

ARCHIE²: An Augmented Reality Interface with Plant Detection for Future Planetary Surface Greenhouses

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ABSTRACT

More than 50 years after the last human set foot on the Moon during the Apollo 17 mission, humans aim to return to the Moon in this decade. This time, humanity plans to establish lunar habitats for a sustainable longer presence. An integrated part of these lunar habitats will be planetary surface greenhouses. These greenhouses will produce food, process air, recycle water, and improve the psychological well-being of humans. Past research has shown that a large amount of crew time, a scarce and valuable resource in spaceflight, is needed for maintenance and repairs in a planetary surface greenhouse, leaving less time for crop cultivation and science activities. In this paper, we present the concept of an augmented reality interface named ARCHIE² to reduce crew time and the workload of astronauts and remote support teams on Earth to operate a planetary surface greenhouse. ARCHIE² allows users to visualize status information on plants, technical systems, and environmental parameters in the greenhouse or other features supporting the greenhouse operations using an augmented reality headset. In particular, we report on the implementation and performance of the ARCHIE² plant detection module that runs locally on the augmented reality headset. Using images with a resolution of 320x192 pixels, arugula selvatica plants were detected using an artificial neural network (based on a YOLOv5s model) from a horizontal distance up to 50 cm with an average inference time of 602 ms and an average of 48 FPS. Based on that, the plants were augmented with labels to visualize relevant plant-specific information supporting astronauts in the maintenance of the plants.

Keywords: EDEN ISS, Augmented reality, ARCHIE², Greenhouse, Space analog, Operations, Crew time, Workload.

Index Terms: J.2 [Physical Sciences and Engineering]: Aerospace; C.1.3 [Processor Architectures]: Other Architecture Styles — Neural nets; H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems — Artificial, augmented, and virtual realities.

1 INTRODUCTION AND MOTIVATION

In the Global Exploration Roadmap [1], 14 space agencies expressed a common interest in expanding human presence into the solar system to reach Mars. As preparation for a crewed mission to Mars, humans are planning to revisit the lunar surface by the end of this decade and establish sustained research infrastructures [2]. From the mid-2030s onwards, long-duration lunar habitats will be established on the Moon [2]. Planetary surface greenhouses to

produce plants will be an integral part of these habitats to reduce the number of expensive transport flights needed for food resupply from Earth and achieve higher independence from Earth. In addition, plants in such greenhouses will be used to produce food, process air, recycle water [3] and increase the astronauts' psychological well-being [4].

In early 2018, the space analog EDEN ISS greenhouse was established in Antarctica near the polar research station Neumayer Station III operated by the Alfred Wegener Institute (AWI) as part of the EDEN ISS project. The EDEN ISS project aimed to investigate key technologies for planetary surface greenhouses under Moon/Mars analog conditions [5]. Studies such as these are needed as baseline work for operating planetary surface greenhouses on the Moon and Mars. During the four one-year analog missions in Antarctica, numerous studies have been conducted on food quality and safety, microbiology monitoring, plant health monitoring techniques, human factors, horticultural sciences, as well as resource consumption and waste production analysis. In addition to these investigations, a significant focus was put on examining crew time, workload, and interaction between the on-site operation team and the remote support teams on Earth.

In space missions, crew time is a valuable and limited resource [6] and needs to be optimized as best as possible [7]. Repairs and maintenance activities account for a substantial portion of the overall crew time required for a space mission [8]. To have more time for scientific activities, the crew's time for repairs and maintenance activities has to be reduced [6]. This has also been confirmed by experience from the space analog EDEN ISS missions [9]. These missions have shown that the required crew time and the specific workload demand for operating a planetary surface greenhouse by on-site operators (astronauts) and remote support teams on Earth must be reduced for future space missions [10].

By augmenting the field of vision of the user with interactive virtual elements, augmented reality (AR) applications, in general, could increase compliance with procedures [11] and reduce errors in the execution of operational activities, resulting in fewer failures and delays [11, 12]. This in turn could increase the user's efficiency [13], and increase the accuracy of executed tasks [11, 13], resulting in reduced overall crew time [11–13] and workload for the user [12]. In addition, the virtual interaction with input and output options of the interface could result in an abandonment of keyboard entries or paper documents while working on a task enabling hands-free operations [11, 13, 14].

All these benefits as mentioned earlier of AR technology could also apply to the use of AR in the operations of a planetary surface greenhouse. However, using AR applications in such a system can reduce not only crew time and workload of the on-site operators (astronauts), but also for remote support teams on Earth, while increasing the safety of on-site operators and plants. Moreover, using AR could lead to facilitated training processes, reduced training needs [11] for new operations in such a greenhouse or as needed, resulting in increased autonomy [11] of the on-site

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operators from Earth support and facilitated integration processes of untrained personnel into planetary surface greenhouse operations [10]. Increased autonomy is particularly important for missions beyond low Earth orbit (LEO), as remote support can be reduced due to cost and communication delay [15], especially in the case of Mars, with a delay of up to 22.2 minutes one way [10]. Also, the loss of knowledge due to the substantial time gap of more than 18 months [16] between the actual space mission and the astronaut training completed on Earth can be countered by using AR during the mission.

