sciendo
DOI: 10.2478/agriceng-2025-0010

ISSN 2083-1587; e-ISSN 2449-5999
2025,Vol. 29,No.1, pp. 157-186
Agricultural Engineering
https://agriceng.org

SMART SOLUTIONS IN AGRICULTURAL ROBOTICS

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ARTICLE INFO

Article history:
Received: January 2025
Received in the revised form:
April 2025
Accepted: May 2025

ABSTRACT

The article contains an overview and prospects for the introduction of smart and robotic technologies in the agricultural industry. Today, robotization of agriculture and food technology is not a leading industry compared to robotization of other sectors of the economy. Analytical

ARTICLE INFO

Keywords:
Robot,
artificial intelligence,
IT,
neural network,
digital agriculture,
Crop production,
animal husbandry

ABSTRACT

review of the global robotics market revealed that robots in the food industry account for 2% of the total, and robots for agricultural operations account for less than 1%. We analyzed global trends in robotization and the introduction of artificial intelligence in agriculture in various countries. A review of smart robotic technologies, in particular, smart sensors and actuators, the Internet of Things, cloud technologies, methods of data analysis, forecasting, classification, and image recognition using neural networks, is provided. Methods and means are considered in relation to both crop production and livestock production. Four main classes of intelligent technologies in agriculture were identified: robotics, Internet of Things, machine learning, and UAVs. In crop production, robots are common in harvesting, controlling weeds, processing trees, monitoring trees at different stages of the growing season, including leaf and fruit diseases, counting the number of flowers and fruits, and other operations. Identification of fruits, leaves, weeds, as well as diseases of fruits and leaves is performed using computer vision, and in recent years convolutional neural networks have become widespread. Field monitoring is performed using UAVs with subsequent image processing using spectral analysis methods. In livestock farming, smart technologies are represented by feeding and milking robots, livestock monitoring, detection of predators, navigation in livestock buildings, monitoring animal health and behavior. Smart technologies are also used in fish farming to create smart farms. In this mini review, we have tried to integrate advanced smart and robotic technologies for various agricultural operations.

Introduction

Robotic technologies have become widespread in various industries. According to the analytical review of the global robotics market (2019), robots are most widespread in the automotive industry (33% of the total), radio electronics (32%), metallurgy (12%), chemical industry (6%), food production (2%), and other industries (15%). Robotization of agriculture ranks last among other areas of activity, despite the growing relevance of this industry in the world. The application of smart robotic technologies in agriculture can improve the efficiency of food production and reduce labor costs.

The classification of agricultural robotics was made by Skvortsov (2017). It can be classified by industry: animal husbandry, crop production and auxiliary industries.

Robotic operations in crop production include:

- land monitoring (product sorting, product collection, garden tree care, spraying plants,
- weeding
- control of crop germination
- transportation of feed
- watering in the greenhouse
- fruit picking
- transportation of seedlings in greenhouses
- sowing crops

Robotic operations in livestock farming include:

- milking

- shearing
- feed preparation
- feed distribution
- manure removal

Next, we divided our review of smart robotic technologies accordingly, i.e., into two main parts: into crop production on the one hand and livestock farming and fish farming on the other. We analyzed the implementation of such technologies, assessed their effectiveness and the prospects for the development of this industry. Next, we reviewed smart hardware and software solutions used in various countries around the world for automation and robotization of agricultural production. Various types of robots and smart systems in digital agriculture were analyzed, and the advantages and disadvantages of introducing such systems were analyzed. The classification of smart robotic technologies in agriculture is shown in Fig. 1.

The hardware component concerns the use of various types of sensors, the design and development of manipulators, grippers, the use of Internet technologies (cloud and IoT), the use of GPS to plot the route of the robot. The software part of such systems is a set of classification algorithms for image recognition, which is primarily the use of neural networks to obtain images. An example is the recognition of fruit on a tree that needs to be collected by a robot, the recognition of a weed that needs to be cut, visual identification of plant and animal diseases, photos of plantings from a satellite or UAV, animal behavior, etc. Software also includes the implementation of robot movement algorithms, route mapping, drivers and other system software for the operation of equipment and interaction with it.

Digitalization of agriculture makes it possible to improve the working conditions of farmers, reduce the harmful impact of this production on the environment, and significantly increases the profits of agricultural holdings. Soon, the concept of "digital agriculture" will become traditional and ubiquitous, and agricultural producers will begin to understand that they can increase production profits by investing in technology, which includes savings in seedlings, fertilizers, herbicides, pesticides, energy and human labor.

There are studies that show that digital and smart technologies can be more profitable than traditional systems. In the work of US researchers (Salfer et al., 2017) the automatic milking systems (AMS) have been shown to be the most beneficial for herds ranging in size from 120 to 240 head of cattle. One of the modern trends is cloud technologies, which allow storing information on remote servers, as well as remotely monitoring and managing production processes. Farmers around the world are using the Internet of Things, robotics, artificial intelligence and big data to optimize and improve the efficiency of agricultural processes. This is especially true for agricultural industrial countries. According to a study conducted by Nesta in 2024, precision farming and investment in new technologies on the farm will increase profitability by almost 20%, which is comparable to reducing the cost of water or fertilizer. The study estimates that "new agricultural technologies can radically reduce fertilizer costs or increase yields by even 5% (Nesta, 2024).

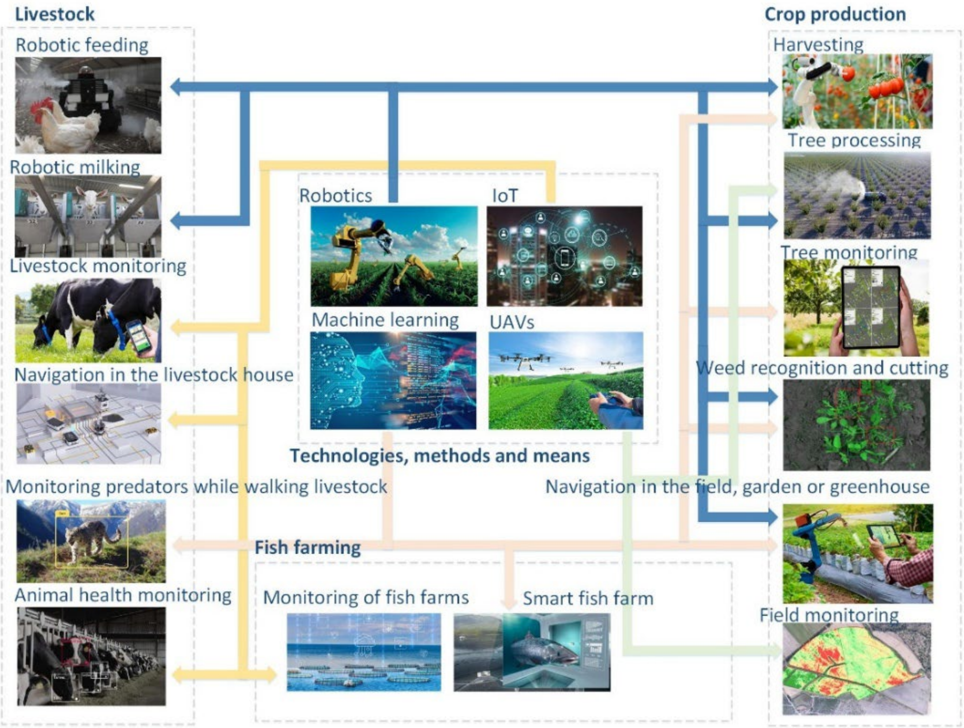


Figure 1. Classification of smart robotic technologies in agriculture

Materials and Methods

The current state and prospects for the development of smart robotic technologies in various countries of the world are described based on research materials from leading scientific and industrial organizations in Europe, America, and Asia. The goals of such programs and agreements as the "European Green Deal" (2022) and the "Project Activate" (2022) have also been studied.

The Green Deal is the largest economic program of the European Union (EU), which provides for the formation of a carbon-neutral space in European countries. If this program is successfully implemented, by 2030 a 40% reduction in greenhouse gas emissions compared to 1990 will be achieved, as well as energy savings and an increase in the share of renewable energy sources to 32%. This project takes into account all sectors of the economy, including agriculture. Within the framework of the Green Deal (2024), it is advisable to use smart robotic technologies to improve the efficiency of agriculture to increase the production of grain, vegetables and fruits, meat and milk, as well as to reduce energy consumption, harmful emissions into the atmosphere and saturate the growing world market with high-quality food products.

The Norwegian-Polish initiative Project Activate (2022) aims to reduce CO_2 emissions into the atmosphere. It has been operating for 1.5 years and is a consortium that is financed by grants from Norway (85%) and Poland (15%). This project aims to replace fossil fuels with carbon-free energy sources such as ammonia (NH_3). There is also a need for renewable and carbon-free energy sources for agriculture. PROJECT ACTIVATE's mission is to use ammonia with biodiesel in agriculture, namely in tractors and autonomous vehicles (robotic platforms).

