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Autonomous Yield Estimation System for Small Commercial Orchards Using UAV and AI

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Abstract: In the context of precision horticulture, decision support tools play a significant role in providing fruit growers with insights into orchard conditions, facilitating informed decisions regarding orchard management practices. This study presents the development of an autonomous yield estimation system designed to provide decision support to small commercial orchards. Autonomous yield estimation is based on the application of UAVs and AI. AI is used to identify and quantify fruitlets and fruits in photographs collected by UAV. In this article, we present our prototype of an autonomous yield estimation system. The adapted "4+1" architecture was applied to design a system with a holistic approach analyzing software, hardware, and ecosystem requirements. Six datasets are presented, which contain the images of fruitlets and fruits of apples, pears, and cherries. Three CNN models were trained: YOLOv8m, YOLOv9m, and YOLOv10m. The experiment showed that the most accurate was YOLOv9m, which achieved mean accuracies of 0.896 mAP@50 and 0.510 mAP@50:95 for all datasets.

Keywords: digital farming; horticulture; object detection; precision farming; system modeling; UAV

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1. Introduction

The modern fruit-growing industry faces significant challenges and needs to change farming methods. The main challenges are (i) efficient use of resources—fruit growing is a resource-consuming industry, the increasing costs of which reduce the competitiveness and economic capacity of farms; (ii) integrated or organic disease and pest management—in the conditions of increasing pathogen pressure, the use of plant protection products should be reduced; (iii) post-harvest management—high-quality storage and delivery of the final product to the consumer should be ensured, excluding the use of chemical agents; and (iv) year-round supply—the consumer requires always available products [1]. One of the ways to help the fruit-growing, industry overcome the existing challenges is the application of precise tools. They can be involved in starting with the selection process of new, more suitable varieties (the perennial nature of the fruit crop seriously affects this process while slowing down the selection process; it is affected by the environment). The second direction of application of precision technologies is the development of net-zero horticulture technologies to reduce the environmental impact [1,2]. In the context of fruit-growing, here are some key aspects of precision farming applications: (1) remote sensing and imaging; (2) sensor technologies; (3) data management and analytics; (4) automated machinery; (5) smart irrigation systems; (6) integration of IoT. UAVs and satellites can provide high-resolution imagery of orchards. This data helps farmers monitor crop health, identify areas of stress, and make informed decisions about irrigation, fertilization, and plant protection agent application [3]. Connected devices (IoT devices), such as sensors and actuators, can be deployed throughout the orchard to collect and transmit data. This connectivity allows for real-time monitoring and control of various parameters. For example, soil sensors measure soil moisture, temperature, and nutrient levels, providing real-time data to help farmers make informed decisions about irrigation and nutrient management. But integrating weather data into precision farming systems allows farmers to anticipate and respond to changes in weather conditions, optimizing farming practices accordingly. As a result, farm management software: platforms and software tools help farmers collect, manage, and analyze data from various sources, including sensors, equipment, and historical records. This data-driven approach enables better decision-making and predictive analytics: analyzing historical and real-time data can help predict trends, disease outbreaks, or other issues that may impact fruit crops. This allows for proactive measures to be taken. In some advanced systems, robotic devices equipped with computer vision technology can be used for automated fruit harvesting, improving efficiency and reducing the reliance on manual labor [4,5]. Another example: smart irrigation systems use sensors and data analysis to deliver the right amount of water at the right time, optimizing water use and avoiding over-irrigation.

The adoption of precision farming in fruit growing is an ongoing process, and its implementation may vary based on factors such as the type of fruit, climate, and the level of technological infrastructure in a given region.

There are several challenges to implementing precision agriculture. One of the main challenges is the high cost of technology. Precision horticulture requires a significant investment in hardware and software, which can be a barrier for small farmers. Another challenge is the lack of technical expertise. Farmers need to have a good understanding of the technology they are using to use it effectively. This can be a challenge for farmers who are not familiar with technology. Finally, data management is another challenge. Precision agriculture generates a large amount of data, which needs to be collected, analyzed, and stored. This requires a significant investment in data management infrastructure and expertise. This is also confirmed by the stakeholders themselves, citing (i) insufficient technical support, (ii) the need for more extensive training, (iii) perceived usefulness in the future, and (iv) cost of investments as the main limitations for the implementation of precise technologies [6]. This also applies to the broader application of UAVs in fruit growing [7,8]. Farmers can overcome the challenges of implementing precision agriculture by taking the following actions [9]: (1) seeking financial assistance; (2) training and education; (3) collaboration; (4) data management; (5) start small. Farmers can seek financial assistance from government programs, grants, and loans to help offset the high cost of technology. They can attend training sessions and workshops to learn about the technology they are using; this can help them use it more effectively and efficiently. The farmers can collaborate with other farmers to share knowledge and resources; this can help reduce the cost of technology and increase the amount of data available for analysis. The farmers can invest in data management infrastructure and expertise to help collect, analyze, and store the large amount of data generated by precision agriculture. They can start with a small land area and gradually expand as they become more comfortable with the technology.

According to an international survey of stakeholders [6], at least 80% of them recognize precision farming technologies as applicable in fruit growing, especially in areas such as reacting and mapping recording. The most significant demand for precision agricultural technologies is prediction, early detection, and precision application against diseases and pests.

To support innovations in precision farming, our team has been developing the autonomous unmanned aerial vehicles-based decision support system for smart fruit growing for apples, pears, and cherries. The concept is depicted in Figure 1, where the yield estimation system completes the role of the decision support system for orchard management.

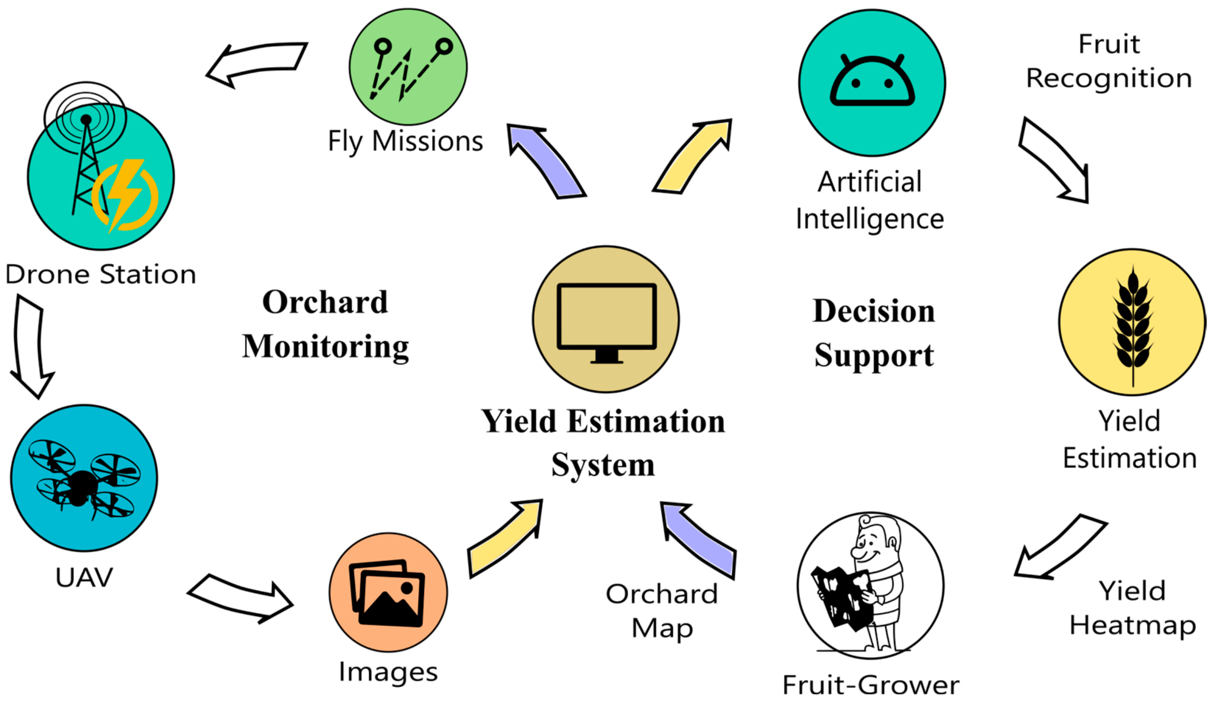

Figure 1. The concept of the yield estimation system to support decision making by using UAVs and AI.

(1) The autonomous orchard monitoring is completed by the UAV and mission planning algorithm;
(2) The yield estimation (the number of fruitlets and fruits) is completed by AI using collected photographs by UAV;
(3) The decision support is achieved through the yield heatmaps and data-based recommendations.

The aim of the study is to develop a prototype of an autonomous yield estimation system. The objectives of the study are: (1) to model the yield estimation system considering fruit-grower business requirements; (2) to automate orchard monitoring using UAV; and (3) to train AI for yield estimation. As a result, we present a methodological and technological stack, which consists of (1) the eco-cyber-physical system modeling methodology; (2) the mission planning algorithm; (3) the training datasets and the AI for a yield estimation.

2. Background

Just a decade ago, the concept of automation in the horticultural sector was groundbreaking. An overwhelming array of cutting-edge technologies is entering the market, offering to automate various tasks such as harvesting, pollination, sorting, climate control, disease and pest monitoring, and irrigation, among others. The constant flow of these innovations poses a challenge in staying abreast of the latest developments. Nevertheless, reaching the current state has demanded perseverance from both automation companies pioneering these technologies and the growers who test and embrace them. Several trends and advancements in horticulture automation included: (1) harvesting robots; (2) precision farming; (3) sensor technologies; (4) research and development.

There were ongoing efforts to develop robots capable of efficiently and accurately harvesting fruits, vegetables, and other crops. These robots aimed to increase efficiency and address labor shortages in the agriculture sector. According to calculations, by automating the cultivation of apples, it is possible to save up to 10% of the total costs, and for blueberries—up to 60%, in addition to saving mainly on harvesting expenses. Harvest automation alone is predicted to grow by 28.72%, or USD 2.4 billion, between 2022 and

2027 (of which 40% growth is only in North America) [10]. Automation technologies were being integrated into precision farming practices, allowing for more precise and efficient use of resources such as water, fertilizers, and pesticides. This helps optimize crop yields while minimizing environmental impact [11]. The use of sensors and monitoring devices to collect data on crop conditions, soil health, and environmental factors continued to grow. These data were often used to inform decision-making processes and automate certain aspects of crop management [12].

Ongoing research and development efforts focused on improving the capabilities of horticulture automation technologies. This included advancements in artificial intelligence, machine learning, and robotics. Meanwhile, collaboration between technology companies, research institutions, and agricultural organizations was increasing. This collaborative approach aimed to address the complex challenges associated with horticulture automation and facilitate the adoption of new technologies.

However, compared to other sectors of the economy, horticulture lags far behind in automation. For example, in contrast to the substantial sales of industrial robots, the agricultural sector has seen a comparatively lower volume of robot purchases. Globally, in 2017, 6055 robots were sold, a notable difference from the 421,000 units of industrial robots sold in 2018 [13]. This is determined by the specifics of the industry: large crop diversity (fruit shape, size, color, cultivars, maturity), different practices across operations, the influence of seasonal, daily, regional, and temperature factors, and available infrastructure [14].

It is important to review the historical development of precision farming, farming automation, and agrobot development to understand the future challenges and trends, drawing out the technological and knowledge gaps nowadays.

