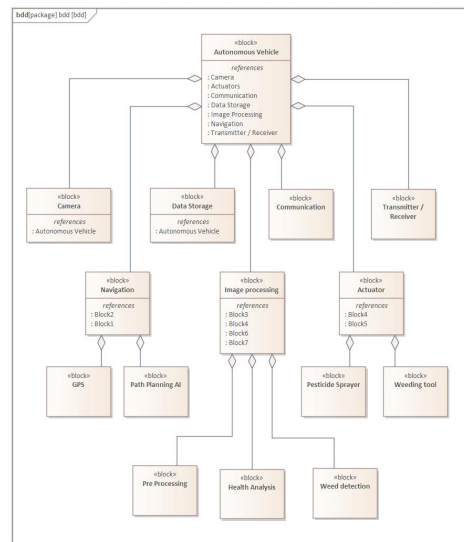


Abb. 3: Block Definition Diagram

The block diagram shown in fig 3 represents an autonomous vehicle designed for agricultural applications, specifically for plant observation, weeding, and pest control. At the center is the "Autonomous Vehicle" block, which references several key subsystems: Camera, Actuators,

Communication, Data Storage, Image Processing, Navigation, and Transmitter/Receiver. Each of these subsystems plays a crucial role in the vehicle's functionality. For instance, the Camera subsystem includes components necessary for capturing images and data from the environment. The Data Storage subsystem is responsible for saving the collected data, while the Communication subsystem ensures data transfer and remote control capabilities.

Further breaking down the subsystems, the Navigation block references GPS and Path Planning AI, essential for guiding the vehicle's movement. The transmitter component is enabled only on AVs which act as observer to provide the location, data and intended role to others and receiver component is active on free AVs as well as AVs taking other roles so that they will receive information for proper functioning. The Image Processing block encompasses Preprocessing of data for Health Analysis, and Weed Detection, which are vital for analyzing plant health and identifying weeds or pests. The Actuator block includes tools like the Pesticide Sprayer and Weeding Tool, enabling the vehicle to perform physical actions based on the image analysis. This diagram effectively outlines the interconnected components, demonstrating how they collectively enable the vehicle to autonomously monitor plant health, remove weeds, and apply pesticides, thereby supporting precision agriculture.

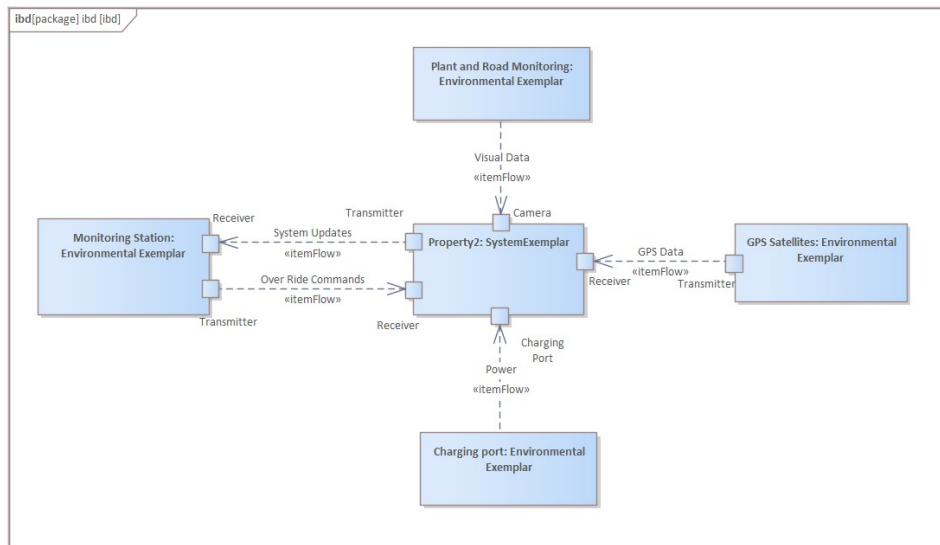


Abb. 4: Internal Block Diagram

This Internal Block Diagram (IBD) shown in fig 4 provides the interactions between the core system, labeled and essential external environmental systems that support its functionality. At the heart of the system, SystemExemplar receives and processes various data inputs to perform its autonomous functions. The Monitoring Station plays a critical

role in maintaining operational integrity by providing system updates and the ability to send override commands. This ensures that in the event of a fault or interference, manual control can be exerted to safeguard the vehicle and its surroundings. The system updates and commands are transmitted and received through dedicated communication channels, highlighting the importance of reliable connectivity for real-time intervention and system management.