Smart robotic systems in agronomy

Remote sensing systems using satellite navigation and UAVs

Scientists (Kitić et al., 2022) proposed an autonomous robotic system for field soil sampling and nitrate analysis. The system includes a cloud platform that uses satellite imagery and applies a smart algorithm that divides the target field into sampling zones. This algorithm optimizes the number and location of samples. In this case, the task for the robot is to automatically take samples at specific locations. The system includes a smartphone application that allows you to view and control the task, change positions, delete and add sampling points. Measurement results are uploaded to the cloud for further analysis and creation of maps for applying base fertilizers with variable rates. The system generates a fertilizer application recipe, while saving more than 7.5% of fertilizers and improving the yield by 1.76%.

Scientists (Thomas et al., 2023) proposed a method for remote detection of perennial weeds in barley fields using UAV photography. The authors proposed a rule-based method that generates labeled data for perennial weeds based on the Normalized Difference Vegetation Index (NDVI). This approach is further used to create labels for the measured data. The pre-processed data combined with the generated labels were used to train U-Net models. Three data combinations are used for training and testing: multispectral, multispectral-thermal, and multispectral-thermal dome-height models. The authors demonstrate that the most effective deep learning model for this task is MTCHM-Unet.

To solve the issue of industrial use of UAVs, Ukrainian researchers (Lysenko et al., 2019) proposed to determine the underside area of the leaf. However, this is only possible at the initial stages of the growing season, and problems with the reliability of the data can arise, given the small size of the plants. The difficulty of defining the boundary between plants and soil should be considered.

Pasichnik et al. (2023) tested a new approach, which is as follows: in images obtained from high-resolution satellite images, objects can be identified using the GaussAmp distribution if an additional parameter is the standard deviation. The analysis was carried out both using individual spectral channels and using vegetation indices calculated in the SlantView program. For the study, a part of the production field was taken, where areas with normal and double the number of seeds were recorded within one frame.

Robotic platforms

A universal robotic platform for apple harvesting, orchard monitoring, branch pruning, spraying and other operations is presented in the article (Kutyrev et al., 2022). A preliminary design of a universal autonomous vehicle for working in an industrial garden using an ammonia engine was proposed in this article. Within the framework of the “Project Activate”, the paper presents calculations of the level of autonomy of the platform, a basic implementation option with an electric motor, as well as the prospect of operating the platform on an ammonia engine.

Grasping mechanisms during fruit harvesting

One of the most important working parts in robotic systems when harvesting fruits and vegetables is the gripper, which allows careful detachment of the fruit. An overview of soft grips is given in an article by Spanish researchers (Navas et al., 2021). Soft grippers are the most suitable solution for harvesting valuable crops, minimizing mechanical damage and ensuring maximum market value for the product.

Human-machine interface

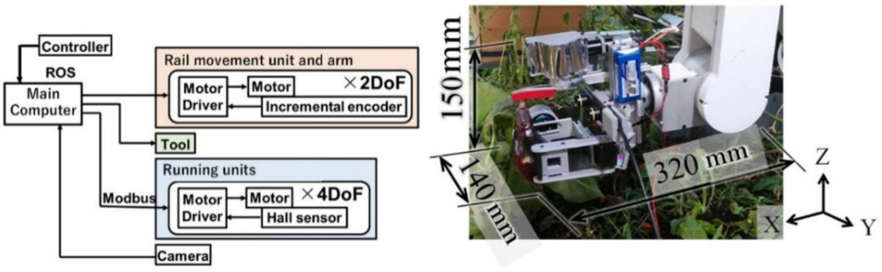
A graphical user interface for remote field control of a universal robot is presented in an article by Japanese researchers (Kamon et al., 2023). This article also describes the development of the design of an electric vehicle (wheeled and tracked versions) intended for exporting grape harvests. In this design, a human operator can control the robot via an interface and select a locomotion system. The goal for such vehicles is to determine a locomotion system based on sensor data collected during its operation.

Otani et al. (2022) proposed a solar-powered robot designed for sowing, pruning and harvesting. This robot, built on wheeled axles, can overcome obstacles and hilly terrain. The configuration of the robot control system is shown in Fig. 2 (Otani et al., 2022). Each component of the robot was integrated using ROS (Robot Operating System). Modbus communication was used between the host computer and the work units, and USB communication was used for the rail, tools and cameras. A BLVD40NM (Oriental Motor Co., Ltd., Tokyo, Japan) is used as a motor drive in the chassis, and in EPOS4 Compact 50/5 and EPOS4 Compact 50/8 (Maxon Co., Ltd., Sachseln, Switzerland) a driving rail knot and telescopic boom. The motor output voltage is controlled by the proportional speed derivative in each motor driver. The operator performs tasks using a game controller based on images from multiple cameras installed on the robot.

A field experiment examined the robot's movement along slopes and overcoming obstacles such as small steps and weeds. Tests also demonstrated the robot's effectiveness in harvesting and weeding with human assistance. In this case, a mechanism for maneuvering the instrument was used, based on recognizing the field environment based on camera imagery. Using the developed control system, the authors achieved a reduction in operating time by 49% and a reduction in the speed of interaction with obstacles by 26% during three-task continuous operation compared to use of a simple controller.

Lysenko et al. (2022) proposed the structure of a crop management system in an industrial greenhouse, which, in addition to traditional components, includes a mobile robot for phytomonitoring. A control algorithm and software for its use have been developed, a mobile bot for phytomonitoring in industrial greenhouses, developed using Node-RED and processing/wiring software environments. The authors proposed a mechanism for the interaction of heterogeneous technical components integrated within the mobile phytomonitoring robot using the flexible ROS platform; this creates conditions for ensuring the client-server architecture of the mobile robot and uniform distribution of computing power. The measuring complex can be used in an industrial greenhouse with a maximum distance of a reliable digital signal of up to 282 meters.

Another important and interesting area where autonomous transport devices are used is the determination of various plant stresses, in particular, the NDVI index. Danish scientists (Avgoustaki et al., 2022) developed and tested an autonomous mobile robot with an attached multispectral camera to monitor crop development and detect nutrient and water deficiencies in vertical farms (Fig. 3).



(a) (b)

Figure 2. Agricultural Robot under Solar Panels for Sowing, Pruning, and Harvesting (Otani et al.): a – Robot system configuration for sowing, pruning and harvesting; b – Harvesting an eggplant in a farm

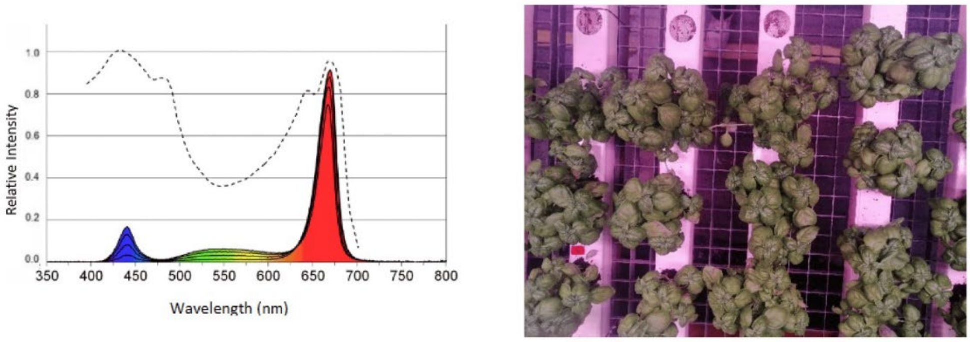


Figure 3. Spectral distribution of the FL100 LED lamp. The dotted line represents the spectral distribution of solar radiation at the corresponding wavelengths (left); Experimental setup, top view (right) (Avgoustaki et al., 2022)

Ji et al. (2024) studied the physical properties of apples and stems for gripping by a robotic mechanism. The authors proposed two new three-finger grasping postures for wrapping the apple horizontally and vertically on the inside of the fingers, as well as a new method for removing the stem using a circular pulling motion of the end-effector to remove the apple. We also analyzed the pressure on the apple under different harvesting schemes and developed a "branch-stem-apple" simulation model. At the same time, the researchers established the constraint conditions: the angle between the apple stem and the vertical direction, the speed of movement, the root impulse, the optimal angle of circular motion of the apple, and the force required to implement the movement. As a result, dynamic modeling experiments were carried out using a flexible three-fingered working body (Fig. 4), which showed a decrease in the gripping force when picking apples by a robot.