There is a relatively long history of agricultural automation. According to Junichi Sato (1997) [15], the active development of farming robots started in the 1980s. The prototypes of harvesting vehicles were developed for the next crops: tomatoes, mini tomatoes, strawberries, cucumbers, and grapes, which were constructed in the period 1985–1995. It must be mentioned that farming robots already applied AI for task automation.

The keywords "farming AND robots" provide the earliest links dated by 1982 in Scopus and—by 1990 in WoS. It is an interesting fact that one of the publications dated 1982 was about "The mechanical farm of 2030" [16]. Its author mentioned three aspects of equipment on farms in 2030: (1) the hardware and software likely to assist farm management—cyber-physical systems in the modern terminology; (2) automatically monitored and controlled farms, including remote viewing and sensing—Internet of Things (IoT) and digital twins; (3) machines linked permanently to national information data banks for planning decisions—data spaces and data-based AI. However, it is possible to find and more earlier publications like "The automatic steering of farm vehicles" dated by 1976 [17].

The automation of tractor navigation and its steering is the main study object in the 2000s. An overview of proposed solutions is provided in the publication "A System for Semi-Autonomous Tractor Operations", written by investigators from Carnegie Mellon University in 2002 [18]. Meanwhile, their presented semi-autonomous solution was based on two modules: (1) path tracking using algorithms and GPS; (2) obstacle detection using neural networks. This period is not restricted only by the development of autonomously moveable platforms; AI-based solutions were developed to automate agricultural tasks. As an example, crop yield estimation using a vision system and AI was developed in 1997 for a tractor to create heatmaps for GIS [19]. The next combination of algorithms was applied to satisfy the previous solution: fuzzy logic, neural networks, and genetic algorithms.

In 2008, Carnegie Mellon University started a project called "Comprehensive Automation for Specialty Crops" (CASC). CASC identified three key themes that together address fruit growers' needs: "Crop Intelligence", "Automation", and "Technology Adoption". In 2011, CASC presented autonomous orchard vehicles trained to drive between tree rows using lasers [20], as well as the computer vision solution for yield estimation in vineyards, which was based on the application of object detection and linear regression algorithms [21].

The final sociotechnical system of an automated orchard using an enhanced tractor was presented in 2012 [22]. A similar conceptual model of the autonomous orchard is presented in the article "Autonomous Robot Supervision using Fault Diagnosis and Semantic Mapping in an Orchard" [23], only the authors mainly describe the mathematical models for vehicle localization and path correction based on the semantic mapping to overcome the problem with GPS signal fault due to tree canopy. Another open-field solution was presented in 2013—fully robot-operated farming from tillage to harvest for rice, wheat, and soybeans [24]. The solution was based on a multitype-vehicle application, where all vehicles were navigated by one system. However, an open-field solution does not require such complex obstacle detection as in the case of orchards.

In 2005, the article "Robotic Agriculture—The Future of Agricultural Mechanisation?" was presented to society, which was written by authors from Denmark, the USA, China, and Russia, who were supported by the ideas of many people around the world [25]. As a result, the authors mentioned many things, which were realized later and are actual nowadays for modern investigations. Some of these ideas should be allocated. It is the application of small light machines and precision farming supported by AI, which are oriented to improve farming efficiency by doing the right things, in the right place, at the right time, in the right way. Looking at the period 2014–2023, the mentioned ideas (small light machines, UAV and agrobots, and precision farming) take attention and grow after 2014 (see Figure 2). It must be mentioned that UAVs can be associated with small light machines and agrobots too.

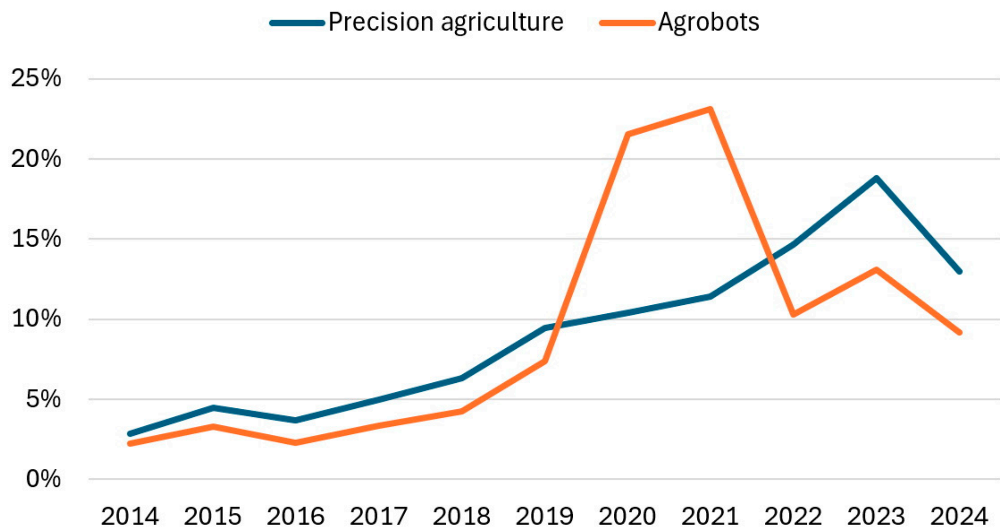

Figure 2. Trends of publications in Scopus (source "Scopus", 19 August 2024).

Considering small light machines, the agrorobot called "Fitorobot" was developed for the greenhouse in 2009 [26]. Meantime, the source [27] mentions the next early argobots: "Agribot" (2011), "Bonirob" (2012), "Grover" (2013), and another three not named robots presented in 2010, 2012, and 2013. Meanwhile, UAVs are becoming more widely applied in agriculture. UAVs are mainly applied for precision farming for monitoring from the sky to overcome satellite restrictions (2015) [27,28]. The interesting hybrid solution of wireless sensor networks was presented in 2013, which included soil and air sensors, while air sensors were mounted on blimp-type airships (kind of zeppelins) [29].

Speaking about precision farming, for example, two monitoring systems for the greenhouse and agriculture field were presented in 2014–2015, which were based on the application of wireless sensor networks, IoT, and RFID technologies [30,31]. In 2018, Shamshiri et al. (2018) [32] provided a review of small-scale robots, grouping them into three main categories: (1) weed control and targeted spraying robots; (2) field scouting and data collection robots; (3) harvesting robots. Meanwhile, Kim et al. (2019) [33] reviewed the application of UAVs in agriculture, grouping them into categories: (1) mapping; (2) spraying; (3) crop monitoring; (4) irrigation; (5) diagnosis of insect pests; (6) artificial pollination. But Jensen et al. (2014) [34] reviewed the existing software platforms for robot development and presented their architecture, FroboMind. Shamshiri et al. (2018) discussed the challenges of farming robots in 2018, mentioning the following things: (1) high temporal and spatial resolution data must be combined to derive new knowledge; (2) embedded knowledge and decision making; (3) multi-robot systems [32]. Kim et al. (2019) [33] underlined swarm robotics importance. Cabreira et al. (2019) reviewed the existing algorithms of coverage path planning, including the cellular decomposition for multiple UAVs [35]. Hooshyar and Huang (2023) [36] completed a systematic review of literature 2018–2022 related to UAV path planning, which included 68 sources, of which 32 were related to multi-UAV solutions.

The period after 2017 is identified as Agriculture 4.0, which is related to the integration of Industry 4.0 technologies in agriculture. Industry 4.0 is a fusion of emerging technologies such as IoT, robotics, big data, artificial intelligence, and blockchain technology [37,38]. Agriculture 4.0 is mainly based on "Precision Agriculture" principles, which are centered around agricultural data and the accuracy of operations to optimize production [21]. The FAO report "Agriculture 4.0—Agricultural robotics and automated equipment for sustainable crop production" (2020) mentions over 60 projects worldwide, which are related to the development of agrobots in 2018 [38]. So, the Agriculture 4.0 technologies are already sufficiently developed. What is "Agriculture 4.0" for scientific investigations then? The FAO report underlines the next challenges and weaknesses of existing solutions: (1) the high purchase price or operation cost of agrobots; (2) the low knowledge, capability, and capacity of farmers to use new technologies; (3) farm systems must be adapted to the agrorobots. Therefore, Agriculture 4.0 is related to the adaptation of innovations to achieve sustainable development. The FAO guidelines "Transforming Food and Agriculture to Achieve the SGDs" (2019) [39] identify the next five key principles of sustainable development until 2030: (1) increase productivity, employment, and value addition in food systems; (2) protect and enhance natural resources; (3) improve livelihoods and foster inclusive economic growth; (4) enhance the resilience of people, communities, and ecosystems; (5) adapt governance to new challenges.

Our study suits the actual challenges of Agriculture 4.0. The article presents a development stack that can be applied to design eco-cyber-physical systems. Our study was related to an autonomous yield estimation system. However, the presented solution can be applied to develop another precision farming system too.

3. Materials and Methods

The developed yield estimation systems are based on the methodological and technological stack, which consists of (1) the eco-cyber-physical system modeling methodology; (2) the mission planning algorithm; (3) the training datasets and the AI for a yield estimation.

3.1. Modeling of Autonomous Yield Estimation System

It is more and more popular to hear the definition "a cyber-physical system", which highlights the combination of robots and software in one solution. Going back to Section 2, the cyber-physical system paradigm was sufficiently studied, and autonomous farming systems have been developed for a relatively long time. However, the studied solutions were unique, expensive, and closed. The modern solutions seek to be low-cost, simple, green, and open to mass production with intensive usage of AI. Meanwhile, the restricted knowledge of farmers and the unresolved restrictions with technology availability remain the gap until the advanced Agriculture 4.0 era. As a result, the paradigm called "eco-cyber-physical systems" was proposed by different authors, which was oriented to highlight the attention of developers on business-oriented decision-making and changing environments.

To identify system requirements and to design the system, we applied a "4+1" architecture adapted for the eco-cyber-physical systems. The modified "4+1" architecture was presented in the source [40]. In this study we applied an improved combination of: (1) *Logical view*—capability diagram; (2) *Process view*—object-process diagram; (3) *Project view*—4EM diagram; (4) *Physical-view*—node-edge diagram; (5) *Risk view*—CORAS diagram.

The system modeling was started from *Logical view* design (capability modeling), which is oriented to design capabilities to adapt business processes considering the changes in the environment. For example, Figure 3 presents the capability to schedule fly missions of UAVs considering weather conditions. A similar approach was applied to identify the business requirements of fruit growers (see Figure 4). The description of capability modeling can be found in the source [41]. Considering a capability-driven development (CDD) approach, the capability must be supported by data-based adjustments, the which optimize the work of the system. In our case study, the adjustments are recommendations, which are provided to fruit growers to support decision making. To understand the concept, we present two examples of data-based recommendations in Table 1. The whole list can be found in the source [42].