Moreover, the GPS Satellites are pivotal in delivering continuous and precise GPS data to the autonomous vehicle. This data is essential for accurate navigation, enabling the vehicle to determine its position and route with high precision. The Charging Port ensures the vehicle remains operational by supplying power when needed, illustrating the importance of maintaining battery levels for uninterrupted operation. Additionally, the Plant and Road Monitoring systems provide crucial visual data via cameras, which is transmitted to the autonomous vehicle. This visual information allows the vehicle to analyze its environment, detect obstacles, and make informed decisions based on real-time analysis of plant and road conditions. The integration of these external systems with the autonomous vehicle ensures a comprehensive approach to autonomous operation, emphasizing safety, precision, and continuous environmental awareness.

4 Mechatronics UML Specification

Autonomous precision farming robots represent a significant advancement in agricultural technology, enabling more efficient and effective farm management. These robots, designed to work collaboratively, perform two distinct roles: observing and protecting. Each robot is equipped with four major components: Navigation, Observer, Weeder, and Pesticide Sprayer. This document details the working of these robots using different components and subcomponents while operating under different roles. Additionally, Fig 5 provide a visual representation of the system architecture.

4.1 Observing Role

In the observing role, the robot leverages its Navigation and Observer components to survey the farm. The Navigation component, comprising the Motor Control, Path Planner, and Central Control System subcomponents, enables the robot to move systematically across the field. The Motor Control manages the movement of the robot, ensuring it follows the planned path accurately. The Path Planner calculates the optimal route for comprehensive field coverage, while the Central Control System coordinates these movements. This precise

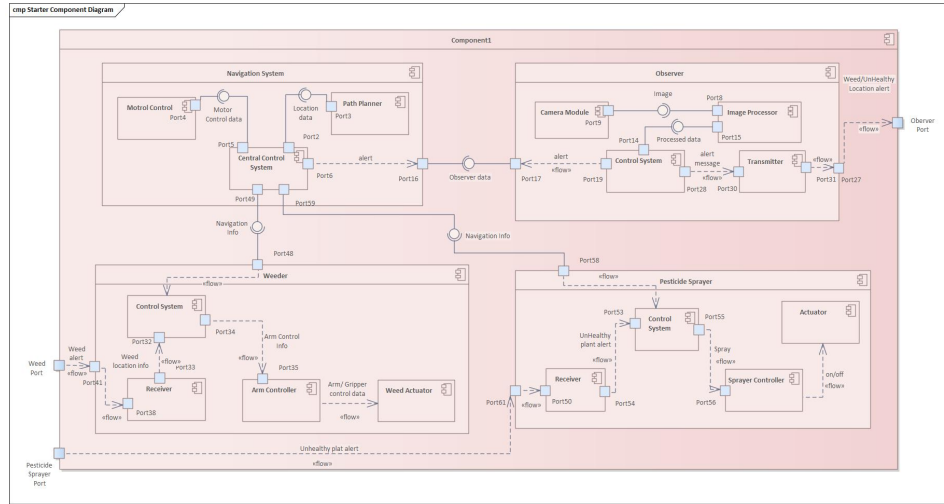


Abb. 5: Component Diagram

navigation is crucial for the robot to cover the entire farm efficiently, minimizing gaps and overlaps.