Therefore, in this paper, we present the concept of an AR interface (Figure 2) called "ARCHIE²" (Augmented Reality Computer-Human Interface for grEEnhouses). ARCHIE² is designed to facilitate the operation of future planetary surface greenhouses by visualizing status information on plants, technical systems, and environmental parameters in the greenhouse on an AR headset. Furthermore, schedules, procedures, various planning tools, or an integrated remote assistance tool can be displayed. [17, 18]

The key contribution of this paper is the concept of an AR interface supporting the operations in a planetary surface greenhouse and the implementation of its plant detection module running locally on the AR headset. We provide details on the implementation as well as the performance of the plant detection and augmentation process. The research presented in this paper could serve as a proof of concept that plant detection can be achieved with an application running directly on an AR headset, and the results could serve as a benchmark for future studies in this area.

2 RELATED WORK

AR use can be spread widely in various fields of application due to individual adaptability. Some examples for use on Earth are the use in medicine [19], textile industry [20], aerospace industry [21], water management [22], navigation/tourism [19, 21], urban planning [19], livestock farming [23], gaming industry [19] or education/training [19]. A growing number of AR applications also exist in the agriculture or space sector.

Some agricultural and space applications, which share similarities to the operations of planetary surface greenhouses, are presented in the following.

2.1 AR Applications for the Terrestrial Agricultural Sector

Katsaros and Keramopoulos [24] developed a prototype application named "FarmAR". The application identifies plants and displays plant-specific information on a mobile device, such as their common name, scientific name, and notes about their cultivation. This information is used to augment the reality of the live camera view. In addition, information about common diseases and environmental parameters are visualized. [24, 25]

Neto and Cardoso [26] developed an AR prototype, which can be used on smartphones as an early warning system for a potential fungal infestation in tomato plants with *Botrytis cinerea*. Furthermore, crop-related information such as crop type or sowing date, environmental conditions and the irrigation schedule can be visualized. [26]

Another prototype application in the agricultural sector was developed by Nigam *et al.* [27]. It aims to support farmers with little knowledge in entomology using an Android application on their mobile devices to precisely define the infestation of insects on their crops and identify possible countermeasures. [27]

Shaleendra *et al.* [28] designed an Android-based AR prototype called "AR-Glasshouse" that allows greenhouse operators to

visualize how their greenhouse could be automated and the potential benefits of automation. [28]

Bekiaris *et al.* [29] developed an application called "Greta" that can be used to monitor and control intelligent greenhouses. It has an AR application part, which can be used on handheld devices to display greenhouse status information such as grown plants, their condition, and environmental conditions. Moreover, hardware in the greenhouse can be controlled via controls visualized in AR. [29]

All mentioned applications are still individual pioneers and not yet broadly used in the agricultural sector. Additional examples of applications in the agricultural context can be found in the literature review conducted by Hurst *et al.* [30].

2.2 AR Applications for Space

AR can also be used in various space application areas. For example, it could be used to artificially augment the constrained habitat volume [31, 32], support early design phases for space hardware [33–37], support planetary research [38, 39], support space hardware assembly, integration and testing activities [40–42] or support astronaut training on Earth [43–46]. It can even be used for surgical training or medical emergencies during long term space missions to provide medical instructions and guidance to astronauts with only basic medical training [40, 47].

The more detailed examples below share similarities to the activities in a planetary surface greenhouse.

2.2.1 Astronaut Support in Space

Additionally, AR can be used to support astronauts on space stations such as the International Space Station (ISS) during their daily work to reduce crew time, increase astronaut efficiency [48] and enable hands-free operations [14, 49].

In 1998, Agan *et al.* [49] published a paper in which the function of a wearable computer coupled to a head-mounted display (HMD) with AR functions was presented. The so-called "WARP" (Wireless Augmented Reality Prototype) system of NASA, intended for use on space stations, is designed to enable the display of text and images as well as measured biosensor data by the system and real-time audio/video communication via the HMD. [49] [50]

The "WEAR" (Wearable Augmented Reality) project funded by ESA investigated how location and context-sensitive information can be visualized and managed on an AR system. Astronauts could look at checklists, execute procedures and get additional information when needed. [14, 51]

Another assistance tool funded by ESA, which was already tested on the ISS in 2015 is the "mobiPV" (mobile Procedure Viewer). The main task of this system was to display procedures to the astronauts and support them during the task execution. [13, 15, 41]

In a follow-up project funded by ESA called "EdcAR" (Engineering data in cross-platform AR), the data provided by the "mobiPV" system was visualized in AR using the EPSON Moverio Pro BT2000. [52]

Markov-Vetter [46] also investigated how AR-based assistance systems should be designed to support and simplify the work of astronauts onboard the ISS, for example when working with payloads. For this purpose the "MARSOP" (Mobile AR for Space Operations) system was developed and field tested. [46]

Building on the experience gained during NASA's "Sidekick" project [53, 54], with the goal of using Microsoft HoloLens to virtually assist astronauts onboard the ISS in performing procedures and enabling remote support from Earth, NASA's "T2 Augmented Reality" (T2AR) project [55, 56] demonstrated the use of Microsoft HoloLens for maintenance and inspection of science and training equipment without support from Earth during ISS Expeditions 64 and 65.