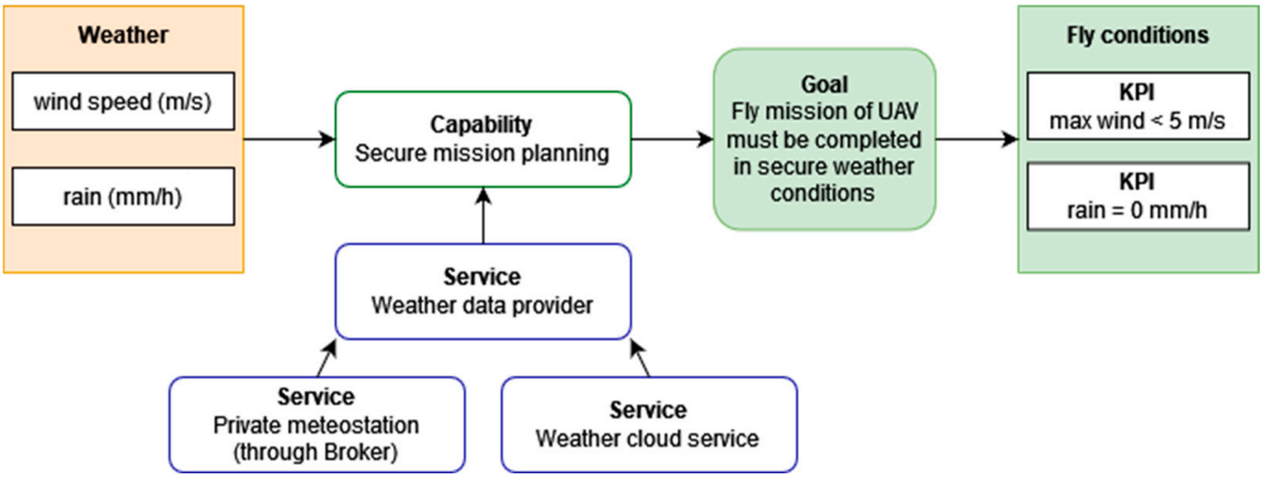

Figure 3. Capability to schedule fly missions of UAVs considering weather conditions.

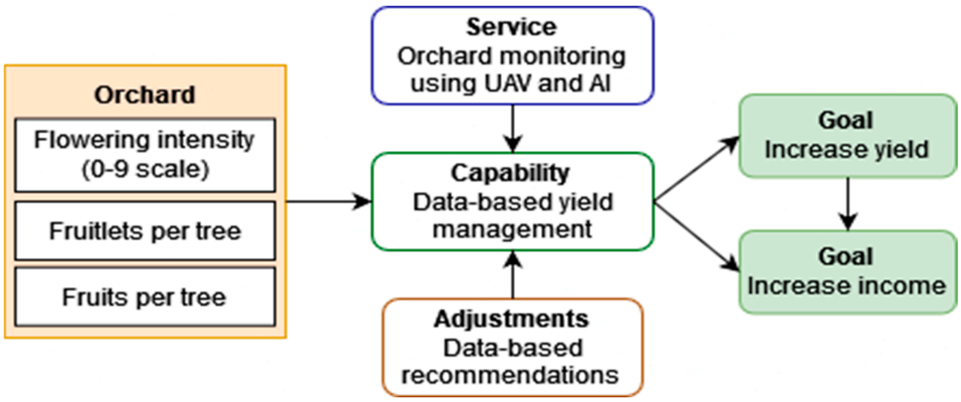

Figure 4. Capability of a data-based decision making.

Table 1. Examples of recommendations to support data-based decision-making [42].

Measurable Properties	Recommendations (Adjustments)	Impact on Goals
Cherries BBCH = 75	Assess the expected yield, plan harvest organization and fruit sale.	Decreases lost yield (over-ripened, rotted fruit) and increases income.
Cherries BBCH = 81	Protect yield from birds (covers, bird repellent devices).	Decreases lost yield (bird-damaged fruit) and increases income.

The design of a yield estimation system is presented in *Process view* (see Figure 5). The *Project view* can be found in the source [40]. We do not present it in this publication because it is mainly related to the project management and design constraints. In this article, we focus on improvements. The *Deployment view* is replaced by the *Risk view*. Risk analysis is crucial for the modern development of smart systems. For example, the risk analysis approach is a framework of Trustworthy AI and the EU AI Act. CORAS visual notation is selected for risk analysis to develop a safe and trustworthy solution. The example of *Risk view* is depicted in Figure 6. The full version is available in the source [43], including Specific Operations Risk Assessment (SORA). The custom UAV was constructed and designed for the yield estimation system. In this study, the *Physical view* of the yield estimation system is modeled using a node-edge diagram (see Figure 7). A full description of custom-designed UAV is available in Appendix A. It includes the *Physical view* of UAS, which is depicted in Figure A2 (Appendix A).

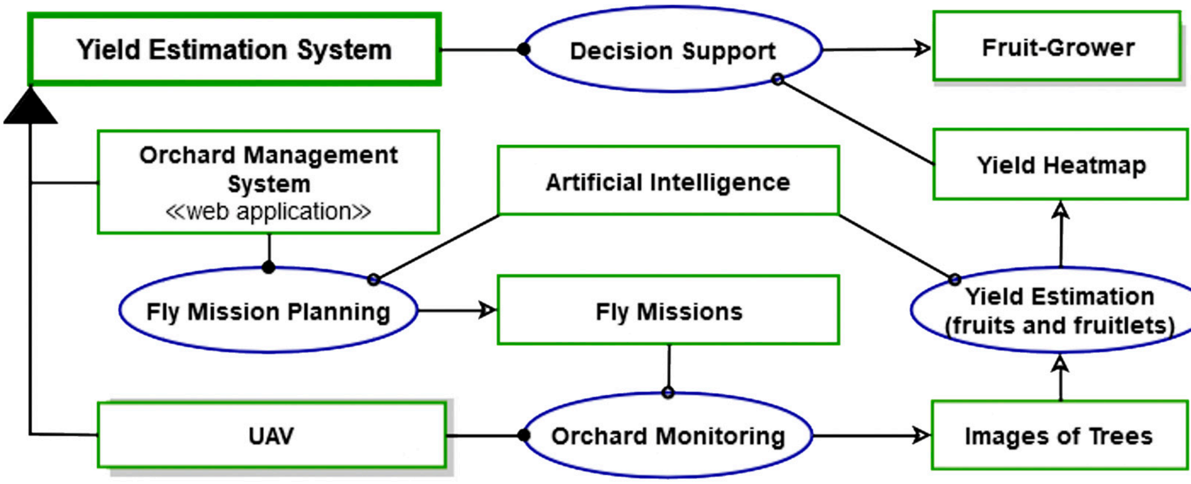

Figure 5. Process view of yield estimation system (authors' construction based on [40]).

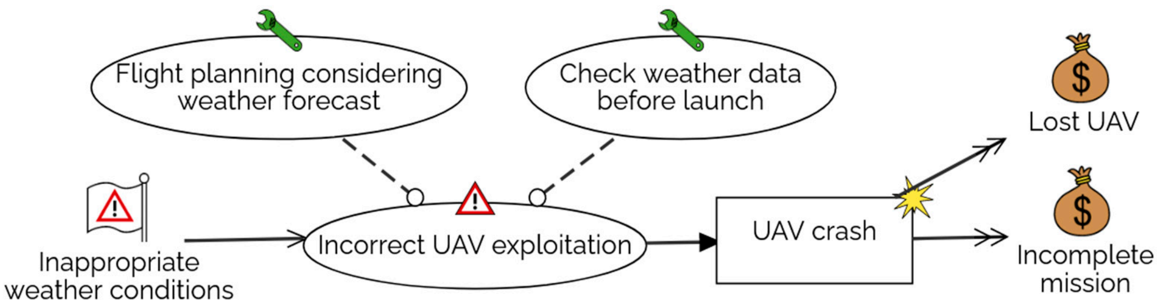

Figure 6. CORAS visual notation for risk analysis (authors' construction based on [43]).

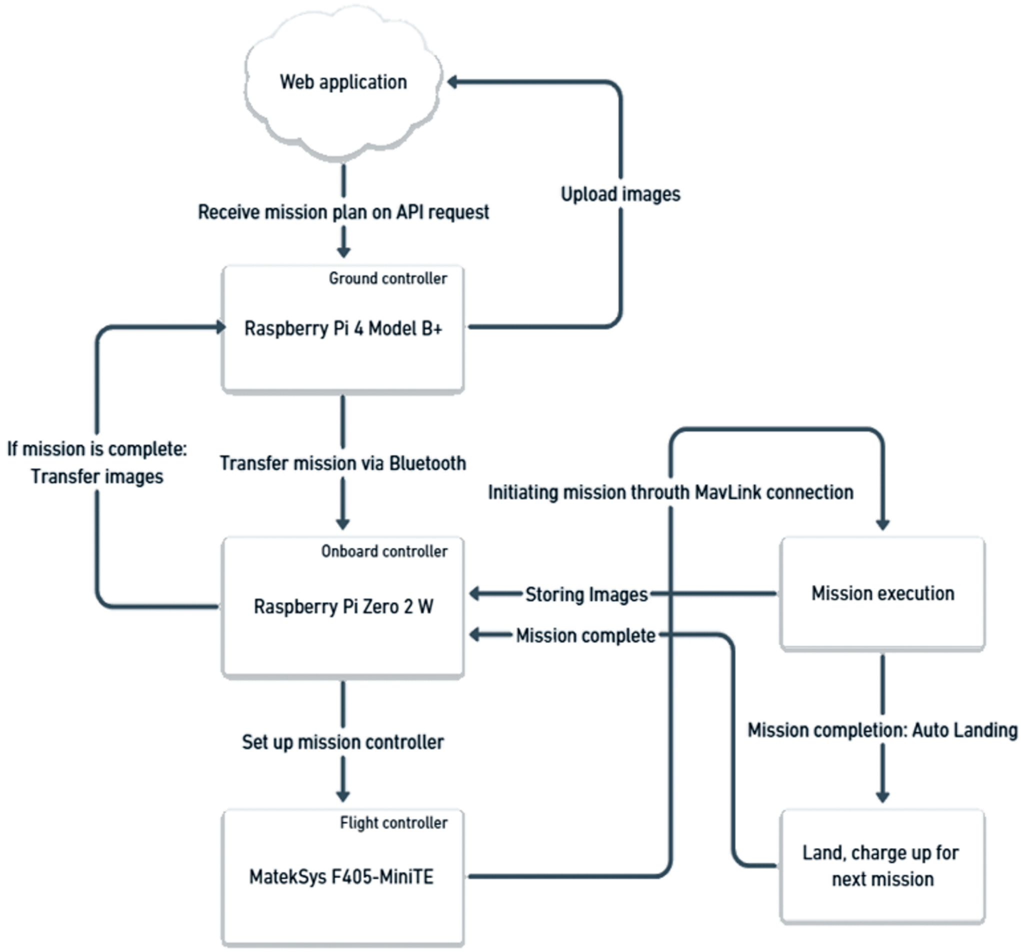

Figure 7. Communication among ground station, UAV flight controller, and web application.

3.2. Mission Planning Method

The mission planning method was designed to generate optimized flight missions for UAVs. The algorithm was specialized for commercial orchards, which have garden blocks with tree rows (see Algorithm 1). The concept of the described algorithm is depicted in Figure 8. The mission planning method is based on the application of existing algorithms used in geographic information systems (GIS): (1) buffering algorithms, which construct safety paths around obstacles; (2) the shortest path-finding algorithm; and (3) geospatial overlay methods to exclude inexistent paths.

Algorithm 1 The Mission Planning Method

Precondition: the ground station with a UAV is located from the side of tree rows.

Step 1. Read orchard parameters: the polygons, of obstacles, the lines of tree rows, the location of the ground station with UAV and the distance between two trees.

Step 2. Read UAV parameters: the photography distance and the distance to obstacles. Construct buffer polygons around tree rows and obstacles.

Step 3. Merge buffer polygons to exclude inaccessible points.

Step 4. If the direct flight from the ground station to the buffer line of the tree row is restricted (see Figure 8, Case A), then the points of obstacle buffers should be connected to the points of the tree row buffers and the ground station through their closest points (see Figure 8, Case B).

Step 5. Construct the flight path using the shortest path finding-algorithm.