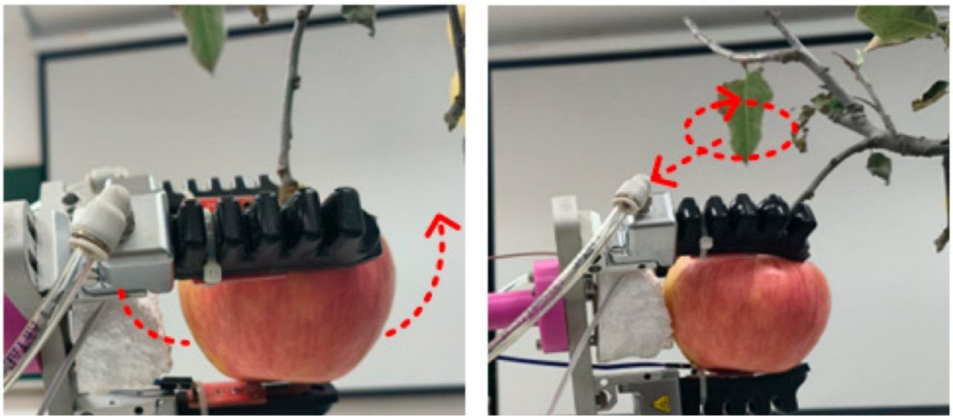


Figure 4. Apple picking patterns of a flexible three-fingered end-effector (Ji et al., 2024)

Zheng et al. (2023) studied the mechanical properties of tomatoes for the design of the working body of a harvesting robot. Research has shown that when harvesting tomatoes at the semi-ripe stage and beyond, attention should be paid to trimming the stalk. Compression tests were conducted on tomatoes, and it was found that at the same stage of ripening, the axial compressive force of tomatoes was greater than the radial breaking force. The gripping direction is axial – this can serve as a new basis when designing the working body.

Qu et al. (2022) conducted performance analysis and optimization of steering mode switching of an agricultural four-wheel mobile robot. The optimal setting for 15° MMS four-wheel steering was 3.96 V at 56 rpm^{-1}, while the 30° optimum was 4.35 V and 72 rpm^{-1}, and 5.50 V and 107 rpm at an angle of 45°, respectively.

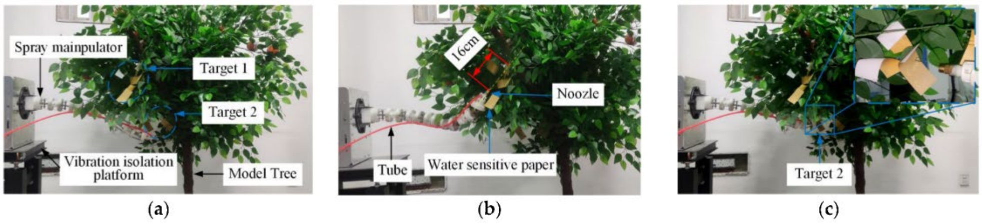
The use of various types of neural networks to detect apples during on-tree harvesting is described in an article by a researcher (Andriyanov, 2023). The paper describes a model of a manipulator for picking apples based on a single-board microcomputer Raspberry Pi 4, a computer vision model based on deep learning through the YOLOv5 neural network. The author claims that the detection efficiency of apples was 92%.

Spraying

The design of a robot for spraying citrus trees is described in the work of Chinese researchers (Bao et al., 2022) (Fig. 5). The objects of spraying were areas of tree crowns affected by pests. To test the effectiveness of the cable-driven flexible sputtering manipulator, a target sputtering experiment was conducted alternately with target 1 in the middle of the dome and target 2 in the inner dome, as shown in Figure 6. The height of the model tree was 1.67 m. The height of the canopy ranged from 0.69 m to 1.67 m, the diameter was 1.53 m.

The mass of the nozzle was 10.6 g. The end of our manipulator had no additional load, and the tube was evenly distributed by manipulator. The manipulator moved smoothly throughout the entire operation.

Figure 5. Example of a single dwarf citrus tree (Bao et al., 2022)



(a) (b) (c)

Figure 6. Three states of the spray manipulator during spray operations: (a) initial state of the spray manipulator; (b) spray state of spray manipulator for target 1; (c) spray state of spray manipulator for target 2 (Bao et al., 2022)

The sprayer manipulator was controlled using a remote control. The nozzle length was about 3 cm, and the distance between the nozzle and the water-sensitive paper immediately in front of it was 16 cm. After 0.5 s, the spray system began spraying; The entire spraying process lasted 3.5 s. The manipulator had a variable stiffness manipulator; the stiffness was related to the manipulator spring. The spray disturbance occurred in the axial direction of the manipulator when spraying without significant shaking, which ensured spray accuracy. Throughout the operation, the manipulator moved smoothly and rarely vibrated during the operation of the spray system. Although the robotic arm was able to avoid tree branches as it moved, it was also hampered by leaves.

Treatment of trees using hot fog spraying is described in the article by (Khort et al., 2022). The authors have established the most effective operating modes of an automated mobile platform for spraying plant protection products with a fog generator unit. The developed device meets the requirements of the spraying procedure for plant protection products (Recommendations for spraying technology of field crops, 2025). The optimal modes of movement of an automated mobile platform and parameters for treating plants with protection products using this technology were identified, in particular: the speed of the automated platform is 3.4 km·h^{-1}, the distance to the tree crown is 1.34 m, the flow rate of working fluid is 44.1 L·h^{-1}. Average fuel consumption was 2.5 L·h^{-1}. Effective penetration of the aerosol made it possible to reduce the amount of working fluid used by up to 50 times.

A description of the electronic control system circuit for a robotic platform for harvesting fruits and berries is given in the work (Kutyrev et al., 2022). The design of grippers is carried out individually for each fruit (strawberries, apples, currants, etc.), the manufacture of grippers in modern conditions is carried out using 3D printing, the quality of the grip and minimization of damage during robotic fruit harvesting depends on the source material. Authors described the development of a somatosensory controller that remotely controls a manipulator for robotic apple picking. The design includes resistive sensors, a gyroscope and an accelerometer. For computer simulation of the process of collecting fruits from the crown of a tree, the Gazebo simulator and a somatosensory controller were used. A comparative experiment to evaluate the results of computer modeling of the process of picking apple fruits using a self-sensory controller and a manufactured sample of a manipulator showed that the average time for collecting one apple fruit with a manipulator is 12.9 seconds, the minimum time is 9.4 seconds, the maximum is 15.9 seconds. The design of a multi-agent robotic system for picking apples and strawberries is described in paper (Kiktev at al., 2020).

Building a robot trajectory

A methodology for real-time path tracking in agricultural robots before their implementation is presented in an article by Canadian researchers (Moreno et al., 2023). In this case, only the motor angular velocity and robot rotational speed information obtained from the encoders and the Inertial Measurement Unit (IMU), respectively, are used. The simulations were performed using MATLAB/Simulink and the experimental results were obtained using the specialized platform "Agribot".

Researchers Lee et al. (2023) developed a route generation algorithm for an autonomous combine harvester using a dual GPS antenna (including path generation, path tracking), as well as an autonomous driving system. The algorithms have been tested in rice harvesting. The combine control system consists of an autonomous motion control subsystem and a vehicle control subsystem. The autonomous control subsystem includes positioning, path generation, path tracking and implementation control. The vehicle control subsystem has two operating modes: autonomous and non-autonomous driving.

Route planning for a seeding robot in hilly terraced rice fields is presented in the work of Chinese researchers (Yang et al., 2023). According to the characteristics of terraces and the agrotechnical requirements of sowing, the working path mainly includes parallel operation and boundaries surrounding the working path. A pre-collision boundary detection method is outlined, and a cyclic detection method determines the turning area. A Bezier curve fitting algorithm was used to smooth the boundary transfer path. The field map was obtained via Google Earth. An existing seeding robot was used as a model and tested using the boundary polyline algorithm based on the Robot Operating System (ROS) kinetic platform.

The platform in this study is a four-wheel differential chassis with navigation function; The test platform is based on the Song-Ling SCOUT 2.0 chassis. The chassis navigation algorithm is recorded by combining GPS location information and heading angle information of Sinan M600mini with two antennas independently. The robot chassis can perform functions such as trajectory tracking, speed control, position detection, and others.

In the article of Sun et al. (2023) used a fuzzy dynamic window algorithm to plan the local path of mobile robots. The moving position of the mobile robot changes after avoiding local obstacles so that it remains on the intended global path. According to the simulation results, the improved dynamic window algorithm reduces planning time and path length by 16% and 5%, respectively, while maintaining good obstacle avoidance and considering the best global path in various dynamic environments.