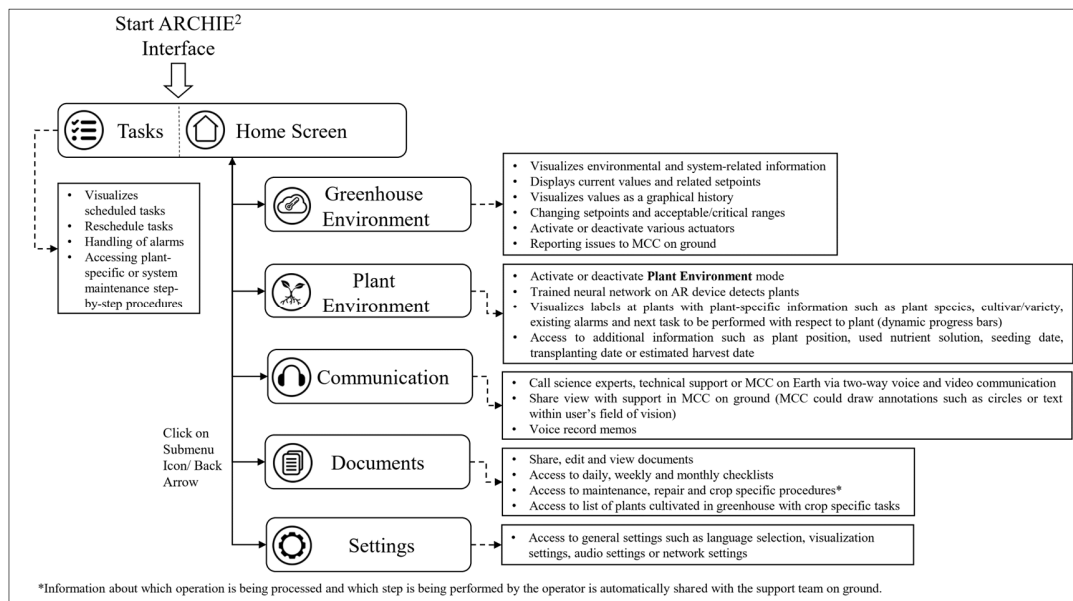


Figure 1: Screen flow of the ARCHIE² AR interface and functions of the interface sorted by dedicated menu/submenus.

Another topic studied is how AR can be used in future planetary missions, such as on the Moon (e.g., as part of the Artemis program). For example, Ahsan *et al.* [57] developed the "ARGOS" (Augmented Reality Guidance and Operations System) system using it for future training or in operational environments to make EVAs safer, more effective and more efficient. [57]

2.2.2 Greenhouses in Space

Since plant cultivation will be an integral part of future space missions, Bhardwaj *et al.* [58] presented an idea at a very basic theoretical level to use multiple robots to interact with plants and maintain bioregenerative life support (e.g., harvesting) in a sealed and controlled part of a spacecraft to reduce the exchange of pathogenic microorganisms between plants and astronauts. For this purpose, the cultivation area is projected into AR. The astronaut's hand gestures are tracked and replicated to control robotic manipulators in the sealed cultivation chamber. However, the main focus of this study was on the design of the spacecraft. [58]

The literature review in this paper has shown that AR applications, despite their multiple potential uses and far-reaching benefits in supporting work processes, have very limited and non-standardized prototypical applications in the greenhouse context on Earth. Xi *et al.* [59] and Hurst *et al.* [30] also confirm that despite the widespread use of AR, there is still a huge need for research on AR in the agricultural sector, also evidenced by the low number of publications in this research area especially with respect to AR in greenhouses.

When considering the general use of AR during space missions, it should be noted that some of the prototypes mentioned have already been tested in space missions, but none of them are standardized. With respect to the use of AR to support the plant growth under space conditions, it was shown that apart from the publication of Bhardwaj *et al.* [58], we are not aware of any other studies on the use of AR or even the practical implementation of AR applications in space greenhouses.

Therefore, a reliable comparison of new AR applications for lunar surface greenhouses with existing ones is hardly possible. It remains an immense need for research to evaluate whether the use of AR in the context of plant cultivation in space is beneficial and could help astronauts in their operations of greenhouses during

future space missions to reduce their crew time and workload and that of the remote support teams on Earth.

2.3 Agricultural Plant Object Detection

The deep learning algorithm YOLO [60] is used for object recognition in various domains. YOLO based detectors with many advancements (e.g. YOLOv3) and modifications (e.g. R-YOLO) have been proven to be effective for recent applications in agricultural contexts.