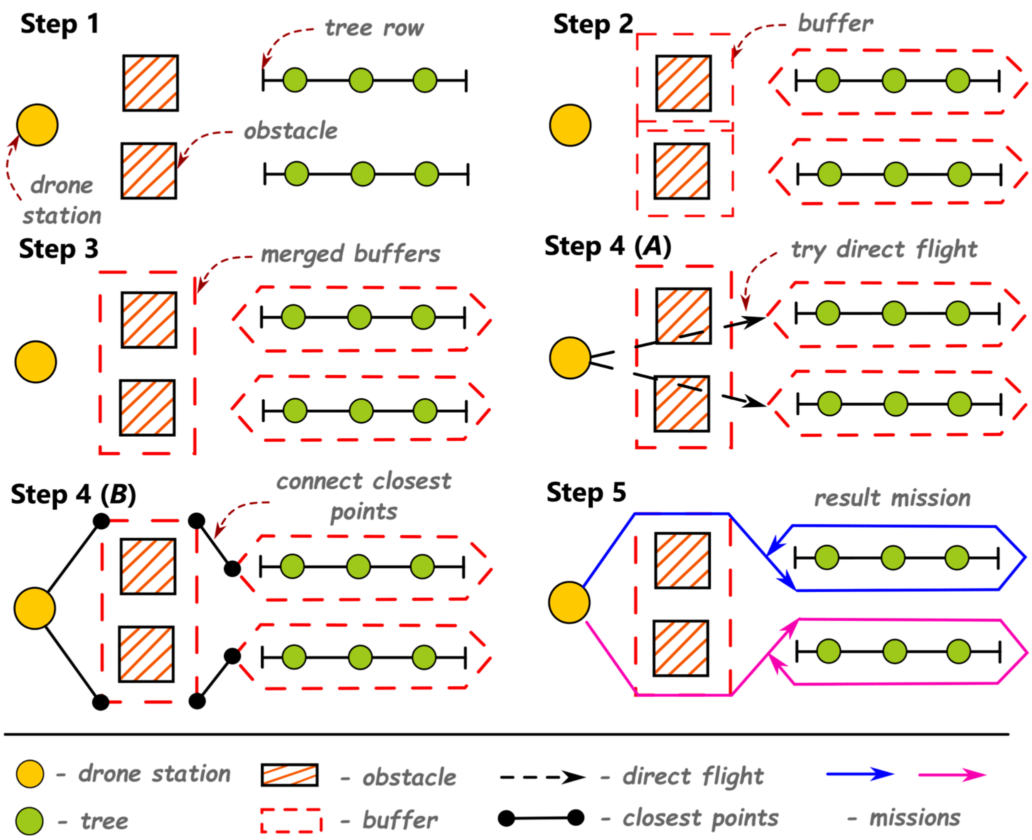

Figure 8. Concept of mission planning algorithm.

We simplified the description of the algorithm because the real algorithm considers more details like flight altitude and the possibility of flying over obstacles; the maximal flight time, the reserve time, the weather conditions, and the maximal speed of UAV are applied to verify the possibility of completing the mission. All these requirements are integrated using "if-else" conditions in the program code.

3.3. Fruit Yield Estimation Using Artificial Intelligence

The definition of "yield estimation" encompasses three distinct concepts that can be grouped sequentially: (1) employing object detection algorithms for fruit counting; (2) utilizing regression models to predict the number of fruits per tree; and (3) employing regression models for yield forecasting. In this study, we consider fruit and fruitlet counting under the definition "yield estimation". The automatic fruit counting can be achieved by using convolutional neural networks (CNNs) specialized for object detection. Nowadays, the most popular object detection solution is the YOLO (You-Only-Look-Once) framework, which was first presented in 2016 [44]. YOLO is a CNN architecture that is prepared for multi-class detection in real-time. The last version is YOLOv10, which was released in May 2024 [45]. These frameworks require an appropriate training dataset. However, the number of agricultural datasets, which are openly available and contain natural images, is quite limited.

We collected 6 datasets with natural images. Three datasets present fruits of apples, pears and cherries and three datasets of the fruitlets (apples, pears, and cherries,). We specially grouped each crop separately. Therefore, AI engineers can combine, considering the requirements of their solutions. We gradually publish our open datasets under the CC-BY 4.0 license in the Kaggle repository. The following datasets have been published by the authors so far: AppleScabFDs, AppleScabLDs [46], Pear640 [47], PFruitlet640 [48], and CherryBBCH81 [49]. In this article, we want to present our three new datasets: CherryBBCH72, AppleBBCH76, and AppleBBCH81. All these datasets were collected in the LatHort orchard in Dobele, Latvia. Two images were taken for each tree—perpendicularly, in a tree-facing view and in an oblique view, at the distance from the tree planting point 2.5 m (middle of alleyway). The images were annotated manually using the online tool “makesense.ai” [50]. The images were split on 640 × 640 px tiles using a Python 3.10 script and manually validated using the tool “makesense.ai”. The split was completed to satisfy the input size of pre-trained YOLO frameworks without image resizing.

Short description of new datasets:

- CherryBBCH72 contains 2521 images of cherry fruitlets. BBCH-scale describes the phenological development of fruits: 7—development of fruit; 72—fruit size up to 20 mm. It is available in Kaggle under CC-BY license [51];
- AppleBBCH76—3169 images of apple fruitlets with BBCH76-78: 76—fruit about 60% final size; but 78—fruit about 80% final size, respectively. It is available in Kaggle under a CC-BY license [52];
- AppleBBCH81—1838 images of apple fruits with BBCH81-85: 81—beginning of ripening; 83—developing color; 85—softening. It is available in Kaggle under a CC-BY license [53].

The examples of collected datasets are depicted in Figure 9.

We applied YOLO architecture for fruit and fruitlet amount estimation. Three object detection frameworks were compared experimentally: YOLOv8, YOLOv9 [54], and YOLOv10 [45]. We selected the medium-size models: YOLOv8m, YOLOv9m, and YOLOv10m. The training process was repeated five times for each model. The accuracy was measured using the testing dataset, which contained 100 images from each dataset extracted before the experiment. The training dataset contained 500 images of each category, but the validation dataset contained 100 images of each category. The training and validation images were randomly selected from the remaining images after extraction of the testing images. The 500 images of the training dataset are the optimal size because the greater number of images provides a small accuracy increase [55]. The models were trained on a videocard MSI RTX 4070 Ti with 7680 CUDA cores and 12GB GDDR6X.

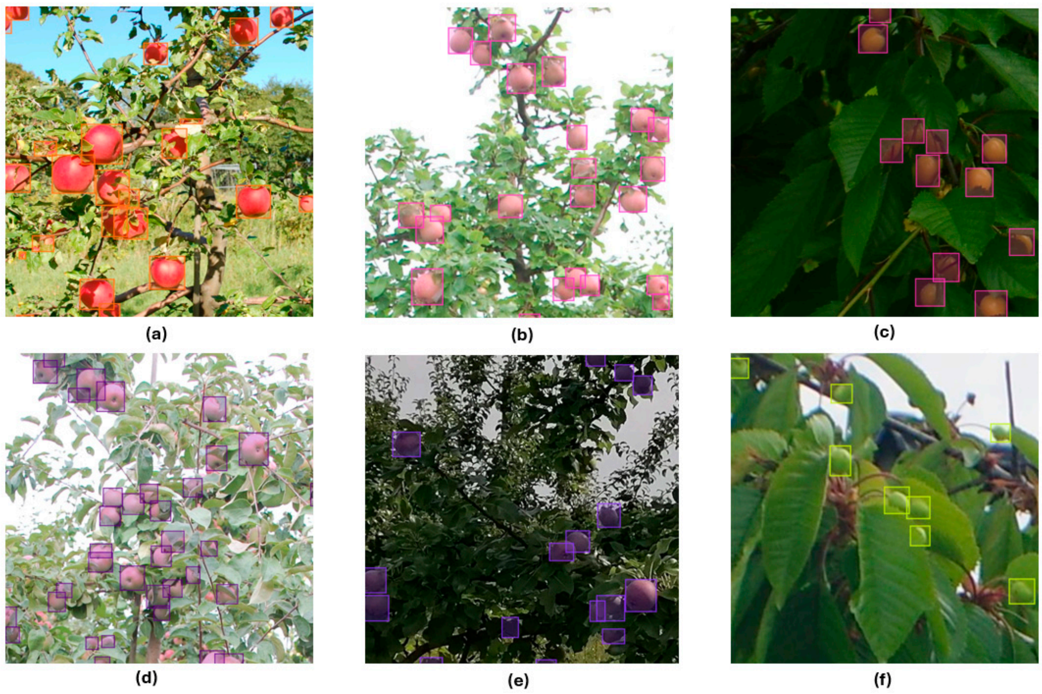

Figure 9. Image examples of collected datasets: (**a**) AppleBBCH81 [53]; (**b**) Pear640 [47]; (**c**) CherryBBCH81 [49]; (**d**) AppleBBCH76 [52]; (**e**) PFruitlet640 [48]; (**f**) CherryBBCH72 [51].

4. Results

The prototype of the yield estimation system was developed in 2023. Initially, we tested that all components communicate correctly under field conditions. The experiment was completed in October 2023, when fruits were already harvested. To verify the prototype in the relevant environment (TRL5), the second experiment was completed in September 2024. The experiment location was the LatHort orchard, Dobele, Latvia. At this moment, we have verified only one-time autonomous flight of UAV. The flight mission was successfully completed under the monitoring of a pilot, who could stop automatic flight and retake control. Two tree rows were selected and processed in one day. The prototype was not tested within a long period yet. The screenshot of the system showcasing successfully processed mission data for an orchard block is depicted in Figure 10, where the estimated yield is converted to a yield heatmap for decision support. The heatmap uses standard color legend (red–yellow–green–cyan–blue) for GIS, where red—max, blue—min. The screenshot depicts the main concept of yield monitoring.