The Observer component, consisting of the Camera Module, Image Processor, Control System, and Transmitter, plays a crucial role in data collection. The Camera Module captures high-resolution images of the crops, which the Image Processor then analyzes to detect the presence of weeds or diseased plants. The Control System orchestrates the functioning of the Observer component, ensuring that the data is collected systematically and accurately. Once the data is processed, the Transmitter broadcasts this information to all the protector robots in the field. The data broadcast includes the precise location and type of issue (weed or disease), ensuring that the information is actionable for the protector robots

4.2 Protecting Role

Robots assigned to the protecting role primarily use the Weeder and Pesticide Sprayer components, along with the Navigation component, to address the issues identified by the observer robots. The Navigation component guides the protector robot to the exact location of the weed or diseased plant using the data received from the observer robot. This component ensures that the robot can navigate accurately and efficiently to the target location, reducing response time and increasing the effectiveness of the intervention.

The Weeder component, comprising the Control System, Receiver, Arm Controller, and Weed Actuator, is activated when the received data indicates the presence of weeds. The Receiver collects the broadcasted data and sends it to the Control System, which then

commands the Arm Controller to position the Weeder Actuator precisely over the weed. The Weeder Actuator performs the weeding process, effectively removing the unwanted plant from the field. This process is crucial for maintaining crop health and maximizing yield by eliminating competition for resources.

Similarly, the Pesticide Sprayer component, which includes the Receiver, Control System, Sprayer Controller, and Actuator, is employed when the data indicates a diseased plant. The Receiver gathers the broadcasted data, and the Control System analyzes it to determine the precise location and extent of the disease. The Sprayer Controller then directs the Actuator to apply the pesticide accurately, ensuring that the diseased plant is treated effectively. This targeted application minimizes the use of chemicals, reducing costs and environmental impact while ensuring plant health.

4.3 Coordination and Communication

Effective coordination and communication between the observer and protector robots are critical for the successful operation of the autonomous farming system. When an observer robot detects a weed or diseased plant, it broadcasts the relevant data, including the precise location and nature of the issue, to all protector robots in the field. Each protector robot receives this data and uses its Control System to analyze the information. The robot closest to the target location will then proceed to address the issue, while others remain on standby, ready to act on subsequent broadcasts. This dynamic and responsive approach ensures that all detected issues are addressed promptly, maintaining optimal field conditions.

The Navigation component plays a crucial role in this process, ensuring that the protector robot can reach the target location accurately. The Path Planner calculates the shortest route, while the Motor Control and Central Control System ensure that the robot follows this route without deviations. This efficient navigation is essential for timely and effective intervention. By leveraging real-time data and adaptive algorithms, the system can optimize the allocation of robots, ensuring that resources are used efficiently and effectively.

4.4 Detailed Component Functions

- **Navigation Component:** The Motor Control ensures smooth movement, enabling the robot to traverse the field with precision. The Path Planner calculates optimal paths to ensure comprehensive coverage and efficient navigation. The Central Control System coordinates navigation efforts, integrating data from the Observer component and ensuring that the robot follows the planned path accurately.
- **Navigation Component:** The Camera Module captures high-resolution images, providing detailed visual data of the crops. The Image Processor analyzes these images to detect weeds and diseased plants, using advanced algorithms to identify issues with high accuracy. The Control System manages data collection and processing,

ensuring that the Observer component operates efficiently. The Transmitter broadcasts the data to protector robots, enabling coordinated and timely responses.

- **Navigation Component:** The Receiver collects data broadcasted by observer robots, ensuring that the Weeder component is aware of any identified weeds. The Control System directs actions based on the received data, commanding the Arm Controller to position the Weeder Actuator accurately. The Weeder Actuator removes weeds effectively, maintaining crop health and optimizing yield.
- **Navigation Component:** The Receiver gathers information broadcasted by observer robots, ensuring that the Pesticide Sprayer component is aware of any diseased plants. The Control System processes the data and determines the precise location and extent of the disease. The Sprayer Controller manages pesticide application, directing the Actuator to apply the pesticide accurately and effectively. This targeted approach minimizes chemical usage and ensures effective treatment of diseased plants.