Zheng *et al.* [61] compiled a plant detection dataset of 31,147 images called CropDeep displaying different crops in varying lighting conditions, growth phases and camera angles in order to train an object detector which could be used in future applications such as picking robots. A comparison among different object detectors on the CropDeep dataset resulted in a recommendation of the YOLOv3 network as it outperformed other object detectors (e.g., Faster R-CNN, SSD, RFB, YOLOv2 or RetNet) in the combination of detection accuracy and speed. It reached a mAP@[0.5] (mean average precision) of 91.44 while performing at 40 FPS. [61]

Yu *et al.* [62] describe how an adjusted YOLO implementation named R-YOLO is utilized to construct a strawberry harvesting robot. The embedded controller on the robot (NVIDIA Jetson TX2) can process 18 640x480 pixels images per second which is described as an excellent real-time performance by the authors. R-YOLO is reaching an overall precision of 94.43%, and the picking robot manages to pick strawberries with a success rate of 84.35% in a harvesting field test. [62]

Another design for a tomato picking robot system is based on the YOLOv5 framework [63]. YOLOv5 detection is combined with a depth camera to determine the three-dimensional coordinates at which the robot can pick the tomato. A set of 1,645 tomato images was collected and used to train the YOLOv5s deep learning model. The network was able to process one image in 104 ms on average which corresponds to a frame rate of 9.62 FPS. [63]

All these contributions show the prevalence of the YOLO framework in agricultural plant detection tasks which underline the decision also to make use of the YOLOv5 framework for plant detection in this work. In the context of this paper, no publications could be found which used an AR headset combined with plant detection in a greenhouse environment.

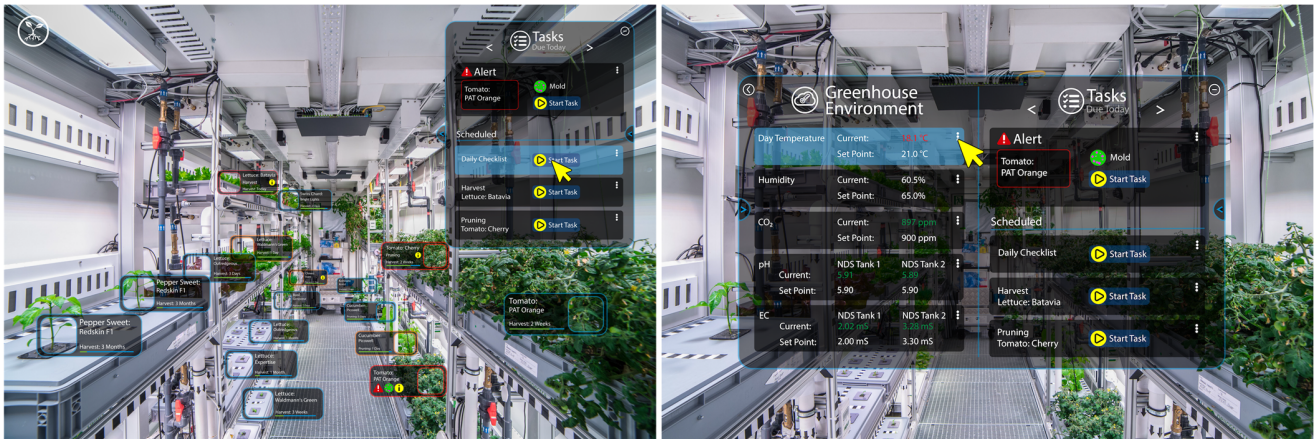


Figure 2: Concept of the ARCHIE² AR interface: Exemplary user view on the AR headset showing the scheduled tasks and plants inside the EDEN ISS greenhouse augmented with labels visualizing plant-specific information (left); **Greenhouse Environment** submenu (right). The yellow mouse pointer only illustrates a selection action on the interface (not part of the prototype). [17]

3 ARCHIE²: AR INTERFACE FOR A PLANETARY SURFACE GREENHOUSE

A research goal of the EDEN ISS operation scenario investigations was to develop and investigate processes for higher plant cultivation [64]. As mentioned previously, research [9, 10] and experience gained during the EDEN ISS missions in Antarctica concerning the operations of a space analog greenhouse have indicated that crew time and workload demand of the operation teams of a planetary surface greenhouse needs to be optimized to enable future space missions with integrated planetary surface greenhouses.

Based on these investigations, five possible application areas: the display of technical greenhouse information, display of plant-specific information, display of planning tools, communication tools and document processing functions (Table 8 in supplementary materials) are derived for implementation in an AR interface, to support on-site operators of planetary surface greenhouses and remote support teams on Earth [18]. Using these application areas and the EDEN ISS operation procedures, the ARCHIE² AR interface concept was developed to facilitate working processes used for planetary surface greenhouse operations and presented in Zeidler and Woekner [18] based on the preliminary work of Woekner [17].

3.1 Structure and Functions of the Design

The ARCHIE² AR interface consists of the main menu (**Home Screen and Tasks** menu) and five submenus **Greenhouse Environment, Plant Environment, Communication, Documents** and **Settings** (exemplary images in supplementary materials). By starting ARCHIE² on the AR headset, the greenhouse on-site operator is presented with the **Home Screen and Tasks** menu. From the **Home Screen**, it is possible to access the submenus. The **Tasks** menu is used for visualization and rescheduling of scheduled activities and accessing related plant-specific procedures. In addition, it lists all existing alarms in the greenhouse. [18]

Figure 1 shows the screen flow of the ARCHIE² AR interface with the functions of the specific menu/submenus.