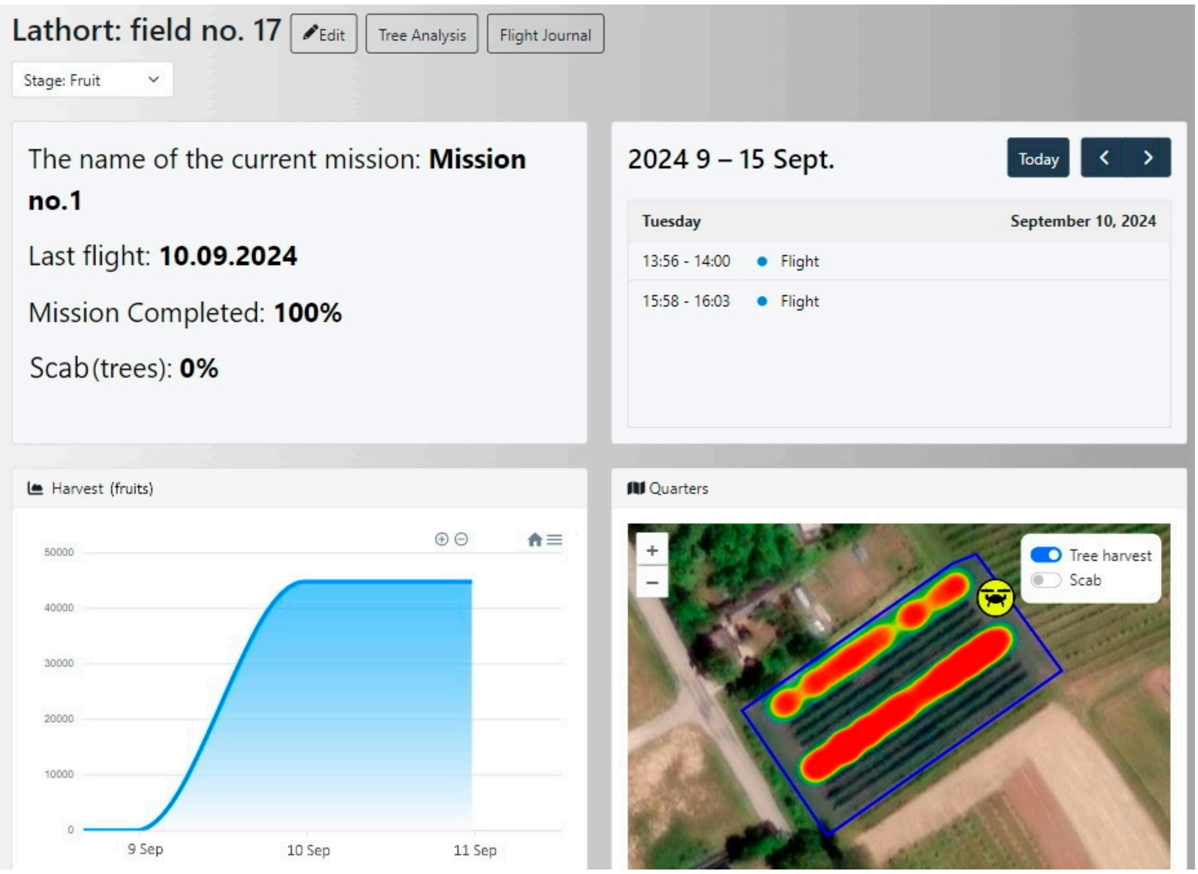

Figure 10. Screenshot of orchard block dashboard captured after experiment (September 2024): orchard flight mission stats (**top left**), flight calendar (**top right**), estimated harvest (**bottom left**), tree harvest heatmap (**bottom right**).

Considering AI, three new datasets were collected, annotated, and published under the CC-BY4.0 license in the Kaggle system: CherryBBCH72 [51], AppleBBCH76 [52], and AppleBBCH81 [53]. As well as we published other datasets, while we completed pilot experiments under TRL3-4 stages: Pear640 [47], PFruitlet640 [48], CherryBBCH81 [49]. Meanwhile, YOLOv9m showed the best results of object detection (see Figure 11).

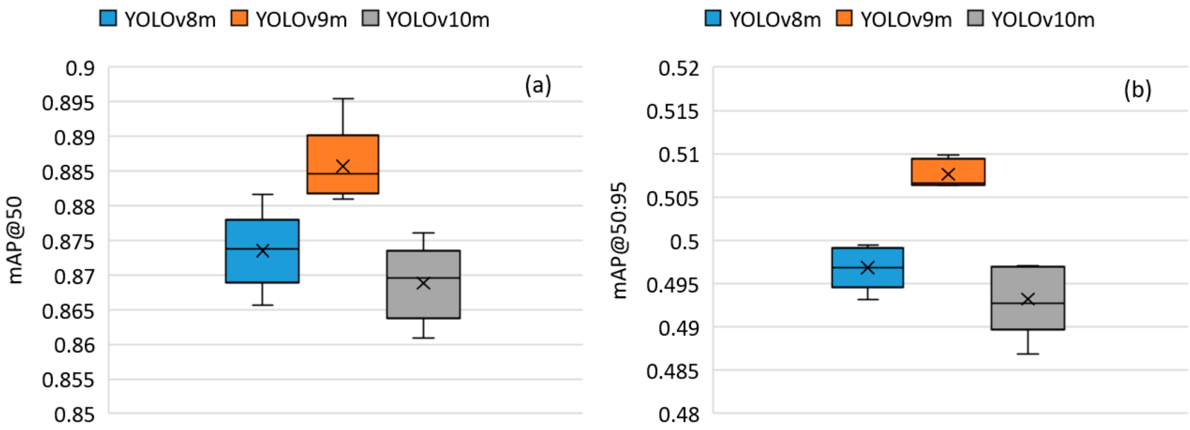

Figure 11. Comparison of three models: YOLOv8m, YOLOv9m, and YOLOv10m: (**a**) mAP@50; (**b**) mAP@50:95.

YOLOv10m provided worse results; its accuracy was lower than the accuracy of models YOLOv8m and YOLOv9m. The experiment results depict that the most complex categories were CherryBBCH72 and CherryBBCH81 for all YOLO models (Figures 12 and 13). The average inference speed was 6.77ms, 7.41ms, and 7.09ms for models YOLOv8m, YOLOv9m, and YOLOv10m, respectively, on the videocard MSI RTX 4070 Ti.

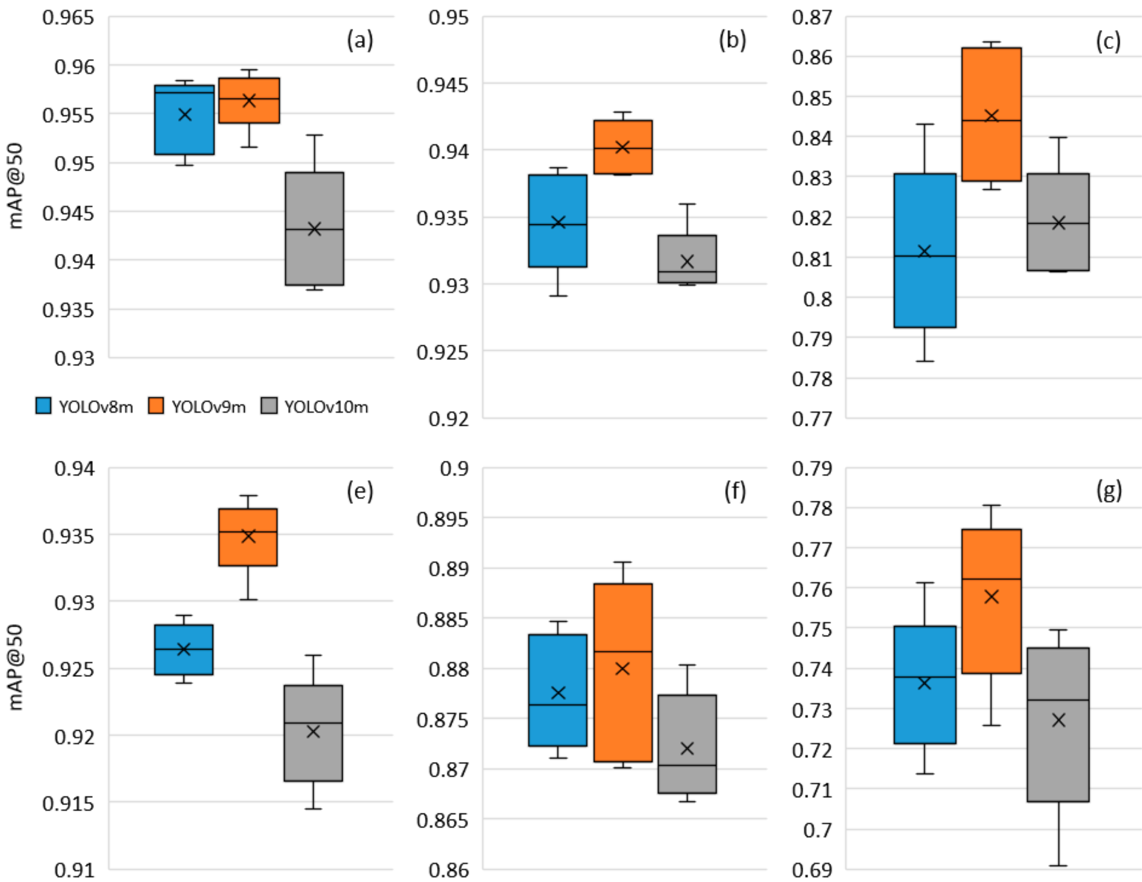

Figure 12. Comparison of models within each category (mAP@50): (**a**) AppleBBCH81; (**b**) Pear640; (**c**) CherryBBCH81; (**d**) AppleBBCH76; (**e**) PFruitlet640; (**f**) CherryBBCH72.

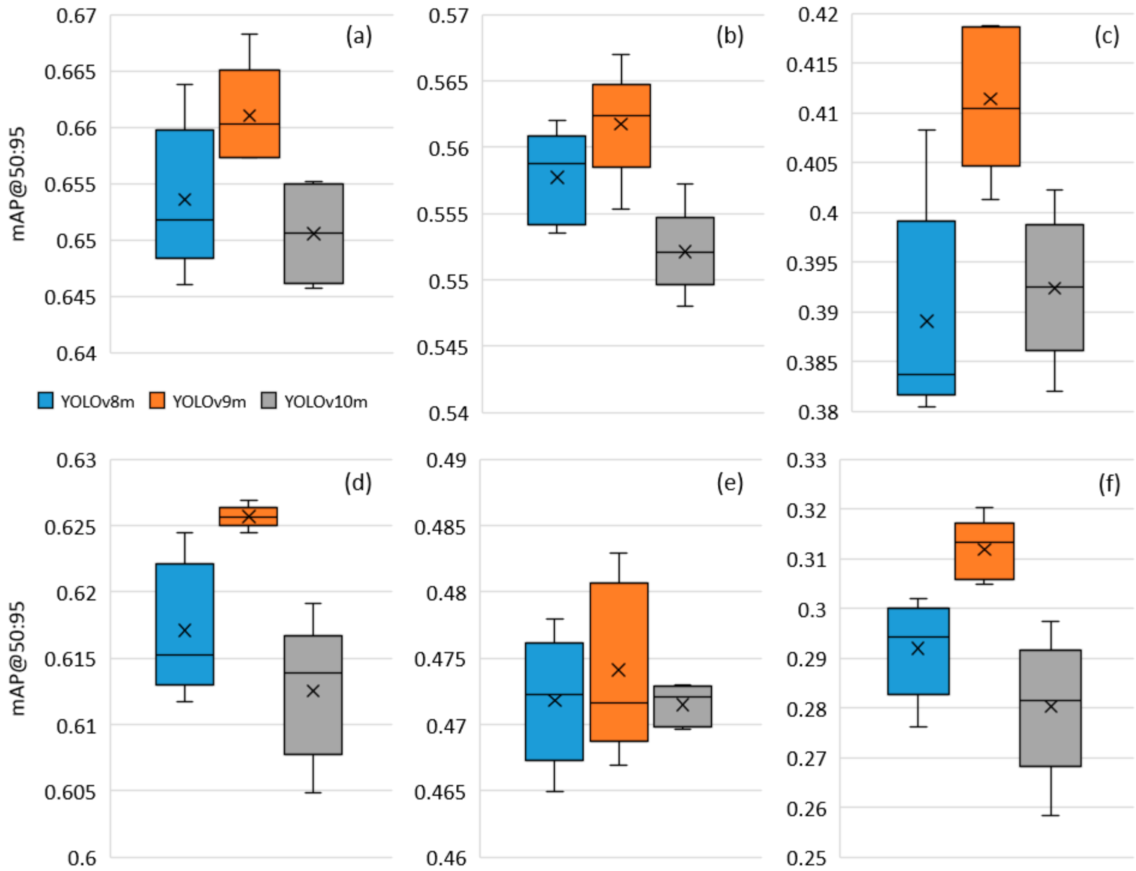

Figure 13. Comparison of models within each category (mAP@50:95): (**a**) AppleBBCH81; (**b**) Pear640; (**c**) CherryBBCH81; (**d**) AppleBBCH76; (**e**) PFruitlet640; (**f**) CherryBBCH72.