In paper (Kutyrev et al., 2024), the authors described in detail the use of a LiDAR laser sensor to construct the optimal trajectory of a robotic platform in an industrial garden. The experiments were carried out both in an artificial garden and in the field. To find the optimal navigation graph, an application was developed using the C# programming language and Visual Studio 2019. The authors substantiated that for the movement of a robotic platform along a given trajectory in field conditions, the most effective conditions are speed - 2.5 $km \cdot h^{-1}$; illumination: 109,600 lux; distance to tree: 0.5 m. The LiDAR sensor provides a high degree of positioning accuracy under different lighting conditions at different speeds in garden aisles 3 m wide with a tree trunk spacing of 1.5 m and tree canopy width. 0.5 m.

Neural networks for image recognition

Powerful modern tools for monitoring plant growth, diseases of leaves and fruits, recognition of fruits and vegetables during robotic harvesting, identification of leaves when cutting weeds, pruning trees, etc. are convolutional neural networks. A paper by Fukada K. et al. (2023) developed a system that detects tomato stems through image analysis and measures thickness and length between flower clusters and growing points. The system uses the YOLO v.5 convolutional neural network. The detection rate for measurable plants (classification accuracy) was 23%.

Assunção et al. (2022) developed an application for real-time identification of fruits of different varieties of peaches. In this case, the SSD MobileDet. model was used, which in turn the authors compared with Modified YOLOv5 and Modified YOLOv3 and also compared recognition processing on CPU and TPU devices (Fig. 7).

Aggarwal et al. (2023) proposed using federated transfer learning (FL) to classify rice leaf diseases in multi-client cross-bin datasets. Unlike *Machine Learning and Deep Learning (*ML/DL) methods, which cannot ensure data privacy because they involve sharing training data with a central server, ignoring competition and regulatory considerations, FL has produced significantly improved results in verification accuracy and verification loss, all without the need for any - additional resources (Fig. 8).

Neural networks can also be used for other tasks in agriculture, for example, building the path of agricultural machinery, optimizing production, etc. The authors of the article (Lysenko et al., 2022) proposed using neural networks for energy-efficient control of energy flows in greenhouse facilities.

Cloud computing and IoT

An article by Emmi et al. (2023) examined the use of Internet resources in agricultural robots, including IoT and cloud computing technologies. This paper presents an architecture for integrating various components of an autonomous robot to enable access to the cloud, taking advantage of the services provided in terms of data storage, scalability, availability, sharing and data analysis. In the application developed by the authors, the selection of recommendations is carried out using a smart navigation manager (scheduler), measurements of quantities are performed using a perception system and an IoT sensor network.

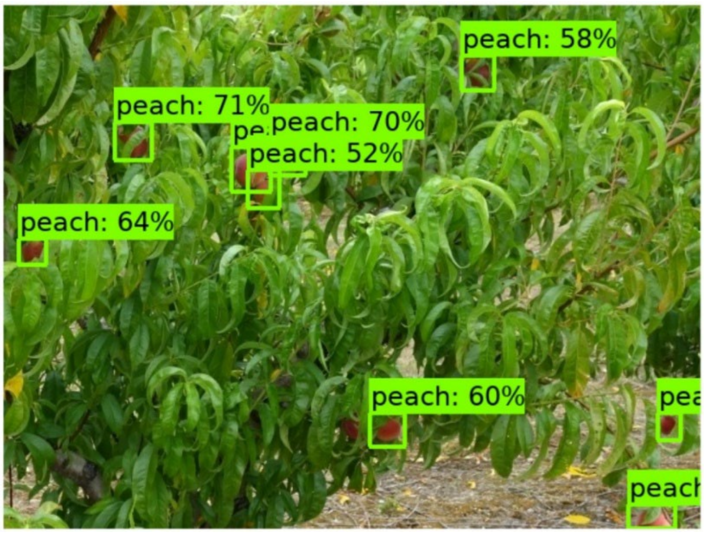


Figure 7. Sample for detection of the Royal Time peach variety (Assunção et al., 2022)

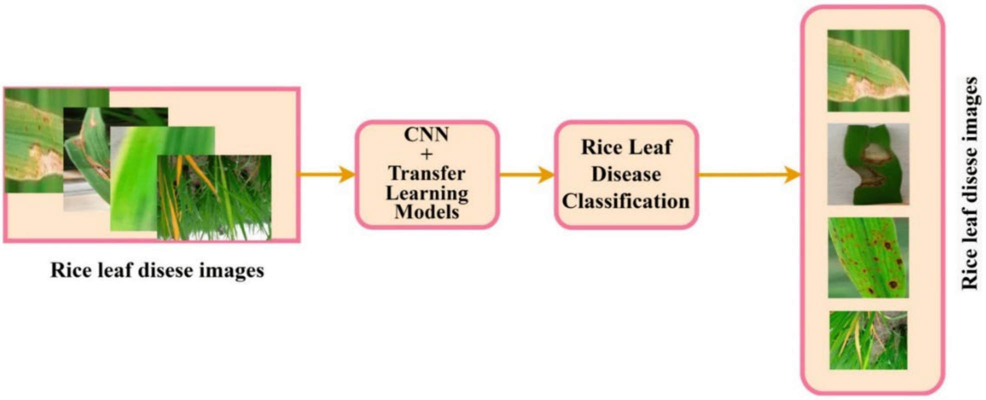


Figure 8. Rice-leaf disease classification using CNN and transfer learning (Aggarwal et al., 2023)

Decisions are made using a smart navigation manager (smart controler), and actions are carried out using agricultural tools and an autonomous robot that move the implement across the field. The system also takes care of interaction with the cloud and the operator. To receive raw information from sensors, cameras, etc. The central controller uses direct connections via Transmission Control Protocol/Internet Protocol (TCP/IP) and Universal Serial Bus (USB) for the RGB and *Time-of-flight* (ToF) camera. All Internet of Things (IoT) devices use available wireless technologies (Wi-Fi and LoRa) to access the Internet and the cloud. To control the robot, the obstacle detection system receives data from the master vision system (RGB and ToF cameras) via Ethernet, which connects the central manager to the perception system.

Mayoral Baños et al. (2023) propose a safe navigation system for robotic grass mowing using a risk management method. The test case for this study was an autonomous lawn mower as part of the Grass Robotics project.

Selected robot Thorvald platform (2025) consists of a four-wheeled robotic platform, with each wheel driven by two electric motors for steering and acceleration. The tool is mounted on the front of the robot to increase control over path planning. The sensor suite includes: RGBD cameras, VLP-16 Velodyne LiDAR, IMU and a set of RTK antennas. The robot is also equipped with two computers and a Wi-Fi router. The platform used is intended for transporting agricultural tools.

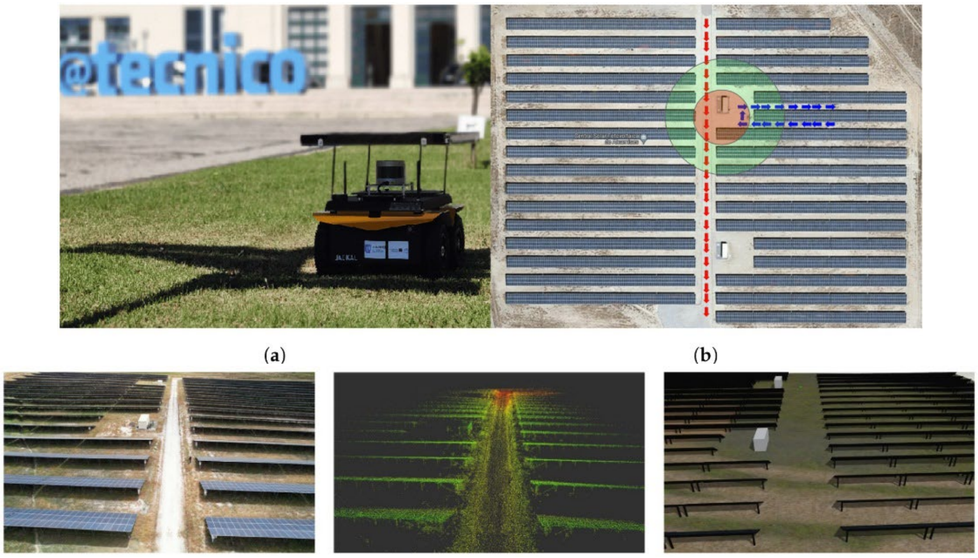
The following risks are considered:

- No living creature was found.
- A living creature is detected in close proximity; the trajectory intersects the trajectory of a person.
- Going beyond boundaries.
- A risk assessment policy is developed for this specific approach whenever an action results in the following consequences in the system.
- Inaction: sets the current state t with the previous risk state.
- Acceleration: Enables full speed.
- Slowdown: Limits the mobile robot by limiting the maximum speed to a safe level.
- Stop: pauses the specified task, movement and turns off power tools.
- Resume: resumes the current task, movement and turns off power tools.
- HI: Requires human intervention and leaves decision making to the human operator.
- Greek researchers (Thomopoulos et al., 2021) proposed solutions for the application of IoT technology in greenhouses. The proposed solution consists of three interconnected devices (3DS):
- A solar-powered cable bot with a spectroscopic camera and a set of other sensors for data collection (analogous to a drone for sowing in the open air).
- Flow control valve for autonomous control of the greenhouse irrigation network.
- Four-legged ground robot (Agribot) – a sensor carrier that can move around the greenhouse and collect data.