3.2 Greenhouse Environment

The **Greenhouse Environment** submenu visualizes all relevant environmental and system-related parameters in the greenhouse and actuator data. Current values and related setpoints are

displayed. The user can manually modify setpoints and activate or deactivate the various actuators. [17, 18]

3.3 Communication

In the **Communication** submenu, the user can approach various points of contact such as science experts, technical support or the mission control center (MCC) on Earth via an integrated two-way voice and video communication interface for assistance in preparing or performing tasks in the greenhouse. It is possible for the interface user to share the view with the support on ground, who then can draw annotations such as circles, arrows or text within the user's field of vision. [17, 18]

3.4 Plant Environment

By clicking on the **Plant Environment** submenu on the **Home Screen**, the **Plant Environment** mode can be activated/deactivated. An activated **Plant Environment** mode is symbolized by a white icon in the upper left corner of the user's field of vision (Figure 2), which can also be used by clicking on it to toggle the **Plant Environment** mode. [17, 18] In activated **Plant Environment** mode, plants are detected by a trained neural network using the plant detection module of the **Plant Environment** submenu on the AR headset by evaluating the camera video stream. Furthermore, labels on the plants in the greenhouse are activated in three-dimensional space. Dimensions and coordinates of the detected plants are used to display corresponding labels visualizing plant-specific information such as plant species and cultivar/variety.

To minimize the scope of additional organizational tasks for the users, such as manual marker placement, the solution approach of fully automated plant detection by machine learning (ML) was chosen. Compared to the use of optical markers or virtual markers in three-dimensional space, which store the plant-specific information, no markers need to be manually moved when a plant changes location. In addition, no misplacement of labels could occur, because the position of the labels does not need to be approximated near the aeroponically/ hydroponically grown plants due to the plant detection process. Furthermore, the markers cannot become soiled or obscured as is the case with optical markers. [65] Furthermore, plant detection could be the first step towards a more sophisticated system that continuously supports the user in the greenhouse. More advanced algorithms could use granular plant detection to guide the user in pruning the correct parts of the plant through visual markers or to assign additional information to plants, such as detected diseases or the maturity of a particular fruit.

If several plants of the same cultivar/variety are grown in various locations in the greenhouse, information such as three-dimensional coordinates of the detected plant would be needed in addition to its cultivar/variety to specify exactly which plant is meant and visualize the correct plant labels. If the coordinates are not yet stored in the system, a new instance for coordinates and cultivar/variety is automatically created in the system. Thus, the plant information stored in the system can be uniquely assigned and displayed to the user upon detection. [65]

In addition, the plant-specific information is complemented by additional information such as existing alarms, visualized as icons, and the next task to be performed concerning the specific plant, which is displayed with a dynamic progress bar illustrating the time remaining until then. Example tasks could be harvesting, transplanting or pruning of plants. A window with additional plant-related data such as plant position, used nutrient solution, seeding date, transplanting date or estimated harvest date can be opened by clicking on the corresponding plant label. For this purpose, the ARCHIE² AR interface is coupled with a database on a server where this information is maintained by the on-site operators of the greenhouse. Furthermore, colored frames indicate the urgency of activities on the specific plant. Blue frames visualize that no task is to be performed today or tomorrow. Orange ones indicate a task to be performed tomorrow, and red ones today. [17, 18]

3.5 Documents

The **Documents** submenu gives the user access to various pieces of information and documents such as checklists and procedures used in the greenhouse. Furthermore, a list of all the plants cultivated in the greenhouse with plant specific information can be accessed. All procedures and checklists are presented on the AR display as step-by-step instructions with additional explanations/information and the option to call for support from MCC on Earth. During the execution of a procedure, it is also possible to record notes or take photos for documentation. Information about which operation is being processed and which step is being performed by the operator is automatically shared with the support team on ground. [17, 18]

4 IMPLEMENTATION OF THE PLANT ENVIRONMENT INCLUDING ITS PLANT DETECTION MODULE

Based on the special conditions of a lunar surface greenhouse, the **Plant Environment** submenu (Section 3.4) represents a central feature of the ARCHIE² AR interface. For this paper, the **Plant Environment** submenu with its plant detection module was implemented on an AR headset (Microsoft HoloLens 2). The steps required for this are: 1) Object detection model selection, 2) Baseline dataset preparation, 3) Iterative training process and preparation of plant detection model for arugula selvatica, 4) Implementation on HoloLens 2. The following explanations are based on the work of Klug [65].

4.1 Object Detection Model Selection

Given the realization of the plant detection, it is necessary to train an artificial neural network accordingly. The implementation of plant detection in this paper mainly relies on the YOLOv5 framework [66]. We refrain from creating another plant detection model or using other frameworks since the successful integration of YOLO-based models in the plant detection context has already been proven by various publications [61, 67].