5. Discussion

Autonomous orchard management systems have been being developed for a relatively long time. E.g., the independent teams of inventors from the USA and Denmark presented the autonomous orchard management systems in 2012 [22,23]. The modern designs are oriented to be mass production solutions with low cost, user-friendly, and available for farmers without the specialized knowledge required for system exploitation. Considering the active development of AI in recent years, scientists are trying to maximize AI application in their solutions by inventing more and more complex and sophisticated solutions. The single tasks are sufficiently automated. However, real autonomous systems must solve multiple connected tasks to achieve optimal solutions. Therefore, new studies are oriented to develop AI for autonomous decision making, which must consider different data together.

The applied modeling methodology proved its potential to design complex eco-cyber-physical systems like an autonomous yield estimation system. The combination of diagrams in this study was more useful and simpler than the original modification of the "4+1" architecture presented in the source [40]. Regarding modification, we replaced geospatial map on CORAS risk analysis diagram. It is strongly important to analyze risks using robots or artificial intelligence. For example, Trustworthy AI and the EU AI Act are based on the concept of risk evaluation. Meanwhile, the geospatial analysis is important only in the specific use cases, which request to optimize geospatial locations of objects. The CORAS model complies with the capability model because both models are based on environment evaluation and adjustments to manage business processes and to overcome risks. Considering the node-edge diagram, it was more flexible to describe hardware, software, and their interfaces than the UML IoT diagram. It is not possible to develop the universal visual notation for all modeling case studies. Therefore, the combination approach proposed by the "4+1" architecture provides adaptability options to tune the modeling methodology considering the specific use case.

Speaking about the future development of the described modeling methodology, it is required to transform it until the framework, which includes the precise description of: (1) system modeling life-cycle; (2) involved developer positions and stakeholders.

Considering the actual AI solutions, they are sufficiently powerful to solve the yield forecasting tasks. However, there is a restricted number of natural agricultural datasets. There are gaps in the diversity of cultures, development stages, and growing states. Many datasets have regional specifics and are not suitable for other regions. As well as data must be interconnected to train AI to make predictions and conclusions using this data. The yield forecasting is based on chain-connected data like flowering index, fruitlet amount, fruit amount, seasons, weather, pests, etc., which must be connected to a unique fruit tree and its geolocation. However, it is not sufficient. The ground properties, weather conditions, field works, and parameters of culture must be collected and placed on a timeline before the beginning of more complex AI development. We believe that our annotated datasets will be useful for the scientific community to develop precision farming systems. Three fruitlet datasets were published: AppleBBCH76 [52], PFruitlet640 [48], and CherryBBCH72 [51], and three datasets with fruit images: AppleBBCH81 [53], Pear640 [47], and CherryBBCH81 [49]. The trained YOLO models achieved accuracy from 0.861 to 0.896 mAP@50. The best accuracy was achieved by YOLOv9m, which showed accuracy of 0.896 mAP@50, and 0.510 mAP@50:95 for all datasets. Considering each culture: apple, pear, and cherry, YOLOv9m achieved the best results too. YOLOv9m provided next accuracy results on each culture (mAP@50): apple fruits—0.958, apple fruitlets—0.938, pear fruits—0.943, pear fruitlets—0.891, cherry fruits—0.864, and cherry fruitlets—0.781. Tianjing and Mhamed (2024) summarized the accuracy of apple recognition based on the literature review, which showed accuracy range 62.3–97.8% [56], where 97.8% was provided by YOLOv5. Parico and Ahamed (2021) modified the YOLOv4 architecture and achieved 0.98 mAP@50 for the detection of pear fruits [57]. Meanwhile, Li et al. (2022) applied YOLOvX for cherry fruit and fruitlet detection [58]. The fruits were detected with accuracy 0.83 mAP@50, but the fruitlets—with 0.77–0.84 mAP@50. Shi et al. (2024) presented a modified YOLOv9s-Pear model, which achieved accuracy of 0.99 mAP@50 for red pear fruitlets; meanwhile, the original YOLOv9s achieved 0.97 mAP@50 [59]. Considering apple fruitlets, Ma et al. (2023) enhanced YOLOv7 architecture (YOLOv7-tiny-Apple) and achieved 0.80 mAP@50 for small apples [60]. Therefore, our results are comparable to other study achievements. Meanwhile, we applied a rapid development approach using existing architectures and "bag-of-freebies" combining different datasets. The mosaic of related datasets provides additional accuracy and stability, which was experimentally investigated in the sources [48,55].

Predicting the number of fruits per tree requires a regression model due to factors such as fruits being concealed by leaves, invisible in photographs, or potentially double-counted. For example, Vijayakumar et al. (2023) applied YOLO and a regression algorithm for citrus load prediction [61]. A similar approach was applied by MacEachern et al. (2023) for blueberry load prediction [62]. Yield forecasting involves estimating the harvest by leveraging historical data on the number of fruits per tree during earlier stages of fruit development. Currently, our system only facilitates fruit counting. However, our future works involve expanding the system to include additional predictive features for yield forecasting.

Regarding future works, the R&D continues to enhance the technologies of precision farming, searching for new innovations providing cheaper and more user-friendly technologies, thereby stimulating the mass application of these technologies. Even some authors have already started to discuss Agriculture 5.0. E.g., Saiz-Rubio and Rovira-Más (2020) mention: "The concept Agriculture 5.0 implies that farms are following Precision Agriculture principles and using equipment that involves unmanned operations, and autonomous decision support systems. Thus, Agriculture 5.0 implies the use of robots and some forms of AI" [63]. Mesías-Ruiz et al. (2023) see Agriculture 5.0 as a new era of intelligent farming management with automatized decision-making processes, unmanned operations and progressively less human intervention supported by the latest AI systems and advanced robotics [64]. However, looking from the perspective of autonomous farming, it is too early to sketch "Agriculture 5.0". Because the current concepts are based on precision farming principles, which already consider the application of robots and AI. And the period before 2017 can be simply called "Early Agriculture 4.0", nowadays—"Agriculture 4.0", meanwhile, fully autonomous farming will be "Advanced Agriculture 4.0", which closes the era of agriculture automation. However, it is important to identify some actual trends for investigations.

Jerhamre et al. (2021) [65] completed a survey about the actual challenges in Sweden to replace traditional farming with smart farming. They found that stakeholders are more interested in decision support systems than autonomous systems because they worry about cyberattacks. Additionally, the stakeholders worry about dependency on technology, whose failure can cause losses, while manual maintenance is restricted due to autonomous system exploitation, and there is a restricted possibility to upgrade existing farms due to insufficient finance, knowledge, and experience. Therefore, there is sufficiently much work in Agriculture 4.0, starting from trustworthy concept development until cost-efficient solution creation, which is related to tuning existing systems.

The actual studies of smart farming are mentioned in the articles presented by Liu et al. (2020) [37], Saiz-Rubio and Rovira-Más (2020) [63], Mesías-Ruiz et al. (2023) [64], Apeināns et al. (2023) [66]. We have depicted some key concepts in Figure 14 based on the previous literature analysis considering the subject of autonomous farming. Separately, large language models (LLMs) can be distinguished, which obtained high attention after the ChatGPT presentation. Because LLMs can stimulate smart farming adaptation by solving problems with insufficient knowledge and experience and providing a decision support system through a chatbot assistant. Some similar studies are already presented; e.g., Qing et al. (2023) [67] developed an image-to-text solution combining GPT with YOLO, which was oriented to present neither raw data nor agricultural diagnostic reports.

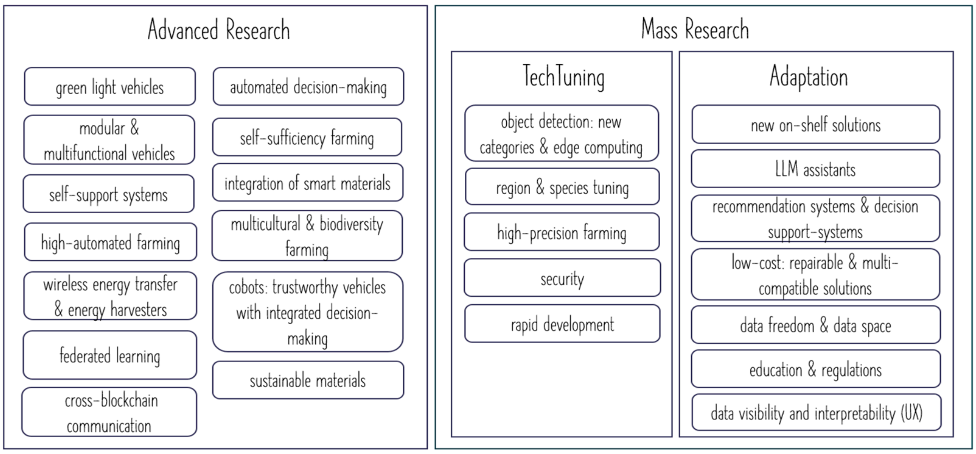

Figure 14. Actual studies in Agriculture 4.0: autonomous farming.

6. Conclusions

In this study, we have presented our prototype of a digital twin for smart orchard management using UAV and AI. The main idea was to depict the methodology applied to model our system, which belongs to eco-cyber-physical systems and a digital twin paradigm. Additionally, we presented the custom-designed UAV, which can be applied by other researchers or startups to overcome the limits of commercial products.

The described architecture "4+1", which was adapted for the eco-cyber-physical systems and digital twins, is useful to provide a holistic modeling approach to consider the aspects of software development, robotics, and ecosystem factors.

The trained YOLO models achieved the accuracy range 0.861–0.896 mAP@50. The best model was YOLOv9m, which achieved the accuracy of 0.896 mAP@50 for all datasets. The researchers traditionally enhance YOLO architectures to detect specific culture and maturity categories. Therefore, we compared achieved accuracy through each culture; the trained YOLOv9m is comparable with tuned architectures. Meanwhile, we achieved results using only "bag-of-freebies": multiple datasets and mosaic augmentation.

Author Contributions: S.K.: conceptualization, methodology, and writing—original draft, writing—review and editing, visualization, and validation. I.Z.: methodology, writing—original draft, writing—review and editing, visualization, supervision, project administration, and validation. G.L. and L.L.: writing—original draft, investigation. I.A. and M.S.: software, writing—original draft, and visualization. A.P.: methodology, writing—original draft, visualization, and validation. All authors have read and agreed to the published version of the manuscript.

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

Appendix A

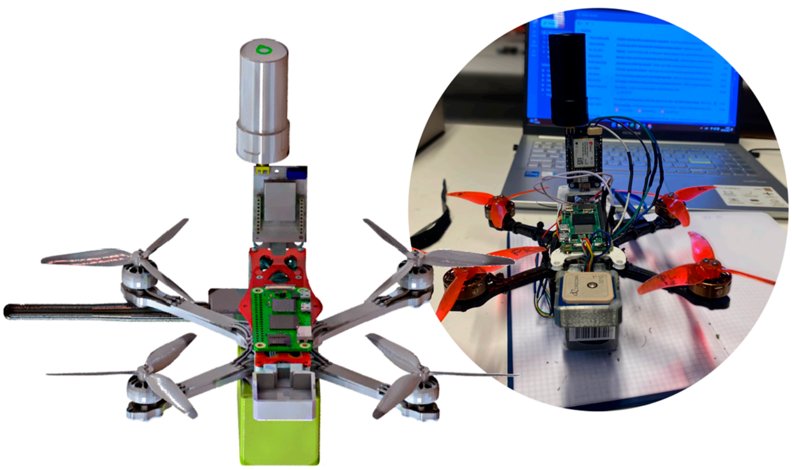

Figure A1. Custom design UAV: **left**—its 3D model, **right**—real prototype.