5 Model Checking

Model checking is a crucial process in verifying the correctness of systems, especially in applications where reliability and safety are crucial. The number of test cases and the variety of states and transitions to be tested are generally extensive, so it is crucial to abstract the model to a manageable set of states for verifying properties such as deadlock and reachability. In precision farming, robots equipped with various roles such as observing, protecting, and navigating must operate flawlessly to ensure efficiency and safety. UPPAAL, a powerful tool for modeling, simulation, and verification of real-time systems, provides an ideal platform for verifying such complex systems.

5.1 UPPAAL Overview

UPPAAL is a verification tool for real-time systems modeled as networks of timed automata, extended with data variables and user-defined functions. It allows for the specification, simulation, and verification of system properties. This capability makes it particularly suitable for applications requiring precise timing and concurrency control, such as robotics in precision farming.

5.2 Precision Farming Model

The precision farming robot is designed to perform three primary roles:

Observing: Monitoring crop health, soil conditions, and environmental factors using various sensors.

Protecting: Implementing pest control measures, applying fertilizers and weeding out

unhealthy crops.

Navigation: Moving through the farming environment to perform tasks efficiently.

Each of these roles is modeled by abstracting the basic states and crucial transition as a separate automaton in UPPAAL.

Observer Role The modelled observer is shown in figure6. The Observer triggers the event 'Start' and moves to location 'Begin Detection'. Once timer3 expires, the location then progresses to 'Detect Issue'. Before moving to the next location 'Send Data', The 'IssueDetected' event is raised and the position where the issue is detected is updated with the statement 'x_position = x_surveyor'. The global clock 'issue' is reset. An invariant for 'Send Data' location is added i.e., $issue \leq 3 * timer6$. By doing so, we simulate the condition of real time delays in communication. The progress from 'Send Data' location to the initial location happens once the Protector confirms that the Request was received. The Observer can then re-start its detection. An independent transition from Initial location to EndOfField happens, when the observer receives the event from the Navigation role that the end of field has been reached and hence it can stop its role of observing.

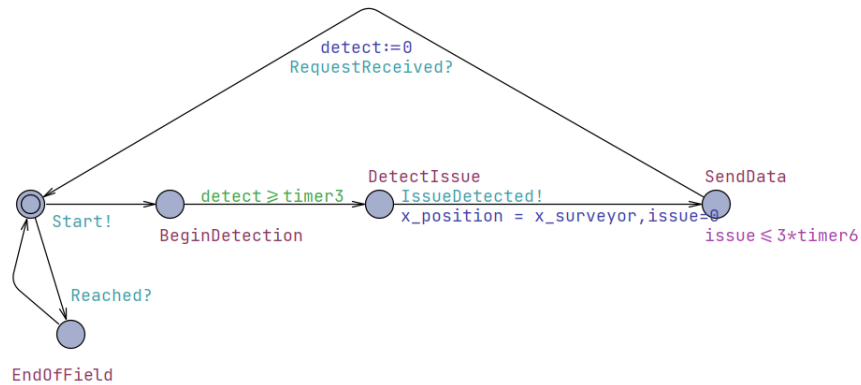


Abb. 6: Model of Observer

Protector Role The modelled Protector is shown in figure7. Once the event of an issue being detected is received via the channel 'IssueDetected' and the clock 'issue' is set to timer6, it then progresses to the location 'ReceiveRequest'. During the transition from 'ReceiveRequest' to 'StartMoving' location, the 'RequestReceived' event is raised to be shared with the Observer to confirm the reception of the request to start protection. The transition to the next location happens by sending the information of 'Start' through the channel 'Protector_Start'. This instructs the navigation role to start moving till the location is reached. Once the location has been reached, the Protector progresses to the next location 'StartProcess' by resetting the clock m. A guard condition before the transition to the next location is added, to simulate the real time taken for completing the process such as weeding

or spraying pesticides. After reaching the 'StopProcess' location, it then moves to the initial state.