As a result of the limited computational power of HoloLens 2, the pre-trained, 283-layer, YOLOv5s deep learning model was trained for plant detection. It was the smallest and fastest model of the YOLOv5 framework at the time of training start, resulting in potentially higher performance and, accordingly, a potentially better user experience on the HoloLens 2. The YOLOv5s model

was pre-trained on the Microsoft Common Objects in Context (MS COCO) dataset [68].

Furthermore, the automatic scaling function of the YOLOv5 framework was used for the images. In addition, the default settings of the data augmentations of the YOLOv5 framework were used during training to achieve robust plant detection even with a small number of training images.

4.2 Baseline Dataset Preparation

To train the neural network for use in the context of the EDEN ISS greenhouse we used a baseline dataset of 731 annotated images. Of these, 314 top-view and 334 side-view images showing arugula selvatica plants in various development states and under relevant lighting conditions, as well as images of other plants and entirely without plants were used from the EDEN ISS greenhouse (Figure 3). This was done since no large datasets of arugula selvatica plant images were freely available.



Figure 3: Exemplary neural network training images: (A) EDEN ISS side-view image showing arugula selvatica plants; (B) EDEN ISS top-view image showing arugula selvatica plants; (C) EDEN ISS greenhouse image without plants; (D) EDEN ISS top-view image showing Brassica rapa ssp. narinosa plants.

The EDEN ISS images were taken from the fixed-mounted cameras during the period from 2018 to 2021 inside the EDEN ISS greenhouse. Two different camera models were used: HIKVISION DS-2CD2542FWD-I 4MP with an image resolution of 2688×1520 pixels and HIKVISION DS-2CD2185FWD-I(S) 8 MP with an image resolution of 3840×2160 pixels.

Images of arugula selvatica were used because the plant does not form fruits or flowers due to early harvesting, and therefore few morphological changes are observed during growth.

Due to limited perspectives and sometimes quality of the side-view images, the baseline dataset was additionally extended by 83 arugula selvatica images from external sources such as plantnet.org and images.google.com.

In Figure 3 white rectangles (upper left corner of image A and C) can be seen covering parts of the image. These manually created maskings hide the time stamp of the cameras and readable labels on the shelves inside the greenhouse. This was conducted to prevent the neural network being trained from using the letters and numbers as features to detect arugula selvatica.

4.3 Iterative Training Process and Preparation of the Optimized Plant Detection Model

To obtain a model for detecting arugula selvatica within the EDEN ISS greenhouse, different datasets were formed using subsets of images of the baseline dataset (Section 4.2) to be used for training the YOLOv5s model. The datasets were modified in an iterative process by augmentation of images, which was applied in addition to the augmentations from the YOLOv5 framework, adding images, or changing the annotations to investigate the effects on the training results.

The basis for the modification of the datasets was a comparison of the performance metrics $mAP@[0.5:0.95]$, object loss and box loss, as well as a review of the images annotated by the models to achieve robust plant detection of arugula selvatica from multiple perspectives.

For each iteration of the dataset, at least one training run was performed. The model was always untrained at the beginning of each run. Therefore, the starting point was the same for all runs.

Before each training run, the datasets were split into training and validation sets. The validation set was unknown to the trained model, ensuring that the model was generalizing and did not learn the specific features of the training data.

At the beginning of each training run, the training configuration values were manually set: on which image size, with which batch size and over how many epochs the model should be trained. The YOLOv5 hyperparameters such as momentum, initial learning rate or weight decay were set to default parameter settings for training as described in Jocher [69]. Following an epoch, the performance metrics of the model trained up to that epoch were calculated for the training and validation set. This allowed a comparison to be made between the performance of the model on known data and unknown data to evaluate whether the model was generalizing. After each batch of images, the weights of the YOLOv5s model were adjusted based on the achieved loss values to minimize the overall loss function.

The composition of the dataset selected to train the model used on an AR headset can be seen in Table 1. The composition of the other datasets and the corresponding evaluation of the training results can be found in the supplementary materials.

Table 1: Composition of the dataset selected to train the model used on an AR headset for arugula selvatica detection. [65]

Source of Images	Content of Images	Number of Images	Number of Annotated Instances
EDEN ISS Greenhouse	Top-view with arugula	618	10,510
	Side-view with arugula	668	1,182
	Without arugula**	57	0
External	Various	67	110
Total		1,410	11,802

** Images without arugula selvatica are from various perspectives.

The configuration values for the training of the dataset selected for the model used on an AR headset were set to an image size of 320×192 pixels, a batch size of 8, and 300 epochs. The resolution of the processed images was 320×192 pixels, scaled by the YOLOv5 framework. The 320×192 pixels resolution was the largest possible resolution that resulted in a good usable application on a laptop¹ and was determined by successively decreasing the model size, with subsequent testing on the laptop. In addition, Zheng *et al.* [61] reported good crop detection results on a similarly sized model (300×300 pixels), a YOLOv3 neural network trained with their CropDeep Agricultural Dataset. In the following, this model is referred to as the YOLOv3 CropDeep model.

The trained and optimized 320×192 pixels plant detection model, hereafter referred to as the arugula model, detects arugula selvatica as one class.