As a result, the authors developed a comprehensive control system for a robotic greenhouse based on the Internet of Things, including an interface application. The system was tested in a greenhouse belonging to the Faculty of Agriculture of the University of Patras. It can collect a number of data necessary for the harvest and autonomously perform a number of tasks, in particular automated smart irrigation.

Digital twins

One of the modern trends in creating and testing robots is digital twins - visual representations of a technological operation in graphical environments. Over the past decade, 3D sensors have become revolutionary data acquisition devices. In robotics, 3D sensor information is used for mapping, localization, obstacle avoidance, and scene recognition. Omnidirectional and unidirectional LiDAR as well as RGBD cameras have found application in this field. Portuguese researchers (Lewis et al., 2023) performed collaborative reconstruction of 3D scenes in large outdoor environments using a fleet of mobile ground robots. Multi-agent SLAM poses many different challenges, such as inter-agent collaboration and communication, distributed sensor fusion, and collaborative planning. The authors' proposed method is tested on a real solar farm with two Unmanned Ground Vehicles (UGVs) and its digital twin with multiple agents (Fig. 9).



(c) (d) (e)

Figure 9. Experimental setup: solar farm, corresponding 3D map of solar farm obtained from LOAM and digital twin (Lewis et al., 2023): a) Robot "Jackal Bright Path", (b) Path traveled, (c) Aerial view, (d) 3D point cloud. (e) Digital twin

Interesting results from the study of various sensors when detecting obstacles in plantings are presented in an article by American researchers (Lohar et al., 2021). The authors combined different types of sensors (radar, Lidar, stereo camera, thermal camera, RGB infrared camera) into a multimodal measurement platform and obtained a result that improves the detection of objects (person, barrel, mannequin). However, the large number of sensors complicate the calculations, therefore, it is recommended to use 2 sensors. The robotic platform is based on the I*ntelligent Robotic and Integration System (IRIS*), The scout robot is a fully autonomous robot created by the Dutch companies Metazet-Formflex and Micothon, with built-in processes developed by the Canadian company Ecoation. This robot is capable of autonomously moving around the greenhouse along heating pipes, as well as making route changes without user intervention. Radio Frequency IDentification (RFID) tags placed at the beginning of each row were used to ensure the robot was in the correct position, and the end of the row was determined by setting a distance of how far the robot could go into the row. Battery life allows you to complete two runs around the entire greenhouse on a single charge.

Dutch scientists (Fonteijn et al., 2021) proposed an image processing system consisting of four Intel RealSense D435 stereo cameras (Fig. 10). They are installed on the robot cart at heights of 930, 1630, 2300 and 3000 mm from the ground in landscape mode and at a distance of 0.5 m from the plants.

The embedded image acquisition software was developed in C# and uses the RealSense SDK. The robot was programmed to stop every 40 centimeters along a 50-meter-long row and take a series of images using 4 cameras at that position.

An example of fruit detection using MaskRCNN is shown in Fig. 11. We reported that precision, recall, and F1 metrics were higher than 0.90 for both one fruit class and two ripeness classes. In Fig. Figure 11 also shows an example of segmentation based on a more classical computer vision algorithm using color space transformations and shape matching

Figure 10. The Phenobot in its starting position in the greenhouse (Fonteijn et al., 2021)

These results are shown in Fig. 11 (A, D) in the form of red or green outlines indicating fruits detected. MaskRCNN clearly outperforms the alternative algorithm, missing fewer fruits and detecting fewer false positives. Additional examples can be found in the article of Afonso et al. (2020) and related supplementary materials.

Roshanianfard et al. (2022) developed a robotic system for collecting heavy agricultural products, using pumpkin as an example. Unlike similar systems where apples, tomatoes, lemons, etc. were collected, here a tractor is used as a platform. The success of the project was assessed based on three main parameters that indicate the quality of the developed robotic system: Harvest Success Rate (HSR), Harvest Cycle Time (CT) and Damage Rate (DR).

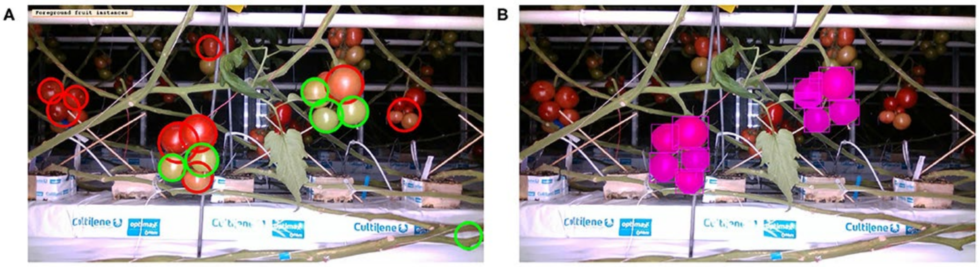


Figure 11. Example of fruit detection using: (A) classical segmentation by shape and color space, (B) MaskRCNN with one fruit class (Afonso et al., 2020)

An interesting area using machine learning is the recognition of diseases of leaves, fruits and other plant defects. To do this, used the convolutional neural network tool described in the work of Ukrainian authors (Koval and Khlevna, 2022).

Shurygin et al. (2022) used machine learning methods coupled with hyperspectral imaging to non-invasively detect damaged apple fruit (Fig. 12). This is very important for the correct operation of sorting lines and ensuring the safety of the harvested fruit. The article discusses the selection of the best method for visualizing fruits and an effective method for image processing. The authors took a holistic approach to the problem of fruit classification using computer vision and discovered potential problems. Computer vision and machine learning at the post-harvest fruit sorting stage have some disadvantages: high classification accuracy can be achieved, but these results are poorly translated into fruit sorting. Converting spectra into vegetation indices allows for 60x compression without significant loss of information and more reliable performance under changing light conditions. The authors substantiated that machine learning methods are more effective if they are supplemented with spectral information about the objects in question.

Andriyanov et al. (2022) solved the problem of determining the real position of an apple relative to the image registration source using convolutional neural networks. As hardware, it is proposed to use the Intel Real Sense stereo depth camera and aggregate information from its depth and brightness channels. Apple identification is carried out using the YOLOv3 architecture; then, based on the distance to the object and its localization in the image, relative distances are calculated along all coordinates. In this case, to determine the coordinates of the apples, a transition to a symmetric coordinate system occurs through simple linear transformations. Estimating the position of the apple allows us to estimate not only the magnitude of the displacement, but also the location of the fruit relative to the camera. This increases the accuracy of position estimation to 90-100%.

Shi et al. (2023) proposed a combined multi-crop row centerline extraction algorithm based on the improved YOLOv8 model and DBSCAN threshold clustering. This combined method makes it possible to build a robot trajectory along rows of agricultural crops with complex terrain, since the curvature of rows of crops poses a threat to the safety of agricultural machinery during movement. The method proposed by the authors increases the stability of visual navigation and field operation of agricultural robotic equipment and ensures the effectiveness of accurate identification and selection of navigation lines of various crops (for example, cabbage and kohlrabi) in the complex environment of agricultural land (Fig. 13).

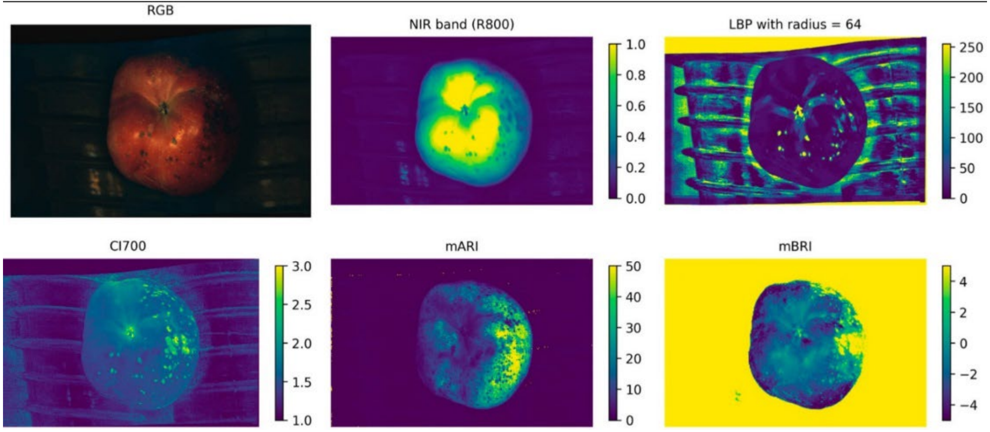


Figure 12. Visual representation of some features (indicated above the figures) used to classify healthy and damaged areas of fruits (Shurygin et al., 2022)

Machine learning is also used in the classification of corn seed varieties, as discussed in the article (Bi et al., 2022). The neural network proposed in this paper can classify seeds accurately and efficiently, meeting the requirements of high-precision image classification of corn seeds. The authors proposed a combined method combining deep learning, computer vision and the use of the Swin Transformer framework (Fig. 14).