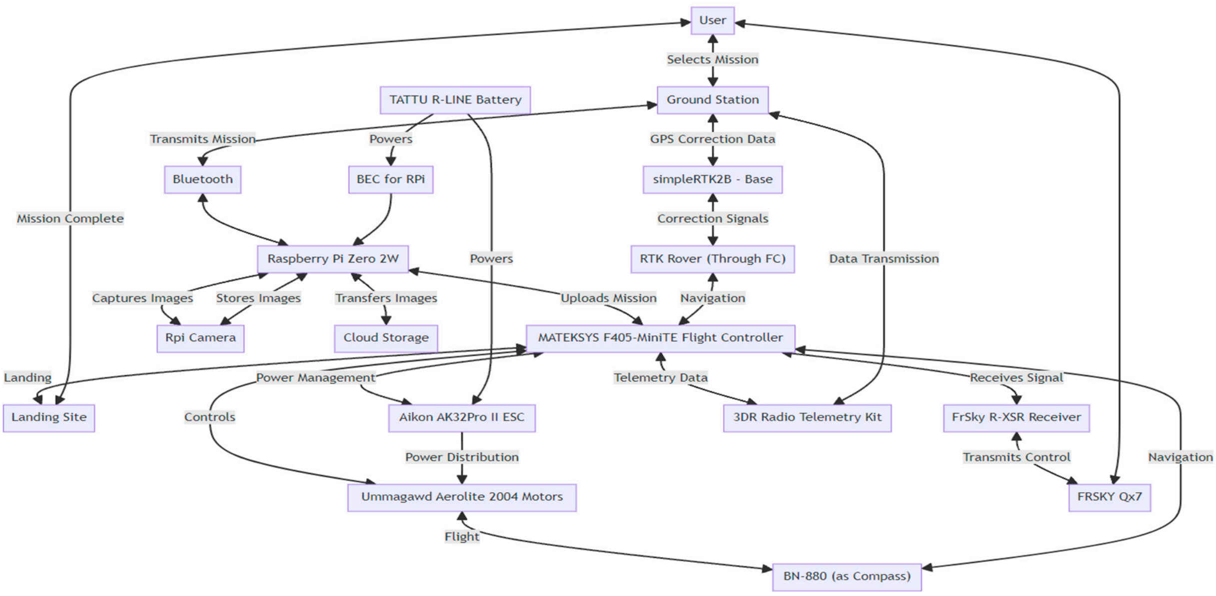

Figure A2. Physical View: structure of UAS to autonomously control UAV.

Table A1. Components of UAV.

Component	Specifications	Purpose
ImpulseRC Apex 4 Inch Frame Kit	4-inch frame	Provides the structural base for all components, ensuring lightweight and robust design for agile flying. ImpulseRC, Brisbane, Australia
MatekSys F405-MiniTE Flight Controller	Mini 20 × 20	Acts as the brain of the quad, processing flight data and controlling the motors for stable flight. MatekSys, Putuo, China
Aikon AK32Pro II ESC	50A, 2-6S, BLHeli32, 4-in-1	Electronic Speed Controller that regulates power to the motors, allowing precise control of the quad's movement. Aikon Electronics, Shenzen, China
Ummagawd Aerolite 2004 Motor (4 pc)	2400 KV	Provides the necessary thrust for flight, working in tandem with the ESC for speed and direction control. Ummagawd, Huntington Beach, CA, USA
GemFan Hurricane 4023 3-Blade	Propellers	Converts motor power into thrust, enabling lift and maneuverability. GemFan, Ningbo, China
Beitian BN-880 GPS	GPS module	Offers compass and GPS data, crucial for autonomous flight and accurate heading. BN-880 GPS must be disabled, if SimpleRTK2B Lite Rover is enabled. Beitian, Shenzhen, China
RPI Camera	Compatible with RPi Zero 2W	Captures images for AI analysis. Raspberry Pi, Cambridge, United Kingdom
RPi Zero 2W	Compact single-board computer	Processes images and handles onboard computations, interfacing with the flight controller. Raspberry Pi, Cambridge, United Kingdom
3DR Radio Telemetry Kit 433 Mhz 500 mw	Long-range telemetry	Facilitates communication between the quad and the ground station, transmitting flight data and receiving commands. Shenzhen ANG Technology, Shenzhen, China
SimpleRTK2B Base	RTK GPS base station	Provides high-precision GPS data to the quad for accurate positioning. SimpleRTK2B Lite Rover must be enabled, BN-880 GPS must be disabled. ArduSimple, Lleida, Spain
SimpleRTK2B Lite Rover	RTK GPS module for quad	Receives corrected GPS signals from the base for enhanced navigational accuracy. If SimpleRTK2B Lite Rover is enabled, BN-880 GPS must be disabled. ArduSimple, Lleida, Spain
FrSky R-XSR Receiver	2.4GHz, 16CH, ACCST, Micro, S-Bus & CPPM	Receives control signals from the transmitter, allowing manual control when needed. FrSky, Anhui, China
FrSky Qx7	Transmitter	Used at the ground station for manual control of the quad. FrSky, Anhui, China
Tattu R-Line 850 mAh 4s 95c LiPo Pack (XT60)	High-capacity battery	Powers the quad, providing energy for all electronic components. Grepow, Shenzhen, China

References

1. Xu, X. Major challenges facing the commercial horticulture. *Front. Hortic.* **2022**, *1*, 980159. [CrossRef]
2. He, L.; Schupp, J.R. Sensing and Automation in Pruning of apple Trees: A review. *Agronomy* **2018**, *8*, 211. [CrossRef]
3. Wang, S.; Song, J.H.; Qi, P.; Yuan, C.; Wu, H.; Zhang, L.; Liu, W.; Liu, Y.; He, X. Design and development of orchard autonomous navigation spray system. *Front. Plant Sci.* **2022**, *13*, 960686. [CrossRef] [PubMed]
4. Verbiest, R.; Ruysen, K.; Vanwalleghem, T.; Demeester, E.; Kellens, K. Automation and robotics in the cultivation of pome fruit: Where do we stand today? *J. Field Robot.* **2020**, *38*, 513–531. [CrossRef]
5. Neupane, C.; Pereira, M.; Koirala, A.; Walsh, K.B. Fruit Sizing in Orchard: A Review from Caliper to Machine Vision with Deep Learning. *Sensors* **2023**, *23*, 3868. [CrossRef] [PubMed]

6. Anastasiou, E.; Fountas, S.; Koutsiaras, M.; Voulgaraki, M.; Vatsanidou, A.; Barreiro-Hurlé, J.; Di Bartolo, F.; Goméz-Barbero, M. Precision Farming Technologies on Crop Protection: A stakeholders survey. *Smart Agric. Technol.* **2023**, *5*, 100293. [CrossRef]
7. Merz, M.; Pedro, D.; Skliros, V.; Bergenhem, C.; Himanka, M.; Houge, T.; Matos-Carvalho, J.P.; Lundkvist, H.; Çürüklü, B.; Hamrén, R.; et al. Autonomous UAS-Based Agriculture Applications: General Overview and relevant European case studies. *Drones* **2022**, *6*, 128. [CrossRef]
8. Mohsan, S.A.H.; Othman, N.Q.H.; Li, Y.; Alsharif, M.H.; Khan, M.A. Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends. *Intell. Serv. Robot.* **2023**, *16*, 109–137. [CrossRef]
9. UNDP. *Precision Agriculture for Smallholder Farmers. United Nations Development Programme, UNDP Global Centre for Technology, Innovation and Sustainable Development*; UNDP: Singapore, 2021; p. 80. Available online: https://www.undp.org/sites/g/files/zskgke326/files/2021-10/UNDP-Precision-Agriculture-for-Smallholder-Farmers.pdf (accessed on 2 June 2024).
10. Anonymous. *Global Harvest Automation Report*; Western Growers, Roland Berger: Irvine, CA, USA, 2021; p. 82.
11. Das, U. Precision Farming A Promising technology in Horticulture: A review. *Int. J. Pure Appl. Biosci.* **2018**, *6*, 1596–1606. [CrossRef]
12. Longchamps, L.; Tisseyre, B.; Taylor, J.A.; Sagoo, L.; Momin, A.; Fountas, S.; Manfrini, L.; Ampatzidis, Y.; Schueller, J.K.; Khosla, R. Yield sensing technologies for perennial and annual horticultural crops: A review. *Precis. Agric.* **2022**, *23*, 2407–2448. [CrossRef]
13. Hutsol, T.; Kutyrev, A.; Kiktev, N.; Biliuk, M. Robotic Technologies in Horticulture: Analysis and Implementation Prospects. *Inż. Rol.* **2023**, *27*, 113–133. [CrossRef]
14. GrowerTalks: The State of the Horticultural Automation Sector. (n.d.). Available online: https://www.growertalks.com/Article/?articleid=26299 (accessed on 2 June 2024).
15. Sato, J. Farming robots. *J. Robot. Mechatron.* **1997**, *9*, 287–292. [CrossRef]
16. Matthews, J. The mechanical farm of 2030. *Interdiscip. Sci. Rev.* **1982**, *7*, 194–201. [CrossRef]
17. Jahns, G. Automatic Steering of Farm Vehicles. ResearchGate 1976. Available online: https://www.researchgate.net/publication/322146912_Automatic_Steering_of_Farm_Vehicles (accessed on 28 November 2024).
18. Stentz, A.; Dima, C.; Wellington, C.; Herman, H.; Stager, D. A System for Semi-Autonomous Tractor Operations. *Auton. Robots* **2002**, *13*, 87–104. [CrossRef]
19. Noguchi, N.; Reid, J.F.; Zhang, Q.; Tian, L.; Hansen, A.C. Vision Intelligence for Mobile Agro-Robotic System. *J. Robot. Mech.* **1999**, *11*, 193–199. [CrossRef]
20. Hamner, B.; Bergerman, M.; Singh, S. Autonomous orchard vehicles for specialty crops production. In Proceedings of the American Society of Agricultural and Biological Engineers Annual International Meeting 2011, Louisville, KY, USA, 7–10 August 2011; American Society of Agricultural and Biological Engineers: St. Joseph, MI, USA, 2011. [CrossRef]
21. Nuske, S.; Achar, S.; Bates, T.; Narasimhan, S.G.; Singh, S. Yield estimation in vineyards by visual grape detection. In Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, San Francisco, CA, USA, 25–30 September 2011. [CrossRef]
22. Moorehead, S.J.; Wellington, C.K.; Gilmore, B.J.; Vallespi, C. Automating Orchards: A System of Autonomous Tractors for Orchard Maintenance. In Proceedings of the IEEE International Conference of Intelligent Robots and Systems, Workshop on Agricultural Robotics, Vilamoura-Algarve, Portugal, 7–12 October 2012.
23. Blanke, M.; Blas, M.R.; Hansen, S.; Andersen, J.C.; Caponetti, F. Autonomous Robot Supervision using Fault Diagnosis and Semantic Mapping in an Orchard. In *Fault Diagnosis in Robotic and Industrial Systems*; Rigatos, G., Ed.; iConcept Press Ltd.: Tsim Sha Tsui, Hong Kong, 2012; pp. 1–22.
24. Tamaki, K.; Nagasaka, Y.; Nishiwaki, K.; Saito, M.; Kikuchi, Y.; Motobayashi, K. A robot system for paddy field farming in Japan. *IFAC Proc. Vol.* **2013**, *46*, 143–147. [CrossRef]
25. Blackmore, B.S.; Stout, W.; Wang, M.; Runov, B. Robotic agriculture—The future of agricultural mechanisation? In Proceedings of the 5th European Conference on Precision Agriculture, Uppsala, Sweden, 4–8 July 2005; Stafford, V.J., Ed.; Academic Publishers: Wageningen, The Netherlands, 2005; pp. 621–628.
26. González, R.J.; Rodríguez, F.M.; López, J.S.; Donaire, J.G. Navigation techniques for mobile robots in greenhouses. *Appl. Eng. in Agric.* **2009**, *25*, 153–165. [CrossRef]
27. Tripicchio, P.; Satler, M.; Dabisias, G.; Ruffaldi, E.; Avizzano, C.A. Towards Smart Farming and Sustainable Agriculture with Drones. In Proceedings of the 2015 International Conference on Intelligent Environments, Prague, Czech Republic, 15–17 July 2015. [CrossRef]
28. Abdullahi, H.S.; Mahieddine, F.; Sheriff, R.E. Technology Impact on Agricultural productivity: A review of precision agriculture using Unmanned Aerial Vehicles. In *Wireless and Satellite Systems. WiSATS 2015. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*; Springer: Cham, Switzerland, 2015; pp. 388–400. [CrossRef]
29. Gerke, M.; Masár, I.; Borgolte, U.; Röhrig, C. Farmland monitoring by sensor networks and airships. *IFAC Proc. Vol.* **2013**, *46*, 321–326. [CrossRef]
30. Zhao, G.; Yu, H.; Wang, G.; Sui, Y.; Zhang, L. Applied research of IOT and RFID technology in Agricultural Product Traceability System. In *IFIP Advances in Information and Communication Technology*; Springer: Cham, Swizerlnad, 2015; pp. 506–514. [CrossRef]
31. Bhanu, B.; Rao, K.R.; Ramesh, J.V.N.; Hussain, M.A. Agriculture field monitoring and analysis using wireless sensor networks for improving crop production. In Proceedings of the 2014 Eleventh International Conference on Wireless and Optical Communications Networks (WOCN), Vijayawada, India, 11–13 September 2014. [CrossRef]