4.4 Implementation

The ARCHIE² plant detection module using the arugula model is implemented on the HoloLens 2 using Microsoft's Mixed Reality Toolkit (MRTK). Unity and the Barracuda framework are used for the integration of the trained neural network. Since the plant detection by the neural network has to be executed on the main thread within the Unity application, the computations required for this are split across multiple frames. Otherwise, the main thread would be blocked, resulting in performance degradation.

The architecture (Figure 4) consists of three modules: the MediaCaptorer, the Neural Network Manager (NNManager) and the LabelRenderer.

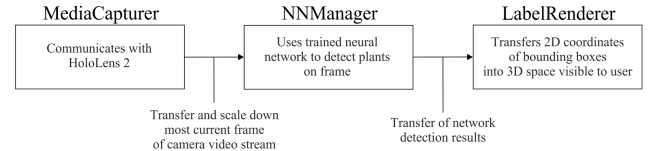


Figure 4: Prototype architecture with functions of its modules. [65]

The MediaCaptorer module is responsible for communicating with the HoloLens 2 to transfer the current frame of the camera video stream to the NNManager. During this process, the resolution of the transferred frames is scaled down to the trained resolution of the neural network. Then the NNManager performs the plant detection on the frame and forwards the results (i.e., the class labels of the detected plants and their bounding box coordinates) to the LabelRenderer. Subsequently, the LabelRenderer transfers the two-dimensional coordinates of the bounding boxes into the three-dimensional space visible to the user.

Augmentation labels (Figure 5) are placed at the three-dimensional location of the bounding box coordinates. The augmentation labels contain placeholders for the plant's name, the duration until harvest and icons for status messages.



Figure 5: Augmentation label of the AR interface for the detected arugula selvatica plants with information on the name of the plant, the duration until harvest and icons to draw attention to status messages. The label is visualized on the ARCHIE² AR interface. [65]

As the plant detection application runs directly on an AR headset, only the five most likely detections on the frame of the camera video stream are visualized for the user to keep the prototype less cluttered. In future work, we will remove this limitation and add the capability to visualize unlimited labels with appropriate off-screen label visualization techniques (Figure 2). Hence, a maximum of five labels are displayed at the same time.

Furthermore, it is checked in each frame whether new and more likely plant detections of the neural network are available. In addition to updating the positions of the labels in each frame, the rotation of the labels in each frame aligns so that they face the user.

¹ Results achieved with a laptop equipped with an AMD Ryzen 7 5800H processor and a GeForce RTX 3060 graphics card.

The user can deactivate or activate the plant detection. In the case of deactivated plant detection, the change of position and rotation of the labels and the deactivation of the labels stop. This allows the user to grab the labels and move them manually to more sufficient positions.

5 EVALUATION AND DISCUSSION

The evaluation of the prototype is divided into performance tests, perspective tests and accuracy evaluation.

5.1 Performance Test

The ARCHIE² plant detection module was launched locally on the HoloLens 2. No user was involved in and no plants were observed during the performance test as applying the plant detection process to any picture puts the same load on the processor of the HoloLens 2. Over 60 seconds, the achieved frame rates, metrics based on them (i.e., x% LOW values) and average inference times of the neural network were measured. Furthermore, the measurement was also performed on a laptop in the Unity editor to form a comparative value. These measurements can provide indications of possible performance improvements using future AR headsets.

Since the computations required for the plant detection by the neural network are split across multiple frames, a trade-off between performance and inference time is required to determine the lowest possible inference time of the model while maintaining a high performance of the ARCHIE² AR interface. Therefore, measurements were taken with a varying number of layers of the neural network computed within one frame to determine the maximum as well as minimum frame rates and inference times (Table 2).

Table 2: Results of the performance tests of the arugula model, conducted on the HoloLens 2. A different number of layers of the neural network were computed within one frame. x% LOW is a measure for the average of all frame rates in the x-percentile (average of lowest frame rates). [65]

Device	Computations ***	Average FPS	0.1% LOW	1% LOW	10% LOW	Inference [ms]
Holo- Lens 2	1	57.18	20.91	26.60	34.95	5,094.58
	2	49.91	14.17	22.94	32.25	2,890.10
	5	49.55	11.96	21.79	31.95	1,175.83
	10	48.21	9.76	21.50	31.95	602.17
	50	37.30	8.80	10.01	11.81	251.33
	100	40.12	4.93	5.11	5.45	207.62
	283	41.44	3.93	4.34	4.65	183.53

*** The term computation indicates how many layers of the neural network are computed per frame.

Using the arugula model on the laptop, frame rates of 40 FPS were not undercut for up to 100-layer computations per frame. The inference time reached a value of 23 ms for 100-layer computations per frame.