Yu et al. (2022) used machine learning to accurately identify weeds in crop fields for subsequent selective spraying with herbicides. Weed identification is difficult due to the overlap of weeds and crops, this makes edge segmentation on overlap inaccurate, meaning that pixels cannot be classified correctly. To solve the problem, the authors propose a weed recognition model in soybean fields by improving the DeepLabv3+ model using the Swin transformer as the basis for feature extraction. The results showed that the developed Swin-DeepLab combination network can successfully improve the quality of boundary contour recognition when weeds are densely distributed among crops. Also, this model can correctly classify when recognition targets overlap (Fig. 15).

Kiktev et al. (2023) presented the processing of high-resolution aerial photographs for monitoring apple yields. For this purpose, a convolutional neural network of modern YOLOv7 and YOLOv8 models and a data set labeled into 4 were used. As a result of the study, we obtained a dataset containing images of flowers, ovaries, ripe and unripe apples.

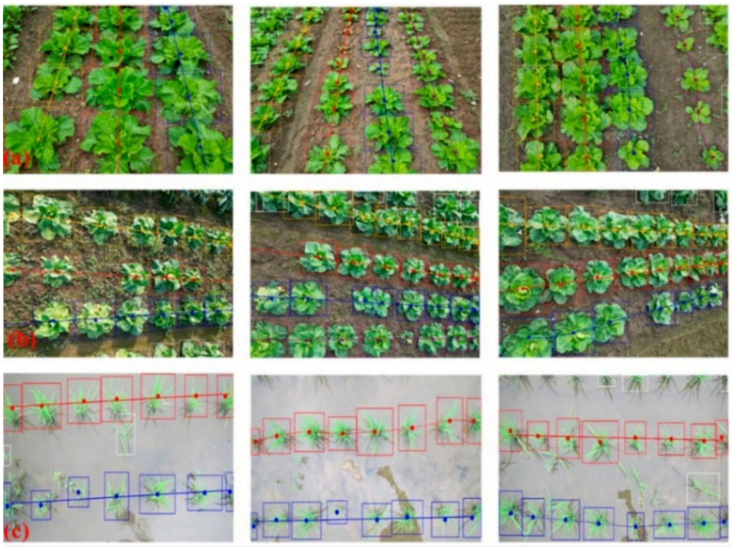


Figure 13. Results of clustering of various rows of crops based on the DBSCAN threshold algorithm: (a) Cabbage; (b) kohlrabi; (c) (Shi et al., 2023)

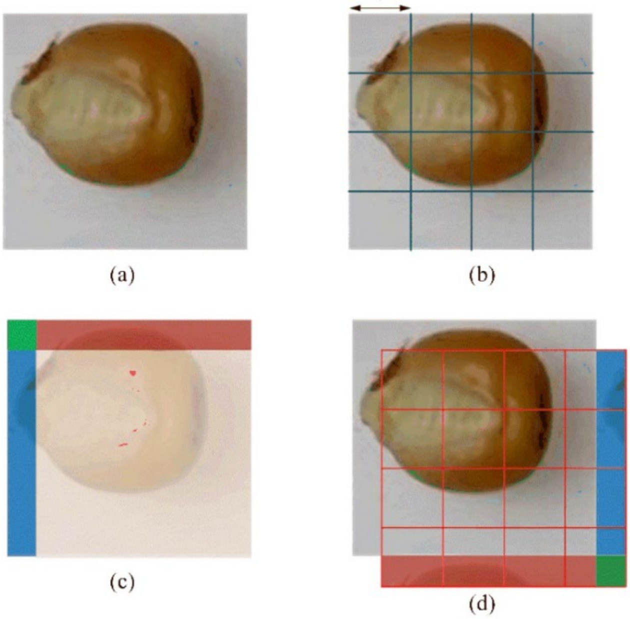


Figure 14. Different window segmentation methods via SW-MSA: (a) Input image (b); Segmentation of the input image window via W-MSA (c); Operation of a moving window (d) (Bi et al., 2022)

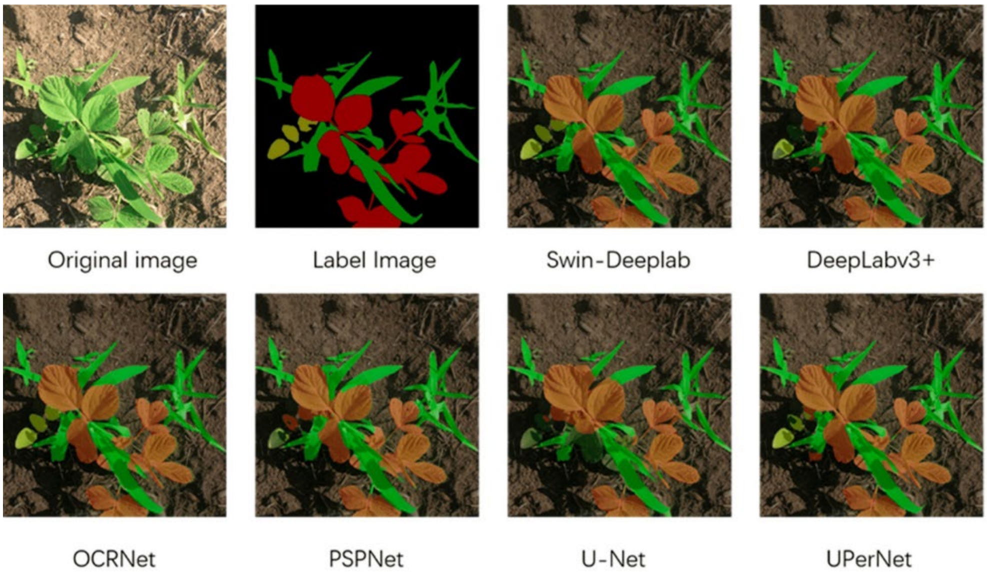


Figure 15. Comparison of segmentation results of different models for dense weed distribution (Yu et al., 2022)

Smart systems in livestock farming

Smart robotic systems are noticeably less represented in livestock production than in crop production. However, this industry also features noteworthy technical and software solutions.

In an article by Pavlovic et al. (2022) and others, a cattle monitoring system is proposed based on the use of various classification algorithms (least squares method, discriminant analysis, Markov models, etc.). The sensing elements are collars, which provide acceleration values oriented in the x, y, and z directions, i.e. parallel, vertical and perpendicular to the animal's body, recording the movements of the muscles of the head and neck. They provide basic information about the following animal states: eating – the animal is ingesting food, cud – the animal is regurgitating to further break down ingested food and improve nutrient absorption, and other – the animal is engaged in activities not related to chewing or eating.

Wutke et al. (2021) and others proposed tracking the state of pigs based on deep learning using convolutional neural networks. This determines the location and orientation of the pigs in the video, tracking their movement trajectory over a certain period of time using the Kalman filter (KF) algorithm. The idea behind this study is to record and analyze the social interactions of pigs to prevent behavioral changes. The CNN was implemented in Python (version 3.7.6) (Rossum, 1995) using the deep learning framework Keras (version 2.2.4).

Stretchable sensors for soft robotic grippers in edge-intelligent IoT applications are presented in the work of Ghosh et al. (2023). Soft sensors have found applications in soft robotics, smart prosthetics, and human-machine interfaces, where these sensors can be integrated for precise and sensitive monitoring. These liquid metal sensors are widely used in biomedical, agricultural and underwater applications. To demonstrate the reliability and practicality of the soft sensor, it was attached to a person's hand to study various human gestures. The authors provided a proof of concept for its application, mainly focused on dynamic responses, showing the change in resistance values when the sensor is stretched. The result proves that this soft sensor demonstrates exceptional deformation performance and can easily recognize hand gesture. Thus, the prospects for application in agricultural technologies, in particular in animal husbandry, veterinary medicine and other related fields, are justified.

The previously mentioned neural networks are also used in smart livestock farming. Thus, in the work of Dac et al. (2022) developed a deep learning model to recognize and identify dairy cows in a robotic dairy farm in Australia using facial recognition. The pipeline presented in this article can be applied to other livestock. The project consists of four main stages: 1 – face recognition, 2 – face cropping, 3 – face encoding and 4 – face search.