32. Shamshiri, R.R.; Weltzien, C.; Hameed, I.A.; Yule, I.; Grift, T.E.; Balasundram, S.K.; Pitonakova, L.; Ahmad, D.; Chowdhary, G. Research and development in agricultural robotics: A perspective of digital farming. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 1–11. [CrossRef]
33. Kim, J.; Kim, S.; Ju, C.; Son, H.I. Unmanned Aerial Vehicles in agriculture: A Review of Perspective of platform, control, and Applications. *IEEE Access* **2019**, *7*, 105100–105115. [CrossRef]
34. Jensen, K.V.; Larsen, M.; Nielsen, S.H.; Larsen, L.B.; Olsen, K.S.; Jørgensen, R.N. Towards an open software platform for field robots in precision agriculture. *Robotics* **2014**, *3*, 207–234. [CrossRef]
35. Cabreira, T.M.; Brisolara, L.; Ferreira, P.R. Survey on Coverage Path Planning with Unmanned Aerial Vehicles. *Drones* **2019**, *3*, 4. [CrossRef]
36. Hooshyar, M.; Huang, Y. Metaheuristic Algorithms in UAV Path-Planning Optimization: A Systematic Review (2018–2022). *Drones* **2023**, *7*, 687. [CrossRef]
37. Liu, Y.; Ma, X.; Shu, L.; Hancke, G.P.; Abu-Mahfouz, A.M. From Industry 4.0 to agriculture 4.0: Current status, enabling technologies, and research challenges. *IEEE Trans. Ind. Inform.* **2021**, *17*, 4322–4334. [CrossRef]
38. Santos Valle, S.; Kienzle, J. Agriculture 4.0—Agricultural Robotics and Automated Equipment for Sustainable Crop Production. In *Integrated Crop Management*; FAO: Rome, Italy, 2020; Volume 24. Available online: https://www.fao.org/documents/card/en?details=cb2186en/ (accessed on 13 May 2024).
39. FAO. *Transforming Food and Agriculture to Achieve the SDGs: 20 Interconnected Actions to Guide Decision-Makers*; IGO: Rome, Italy, 2019; p. 74. Available online: https://www.fao.org/3/ca1612en/ca1612en.pdf (accessed on 28 November 2024).
40. Kodors, S.; Zarembo, I.; Majore, G.; Rubauskis, E.; Litavniece, L. Digital twin modelling for smart fruit-growing: Eco-cyber-physical system 4+1 architecture. *Eng. Rural Dev.* **2023**, *22*, 700–706. [CrossRef]
41. Grabis, J.; Deksne, L.; Roponena, E.; Stirna, J. A Capability-Based method for modeling resilient data ecosystems. In *Domain-Specific Conceptual Modeling*; Springer: Cham, Switzerland, 2022; pp. 339–363. [CrossRef]
42. Zarembo, I.; Kodors, S.; Apeināns, I.; Lācis, G.; Feldmane, D.; Rubauskis, E. Digital Twin: Orchard Management Using UAV. *Vide. Tehnol. Resur.* **2023**, *1*, 247–251. [CrossRef]
43. Litavniece, L.; Kodors, S.; Dekšne, J.; Lācis, G.; Zarembo, I.; Pacejs, A. Risk Analysis for Apple Orchard Survey and Monitoring Using UAV. *Vide. Tehnol. Res.* **2023**, *1*, 116–122. [CrossRef]
44. Redmon, J.; Divvala, S.; Girshick, R.; Farhadi, A. You Only Look Once: Unified, Real-Time Object Detection. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27 June–1 July 2016. [CrossRef]
45. Wang, A.; Chen, H.; Liu, L.; Chen, K.; Lin, Z.; Han, J.; Ding, J. YOLOv10: Real-Time End-to-End Object Detection. *arXiv* **2024**, arXiv:2405.14458. Available online: https://arxiv.org/pdf/2405.14458 (accessed on 15 July 2024).
46. Kodors, S.; Lācis, G.; Sokolova, O.; Zhukovs, V.; Apeinans, I.; Bartulsons, T. Apple scab detection using CNN and Transfer Learning. *Agron. Res.* **2021**, *19*, 507–519. [CrossRef]
47. Kodors, S.; Sondors, M.; Lācis, G.; Rubauskis, E.; Apeināns, I.; Zarembo, I. Rapid Prototyping of Pear Detection Neural Network with YOLO Architecture in Photographs. *Vide. Tehnol. Res.* **2023**, *1*, 81–85. [CrossRef]
48. Kodors, S.; Sondors, M.; Apeinans, I.; Zarembo, I.; Lacis, G.; Rubauskis, E.; Karklina, K. Importance of Mosaic Augmentation for Agricultural Image Dataset. 2024. Available online: https://dspace.emu.ee/handle/10492/8871 (accessed on 2 June 2024).
49. Apeinans, I.; Sondors, M.; Litavniece, L.; Kodors, S.; Zarembo, I.; Feldmane, D. Cherry Fruitlet Detection using YOLOv5 or YOLOv8? *Vide. Tehnol. Res.* **2024**, *2*, 29–33. [CrossRef]
50. Piotr Skalski, Make Sense. 2019. Available online: https://github.com/SkalskiP/make-sense/ (accessed on 28 November 2024).
51. Project lzp-2021/1-0134, CherryBBCH72. 2024. Available online: https://www.kaggle.com/datasets/projectlzp201910094/cherrybbch72 (accessed on 29 November 2024).
52. Project lzp-2021/1-0134, AppleBBCH76. 2024. Available online: https://www.kaggle.com/datasets/projectlzp201910094/applebbch76 (accessed on 29 November 2024).
53. Project lzp-2021/1-0134, AppleBBCH81. 2024. Available online: https://www.kaggle.com/datasets/projectlzp201910094/applebbch81 (accessed on 29 November 2024).
54. Wang, C.-Y.; Yeh, I.-H.; Liao, H.-Y.M. YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information. *arXiv* **2024**, arXiv:2402.01361. [CrossRef]
55. Apeinans, I. Optimal Size of Agricultural Dataset for YOLOv8 Training. *Vide. Tehnol. Res.* **2024**, *2*, 38–42. [CrossRef]
56. Tianjing, Y.; Mhamed, M. Developments in automated harvesting equipment for the Apple in the Orchard: Review. *Smart Agric. Technol.* **2024**, *9*, 100491. [CrossRef]
57. Parico, A.I.B.; Ahamed, T. Real time pear fruit detection and counting using YOLOV4 models and Deep SORT. *Sensors* **2021**, *21*, 4803. [CrossRef]
58. Li, Z.; Jiang, X.; Shuai, L.; Zhang, B.; Yang, Y.; Mu, J. A Real-Time detection algorithm for sweet cherry fruit maturity based on YOLOX in the natural environment. *Agronomy* **2022**, *12*, 2482. [CrossRef]
59. Shi, Y.; Duan, Z.; Qing, S.; Zhao, L.; Wang, F.; Yuwen, X. YOLOV9S-Pear: A lightweight YOLOV9S-Based improved model for young Red Pear Small-Target recognition. *Agronomy* **2024**, *14*, 2086. [CrossRef]
60. Ma, L.; Zhao, L.; Wang, Z.; Zhang, J.; Chen, G. Detection and Counting of Small Target Apples under Complicated Environments by Using Improved YOLOv7-tiny. *Agronomy* **2023**, *13*, 1419. [CrossRef]

61. Vijayakumar, V.; Ampatzidis, Y.; Costa, L. Tree-level citrus yield prediction utilizing ground and aerial machine vision and machine learning. *Smart Agric. Technol.* **2023**, *3*, 100077. [CrossRef]
62. MacEachern, C.B.; Esau, T.J.; Schumann, A.W.; Hennessy, P.J.; Zaman, Q.U. Detection of fruit maturity stage and yield estimation in wild blueberry using deep learning convolutional neural networks. *Smart Agric. Technol.* **2023**, *3*, 100099. [CrossRef]
63. Sáiz-Rubio, V.; Rovira-Más, F. From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. *Agronomy* **2020**, *10*, 207. [CrossRef]
64. Mesías-Ruiz, G.A.; Pérez-Ortiz, M.; Dorado, J.; De Castro, A.I.; Peña, J.M. Boosting precision crop protection towards agriculture 5.0 via machine learning and emerging technologies: A contextual review. *Front. Plant Sci.* **2023**, *14*, 1143326. [CrossRef] [PubMed]
65. Jerhamre, E.; Carlberg, C.J.C.; Van Zoest, V. Exploring the susceptibility of smart farming: Identified opportunities and challenges. *Smart Agric. Technol.* **2022**, *2*, 100026. [CrossRef]
66. Apeināns, I.; Litavniece, L.; Kodors, S.; Zarembo, I.; Lācis, G.; Dekšne, J. Smart Fruit Growing through Digital Twin Paradigm: Systematic review and Technology Gap analysis. *Eng. Manag. Prod. Serv.* **2023**, *15*, 128–143. [CrossRef]
67. Qing, J.; Deng, X.; Lan, Y.; Li, Z. GPT-aided diagnosis on agricultural image based on a new light YOLOPC. *Comput. Electr. Agric.* **2023**, *213*, 108168. [CrossRef]