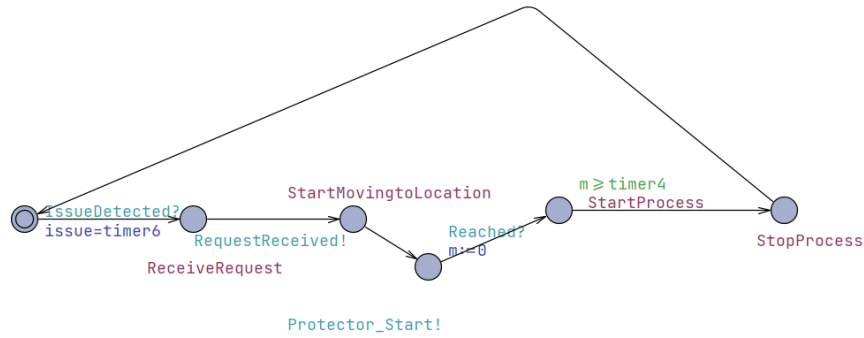


Abb. 7: Model of Protector

Navigation Role The modelled Navigator is shown in Figure8. The navigator once receiving the event 'Start' from either the Protector or Observer, transitions to the location 'Move'. Once the position is reached, the event 'Reached' is triggered and transitions to 'LocationEnd' and then goes to the initial state.

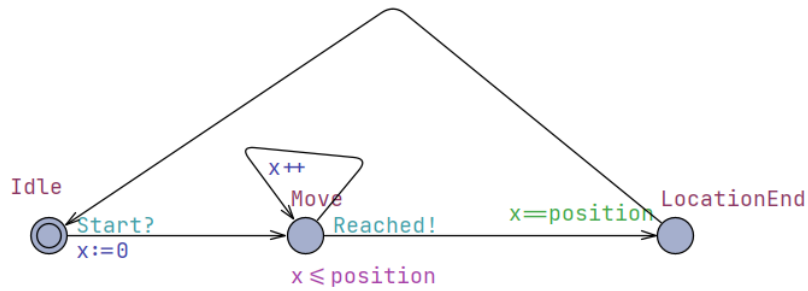


Abb. 8: Model of Navigator

Verification The model is then simulated as shown in figure9 and is checked for properties such as Deadlock freedom and reachability. Deadlock detection is a critical feature in model checking, ensuring that the system can always proceed with its operations without getting stuck in a particular state. In UPPAAL, deadlock detection can be performed by verifying that there are no reachable states where the system has no outgoing transitions. For the

precision farming model, deadlock checks are implemented for the entire system to ensure smooth and continuous operation and interaction.

$A[]$ not deadlock property is satisfied indicates that no deadlock is present in the system. $Observer1.SendData \rightarrow Protector1.ReceiveRequest$ property is satisfied indicates that when Observer sends the data, it implies that the Protector receives the request. $E<> Protector1.StopProcess$ property is satisfied indicates that this location is reachable in the model.