The pipeline loads a still image and outputs the matching identification number (ID) of the detected cow with the corresponding confidence score. The first three stages involve three deep learning models, respectively: a face detector, a landmark predictor, and a face encoder (Fig. 16).

Figure 6. Example of face detection showing confidence rating (Dac et al., 2022)

Bist et al. (2023) investigated the behavior of cage-free laying hens. This causes birds to pile on top of each other, which can lead to physical injury (bruising or suffocation) and even death. Birds' behavior outside cages can also cause stress and anxiety, leading to decreased immune function and increased susceptibility to disease. The authors developed a new deep learning model to detect the behavior of laying hens, tested its effectiveness, and tested it on farms. The study used different versions of YOLOv6 models. The initial dataset consisted of

9000 images (e.g., 6300 for training, 1800 for validation, and 900 for testing). As a result, the YOLOv6l relu-PB model was developed, which showed the best performance compared to other tested models (Fig. 17).

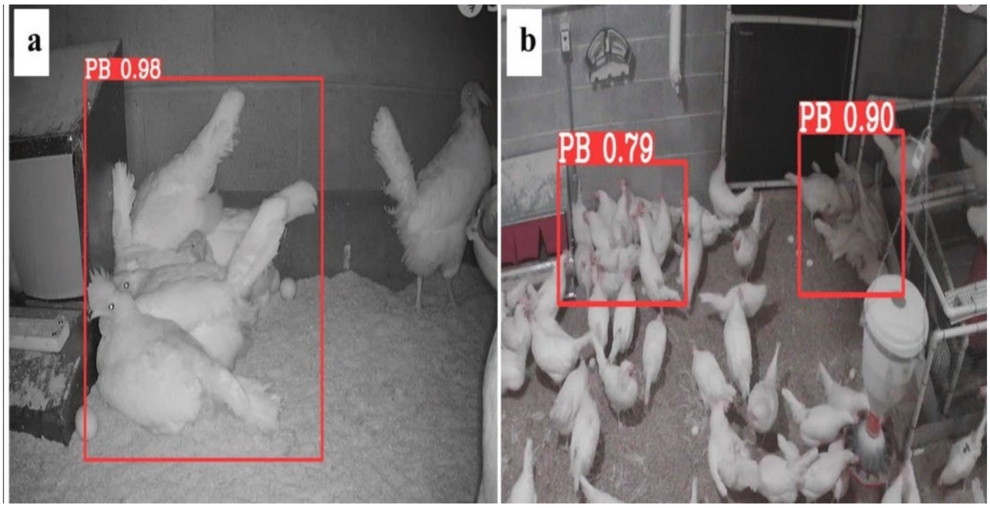


Figure 17. Results of behavior detection based on different camera settings (a) height 0.5 m (ground) and (b) height 3 m (ceiling) (Bist et al., 2023)

The technical means for the deployment phase of the deep learning model used a 12 MP camera installed on the farm to monitor and identify cows at any point that farmers or producers find convenient. For real-time cow identification, the integrated high-power NVIDIA Jetson Nano board is used. Pavkin et al. (2021) developed a robotic feed pusher on a dairy farm, which can significantly facilitate the farmer's work by performing labor-intensive operations of feeding feed to the feed table without human intervention. In this case, inductive sensors (designed to detect the proximity of the sensor to the metal) were used, as well as a binocular vision system. This is implemented in the form of a metal strip or cable capable of reflecting a signal, installed at the level of the surface of the feeding table along which the robot moves. The control circuit includes a microprocessor-based controller that processes and analyzes input telemetry from inductive sensors and the binocular vision system. In turn, control is carried out according to the output signals of the mobile robotic system.

Yurochka et al. (2023) studied increasing the efficiency of milk production through the introduction of technology for automatically assessing the body condition of dairy herds in increments of 0.25 points on a 5-point scale. Experimental data was collected using a 3D ToF (*Time-of-flight*) camera installed in a walk-through machine on robotic free-stall farms. The authors collected data on 182 animals and processed 546 images. All animals weighed between 450 and 700 kg.

The set of equipment for determining the fatness, height and weight of dairy cows weighing up to 1200 kg includes: automatic gates; weight module; single control unit three-dimensional camera for assessing body condition - 3D ToF (*Time-of-flight*) camera and software. The authors supplemented and modified the algorithm for automatically assessing the body condition of animals (fatness) with subsequent staging of their physiological state Wang et al. (2023) developed a model of a robotic milking cup attachment. The detection device was created based on a computer vision system for detecting dairy cow teats based on an improved Faster R-CNN (Region Convolution Neural Network). In this study, a simplified prototype was built that combined a visual perception system, a six-degree-of-freedom manipulator, and a mechatronic control system for attaching teat cups.

Jo et al. (2022) used a robotic milking system and a rumen sensor to study changes in milk and rumen composition. Also, robotic milking systems and rumen sensors were used by the author to understand the effects of summer HS (heat stress) on milking cows. This is important for on-farm assessment of how high milk yields can be achieved in dairy cows using AMS (automated milking systems) and rumen biosensors.

The effect of heat stress on daily milk yield and average milk flow rate during robotic milking is described in the work of Gálik et al. (2021). Also, automatic milking machines make it possible to evaluate the clinical detection of mastitis, which affects animal health and food safety. Bausewein et al. (2022) showed the application of this technique in Bavarian dairy herds in southern Germany. Robots have also found their application in poultry farming. Chang et al. (2020) designed and implemented a mobile poultry farming robot with a computer vision-based platform. The authors have developed a new mechanism that includes a channel for collecting eggs, a turntable mechanism for collecting eggs, a sorting device and a storage tank that allows you to collect, sort and store eggs, as well as a control unit. The GNSS-RTK module is used to record the robot's navigation path. Ultrasonic sensors are installed in the center of the robot on the front and back on both sides to detect obstacles. The detection range of the front ultrasonic sensor and the two rear sensors is 35 and 25 cm, respectively (Fig. 18). Using a vision system, eggs can be successfully identified in a variety of outdoor climates. At a visual observation distance of 75 cm, according to the authors the egg detection rate can reach 97.6%, and the centralized distribution of eggs ensures the shortest collection time. The combination of vision system and behavioral logic control methods can effectively enable the robot to avoid obstacles. He is able to collect eight eggs in 10 minutes on a field of 25 m².

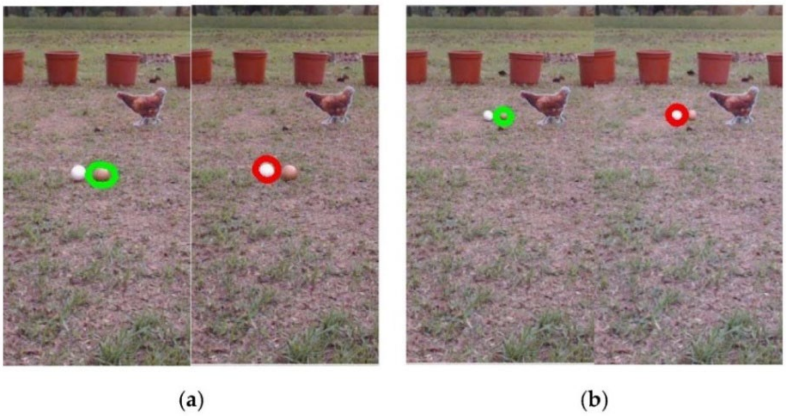


Figure 18. Results of egg recognition for different positions: a - 85 cm; (b) 105 cm. (Chang et al., 2020)

Riego del Castillo et al. (2022) proposed a computer vision system that provides herders with valuable information from on-site robotic shepherds. This will increase the profitability of the sheep farm while avoiding some of the threats. The system identifies threats such as the presence of wolves, which helps make decisions about which pastures to move the herd to (Fig. 19, 20). The authors also developed a method for automatically constructing image datasets of certain potential predators from various regions of the world using the iNaturalist API The authors (Matheson, 2014) studied several models of convolutional neural networks, and as a result, YOLOv5m was selected, giving an inference time of 15.62 ms. To train the neural network, a data set was obtained on a type of predator in the north-west of the Iberian Peninsula, namely the Iberian wolf.

In a review of Džermeikaitė et al. (2023) paid much attention to the issues of automation and robotization in animal husbandry, in particular, biosensors. Wearable sensors connected to or inside cows can monitor feeding, rumination, pH, body temperature, egg behavior, animal activity, animal position or placement, and more. This research focused on biosensor technologies that can improve the early detection, management and operation of livestock diseases.

A similar problem was solved by Lee et al. (2022) in their work on monitoring wildlife intrusion using computer vision. The authors improved the model's detection performance by generating a large wildlife dataset with different background images, particularly water deer and wild boar, which are currently the most problematic social issues. Training using the proposed extract-add method, compared with existing detectors, showed an improvement of about 2.2% in the mean average precision (mAP). The study used YOLOV4-tiny as a model to evaluate object detection performance, and training was carried out using an NVIDIA RTX 3060 processor and an Intel Core i7-1200F.