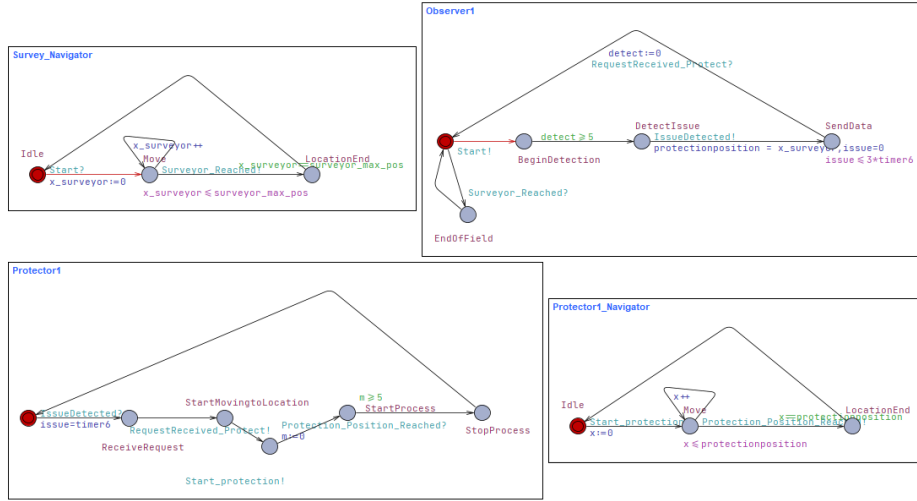


Abb. 9: Simulation of Model

```
Observer1.SendData--> Protector1.ReceiveRequest
Verification/kernel/elapsed time used: 0.031s / 0s / 0.069s.
Resident/virtual memory usage peaks: 18,888KB / 64,768KB.
Property is satisfied.
E<> Protector1.StopProcess
Verification/kernel/elapsed time used: 0.016s / 0s / 0.015s.
Resident/virtual memory usage peaks: 18,964KB / 64,864KB.
Property is satisfied.
A[] not deadlock
Verification/kernel/elapsed time used: 0.015s / 0s / 0.086s.
Resident/virtual memory usage peaks: 18,948KB / 64,672KB.
Property is satisfied.
```

Abb. 10: UPPAAL Model Verification

The application of UPPAAL for model checking in precision farming robots illustrates its effectiveness in verifying complex systems with stringent real-time requirements. By modeling the observing, protecting, and navigation roles, and performing deadlock and reachability checks, we ensure that the system can operate seamlessly and efficiently.

6 Cognitive Behavior in Mechatronic Systems

Cognitive behavior in mechatronic systems refers to the integration of cognitive functionalities within mechanical and electronic systems. This interdisciplinary field combines principles from engineering, artificial intelligence, and cognitive science to enhance the capabilities of mechatronic devices, enabling them to perform complex tasks autonomously and intelligently.

6.1 Core Concepts of Cognitive Behavior in Mechatronic Systems

The core concepts involve the implementation of cognitive processes such as perception, learning, decision-making, and adaptation within mechatronic systems. These systems are designed to interact with their environment, process sensory information, and make decisions based on that information. For instance, a cognitive mechatronic system can adapt its behavior in real-time to changing conditions, improving efficiency and performance.

6.2 Cognitive Systems and Learning

One of the significant aspects of cognitive behavior in mechatronics is the ability of systems to learn from experience. Machine learning algorithms are employed to allow these systems to recognize patterns, predict outcomes, and optimize their functions over time. This learning capability is crucial for applications where the environment is unpredictable or where the system needs to improve its performance continually.

6.3 Applications and Research

The document outlines several applications and research projects focused on cognitive mechatronic systems. These include: 1. Autonomous Robotics: Development of robots that can navigate and perform tasks in dynamic environments without human intervention. These robots use cognitive behaviors to understand their surroundings, make decisions, and execute complex tasks. 2. Smart Manufacturing: Implementation of cognitive systems in manufacturing processes to enhance flexibility, precision, and efficiency. Cognitive mechatronic systems in factories can adapt to new products, optimize workflows, and reduce downtime through predictive maintenance. 3. Assistive Technologies: Creation of devices that aid individuals with disabilities by incorporating cognitive functions. These systems can adapt to the user's needs and preferences, providing personalized assistance.

6.4 Research Highlights

Several key research projects which advancements in cognitive mechatronic systems are:

Adaptive Control Systems: Research on control systems that can adjust their parameters in real-time based on feedback from the environment. This adaptability improves the system's robustness and performance in varying conditions.

Cognitive Robotics: Studies on robots with advanced cognitive capabilities, such as understanding natural language commands, recognizing objects, and interacting with humans seamlessly. These projects aim to create robots that can assist in everyday tasks and collaborate with humans in various settings.

Intelligent Monitoring Systems: Development of monitoring systems that can analyze data from sensors, predict potential failures, and take preventive actions. These systems are crucial for applications in critical infrastructure and industrial automation.