Figure 19. Samples of dogs (top row) and wolves (bottom row) in Europe (left) and the rest of the world (right) with detection of YOLOv5m. (Riego del Castillo et al., 2022)

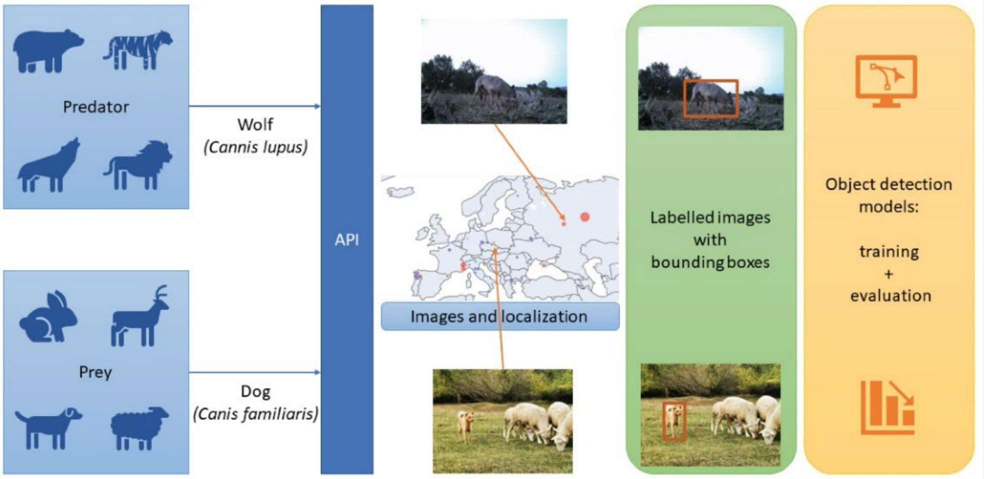


Figure 20. Machine vision module conveyor. First, the images and their locations are obtained using an API; the images are then labeled to train object detection models (Riego del Castillo et al., 2022)

Smart and robotic technologies in fish farming.

Chen et al. (2022) proposed a fish farm monitoring system using IoT technology. The authors integrated a programmable logic controller (PLC) with a signal processing microprocessor and a PC-based server and used NB-IOT technology to transmit the measurement data to the server. The main advantages of this system are lower power consumption, the ability to run multiple threads simultaneously, and improved processing performance. Each pond uses a submersible motor to pump water into a measuring reservoir under the robotic arm, which then uses a pH sensor mounted on the robotic arm to take measurements. After a measurement, the robotic arm automatically cleans the sensor head to prevent previous use from affecting the accuracy of the pH sensor. Each pond has a temperature, dissolved oxygen and water overflow sensor. Each sensor sends data from the embedded system to the server via a wireless transmission module. Data is conveniently collected via mobile devices and web pages, so fishermen can easily view the water quality status of each pond.

Stenius et al. (2022) proposed the use of an underwater robot to survey a seaweed farm. AUV (autonomous underwater vehicle) SAM (Smart AUV-based Magnetics) is used to demonstrate seaweed farm survey methodologies. The SAM is a torpedo-shaped underwater vehicle with reduced drive, the unique drive configuration of which makes it highly maneuverable and hydrobatic. The drive subsystems include counter-rotating propellers for propulsion and a thrust vectoring nozzle for maneuvering. The variable buoyancy system facilitates static depth control by pumping water into and out of the tank. From a software perspective, the SAM autonomy stack runs within the Robot Operating System (ROS) environment and its subcomponents:

Mission planning via Neptus (a structure for command, control, communication and information, which is being developed in the Laboratory of Underwater Systems and Technologies):

- Execution using behavior trees.
- Path planning using spline fitting.
- Feedback control using waterfall PID controllers.
- Calculus with extended Kalman filter.

Conclusions

1. In this review, we looked at examples of the implementation of smart robotic technologies in the agricultural sector, in particular in crop production and livestock farming. Having analyzed the developments of scientists from various countries, we can state that these technologies are being tested and have proven themselves in the following operations:
   - harvesting fruits and vegetables, both “tenders”, requiring a soft grip (for example, strawberries, grapes), and heavy, requiring serious agricultural machines (for example, pumpkins); pruning trees, cutting weeds;
   - monitoring of trees in the garden, remote monitoring of plantings and crops from UAVs (or satellite images), monitoring of ripeness and plant diseases in greenhouses.
   - gardening operations (spraying, fertilizing, soil monitoring);
   - control over the herd of livestock, control over the appearance of predators when walking livestock;
   - robotic milking, feed supply, monitoring the condition of animals (position, fatness, etc.), remote control of the poultry house, monitoring of fish on the farm, etc.
2. Thus, the range of operations in which smart robotic technologies are used is quite wide and promising. The most popular technologies, in our opinion, are IoT for remote control of equipment and neural networks for high-quality recognition of objects (both animals and plants).
3. The authors plan to further study various neural networks for recognizing fruit varieties and their quality, monitoring the period of flowering and ripening of trees, improving technical means of collection, the quality of gripping mechanisms when collecting fruits to reduce their deformation, improving the electronic database (Hutsol at al., 2023), as well as navigation algorithms and systems. In accordance with the European Green Agreement, the development of robotic platforms using ammonia engines is promising.

Author Contributions: Conceptualization, N.K. and T.H.; methodology, N.K., T.H. and O.V.; software, I.H., A.P.; validation, S.S. and M.K; formal analysis I.H. and Z.S; supervision, T.H. and M.K All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Funding: Financed from a subsidy of the ministry of Education of Science for the Hugo Kołłątaj Agricultural University in Kraków for the year 2025.

Acknowledgements: The anonymous reviewers are gratefully acknowledged for their constructive reviews that significantly improved this manuscript, as well as the International

Visegrad Fund (www.visegradfund.org, accessed on 21.02.2025) and Ukrainian University in Europe (https://universityuue.com/, accessed on 21.02.2025).

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INTELIGENTNE ROZWIĄZANIA W ROBOTYCE ROLNICZEJ

Streszczenie. Artykuł stanowi przegląd inteligentnych i zautomatyzowanych technologii stosowanych w przemyśle rolniczym. Jego celem jest analiza perspektyw wdrożenia i integracji najnowszych rozwiązań z zakresu inteligentnych i zrobotyzowanych technologii wspierających różne aspekty tego sektora. Obecnie poziom robotyzacji rolnictwa i produkcji żywności pozostaje niski w porównaniu z innymi sektorami gospodarki. Zgodnie z danymi z globalnego rynku robotyki, roboty wykorzystywane w przemyśle spożywczym stanowią jedynie 2% ogółu, a udział robotów w operacjach rolniczych nie przekracza 1%. W artykule przeanalizowano światowe trendy w zakresie robotyzacji i wdrażania sztucznej inteligencji w rolnictwie, z uwzględnieniem doświadczeń różnych krajów. Przedstawiono przegląd technologii inteligentnej robotyki, w tym: inteligentnych czujników i siłowników, Internetu rzeczy (IoT), technologii chmurowych, metod analizy danych, prognozowania, klasyfikacji oraz rozpoznawania obrazów przy użyciu sieci neuronowych. Omówiono ich zastosowanie zarówno w produkcji roślinnej, jak i zwierzęcej. Wyróżniono cztery główne klasy inteligentnych technologii w rolnictwie: robotykę, Internet rzeczy, uczenie maszynowe oraz bezzałogowe statki powietrzne (drony). W produkcji roślinnej roboty są stosowane m.in. w zbiorach, zwalczaniu chwastów, pielęgnacji i monitorowaniu drzew w różnych fazach sezonu wegetacyjnego – w tym w wykrywaniu chorób liści i owoców, liczeniu kwiatów i owoców oraz innych procesach. Identyfikacja owoców, liści, chwastów i chorób odbywa się przy użyciu technik wizji komputerowej, a w ostatnich latach szczególną popularność zyskały konwolucyjne sieci neuronowe. Monitoring upraw realizowany jest za pomocą dronów, a pozyskane obrazy poddawane są analizie spektralnej. W produkcji zwierzęcej inteligentne technologie obejmują roboty do karmienia i dojenia, systemy monitorowania zwierząt gospodarskich, detekcję drapieżników, nawigację w budynkach inwentarskich oraz monitorowanie stanu zdrowia i zachowań zwierząt. Zaawansowane technologie znajdują również zastosowanie w hodowli ryb – w tworzeniu inteligentnych gospodarstw akwakultury.

Słowa kluczowe: robot, sztuczna inteligencja, IT, sieć neuronowa, rolnictwo cyfrowe, produkcja roślinna, hodowla zwierząt