7 Project Overview for Cognitive Behaviour

The project implementation of cognitive behavior in mechatronic systems revolves around creating an autonomous navigation system using advanced machine learning techniques. The primary goal is to enable a vehicle equipped with a camera and Nvidia JetRacer to navigate and recognize traffic signs autonomously. Here's an elaboration of the project phases: **Image Regression** The project employs a cognitive model using the ResNet-18 neural network architecture. This model is implemented on a rover equipped with Nvidia JetRacer and a camera for autonomous navigation and traffic sign recognition. This setup allows for efficient path following and accurate identification of traffic signs by leveraging deep learning for high-level feature extraction and decision-making. **Data Collection** In this phase, 1,020 images annotated with (x, y) coordinates indicating the ideal driving path on the road were collected. The images were manually reviewed to remove any incorrectly marked or improper images, ensuring a high-quality dataset for training the model.

Feature Extraction- Using ResNet18, a convolutional neural network implemented in PyTorch, meaningful features were extracted from the collected images. This step is crucial for training the regression model effectively.

Model Training-The extracted features were used to train a regression model. The model was trained for 10 epochs using the PyTorch library, achieving an accuracy of 57.5

Model Optimization-For optimization, the TensorRT library was used to enhance inference speed and efficiency on embedded platforms. By leveraging TensorRT, the trained PyTorch model was transformed into a format compatible with NVIDIA GPUs, ensuring accelerated performance without compromising accuracy.



Abb. 11: Sample Image of Track(1)

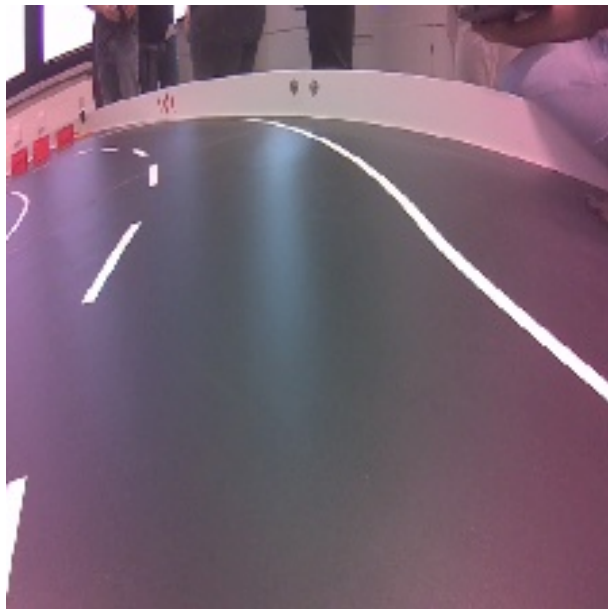


Abb. 12: Sample Image of Track(2)

Deployment-The optimized model, now in TensorRT format, was seamlessly deployed on the JetRacer platform. This deployment strategy not only streamlined integration but also facilitated real-time predictions of the continuous (x, y) coordinates for the ideal driving path. The efficient deployment on JetRacer underscores the commitment to delivering robust and responsive solutions for autonomous navigation applications.

Image Classification-The project tackled a binary classification problem to classify two different categories: priority roads and stop signs. The training phase faced challenges like varying lighting conditions and required transfer learning. The classification model was trained for 10 epochs, achieving an accuracy of 98.65



Abb. 13: priority sign

The project showcases a comprehensive implementation of cognitive behavior in mechatronic systems, focusing on autonomous navigation and traffic sign recognition. By employing advanced neural networks, optimizing models for real-time performance, and deploying them on a practical platform, the project highlights significant advancements in the field of autonomous systems. The achieved accuracies in both regression and classification tasks demonstrate the potential of integrating cognitive functionalities into mechatronic systems for enhanced performance and reliability.

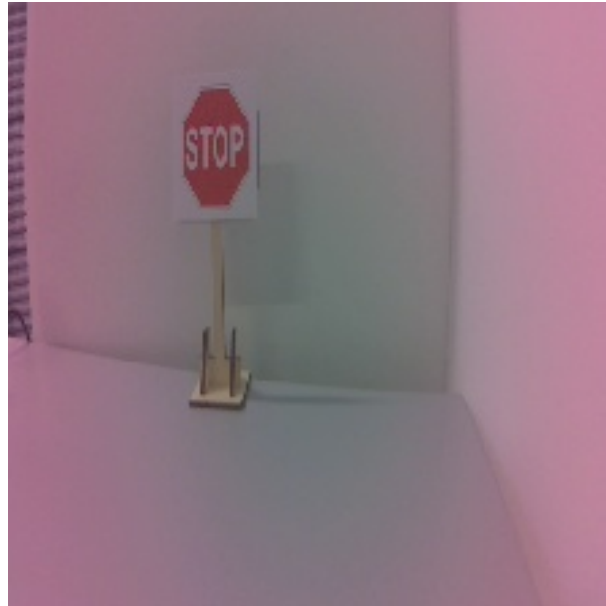


Abb. 14: Stop sign

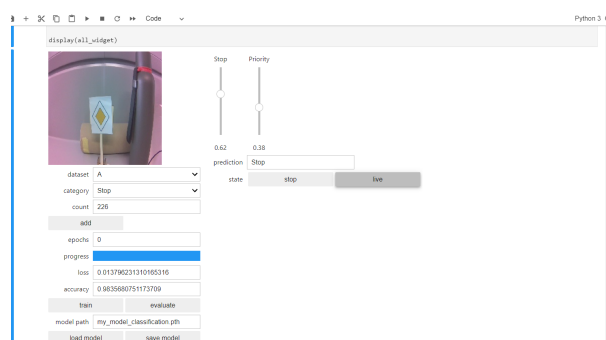


Abb. 15: Accuracy

8 Conclusion

The development of autonomous precision farming robots equipped with sophisticated components for observing and protecting roles marks a significant advancement in agricultural technology. By leveraging the Navigation, Observer, Weeder, and Pesticide Sprayer components, these robots can effectively survey the field, detect issues, and address them with precision and efficiency. The integration of ResNet-18 for high-resolution image processing and analysis enhances the robots' ability to identify weeds and diseased plants accurately, ensuring timely interventions and optimal crop health. The use of UPPAAL for mechatronics modeling provides a robust framework for verifying the system's performance and reliability. Through formal verification and simulation, UPPAAL ensures that the robots operate as intended, with coordinated actions and efficient communication between observer and protector roles. This comprehensive approach minimizes errors and maximizes the efficiency of the autonomous farming system. The collaborative operation of multiple robots, with each bot dynamically taking on the roles of observer or protector based on real-time data, exemplifies the future of precision farming. This system not only improves the efficiency and effectiveness of farm management but also reduces the reliance on manual labor and minimizes the use of chemicals, contributing to sustainable agricultural practices.

9 References

- [1] Wilhelm Schafer Jurgen Gausemeier, Franz Josef Rammig. Design Methodology for Intelligent Technical Systems. Springer, 2014.
- [2] Alexandre David Gerd Behrmann and Kim G. Larsen. A tutorial on uppaal. Department of Computer Science, Aalborg University, Denmark, pages 5-10, 2004.

10 Affidavit

We Arjun Veeramony , Vipin Krishna Vijayakumar , Akhilesh Kakkayamkode , Krithika Premkumar and Angel Mary herewith declare that we have composed the present paper and work ourself and without use of any other than the cited sources and aids. Sentences or parts of sentences quoted literally are marked as such; other references with regard to the statement and scope are indicated by full details of the publications concerned. The paper and work in the same or similar form has not been submitted to any examination body and has not been published. This paper was not yet, even in part, used in another examination or as a course performance.

Dortmund , 16 July 2024

Arjun Veeramony

Vipin Krishna Vijayakumar

Akhilesh Kakkayamkode

Krithika Premkumar

Angel Mary