5.1.1 Discussion of the Performance Results

For the classification of the frame rates achieved by the ARCHIE² AR interface during the performance tests, a study from 2007 is used [70], which measured the performance of test persons within a first-person shooter computer game depending on different frame rates. The tasks to be completed by the test persons were the control of a virtual avatar, with mouse and keyboard, through an obstacle course and accurate shooting within the computer game. It was found that such games are almost unplayable up to a maximum of constant 7 FPS. The study found significant performance increases in the test subjects starting at 7, 15 and 30 FPS, with the maximum

performance at 60 FPS. In addition, the measurements suggest that increasing the frame rate above 60 FPS does not provide much added value. [70]

As a result, the prototype is considered unusable up to a maximum performance of 7 FPS, limited usable between 7 and 30 FPS, and good usable from a constant performance of 30 FPS. The assumption of good usability from 30 FPS is supported by the elaboration on YOLOv4 by [71], in which models with at least 30 FPS were called real-time detectors. Zheng *et al.* [61] also described a frame rate of similar magnitude (40 FPS) for the YOLOv3 CropDeep model as appropriate for crop detection tasks in an agricultural context, such as in greenhouses.

The maximum performance by computing one layer per frame on HoloLens 2 using the arugula model, was at a 1% LOW value of approximately 27 FPS and a 10% LOW value of approximately 35 FPS, with an inference time of approximately five seconds. Since only one frame of the camera video stream was evaluated every five seconds at this inference time, this configuration is not practical.

In terms of higher performance and lower inference time, the results of the experiment with the calculation of 10 layers per frame stand out. In this configuration, an inference time of 602 ms and an average of 48 FPS, a 10% LOW value of approximately 32 FPS, and a 1% LOW value of approximately 22 FPS were reached on the HoloLens 2. Thus, the 1% LOW value decreased by 5 FPS and the 10% LOW value decreased by 3 FPS, but in return, the inference time decreased by 8.5 times compared to the results with a one-layer computation per frame. Accordingly, the HoloLens 2 prototype with the arugula model (320x192 pixels) could mostly be used well with 10-layer calculations per frame, although a constant 30 FPS was not achieved.

5.1.2 Limitations of the Performance Results

The significance of the results concerning the performance is limited by the fact that only by conducting a user study can it be concretely proven whether and from what level of performance the ARCHIE² AR interface is usable in plant detection.

The performance fluctuations can be reduced by temporarily deactivating plant detection. Plants detected up to that point remain augmented while performance normalizes to 60 FPS, which is the target frame rate of the HoloLens 2. Therefore, only short phases of activated plant detection are necessary to display the required information. Nevertheless, permanently turning the plant detection on and off could also have a negative impact on the user experience.

Further, the validity of the prototype's usability is limited due to the comparison with the study on first-person shooters [70]. Both the modalities of interaction and the goals of the application are different between the computer game and the prototype. It could be assumed that compared to the presented prototype, the impact of the achieved frame rates on the performance is higher for first-person shooters. This is because first-person shooters require high responsiveness, precision and hand-eye coordination. Due to that, the prototype could already be considered consistently usable using the arugula model, as the threshold for good performance, in this case, could be lower than 30 FPS.

Similarly, the comparison with the frame rates of 30 and 40 FPS from the YOLOv4 model [71] and YOLOv3 CropDeep model [61] elaboration should be critically considered. Both elaborations did not justify why these values are sufficient for a real-time application and did not explicitly address AR applications with user interaction. In the context of this paper, no references could be found that investigate the usability and performance parameters such as frame rates and inference times of AR applications using plant detection.

5.2 Perspective Test

The perspective test was conducted to check the practicality of the prototype and to test the capability of detecting a real arugula selvatica plant from different perspectives.

For the experimental setup (Figure 6), the plant was placed at three different heights (0 cm, 55 cm and 110 cm) and viewed at each height from four different horizontal distances (25 cm, 50 cm, 75 cm and 100 cm).

As a result, it was recorded whether or not detection and annotation occurred at the corresponding combination of height and distance. The HoloLens 2 was carried by a 184 cm tall test person throughout the entire test series. The positioning of the test person in front of the arugula selvatica plants was frontal and centered. The test person's gaze was directly on the plants at the various heights.

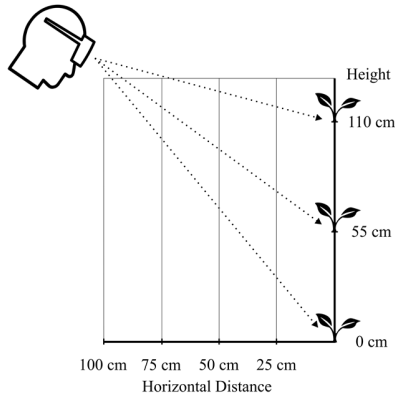


Figure 6: Experimental AR interface setup for perspective test. [65]

The results of the perspective tests show that the arugula model was unable to detect arugula selvatica plants at height of 0 cm (placed on the floor) and 55 cm. The prototype detected and augmented arugula selvatica plants at a height of 110 cm up to a horizontal distance of 50 cm.

5.2.1 Discussion of the Perspective Results

The fact that the detection and augmentation of the plants only occurred when the user was in the vicinity of them slightly limits the usability of the prototype in a practical use case. New plants in the greenhouse would always need to be viewed at close range with the HoloLens 2 in order to detect the plants and link the plant labels with the actual 3D coordinates.

In the concept, the potential time savings of the HoloLens 2 compared to conventional methods is the main argument for its use. Therefore, the **Plant Environment** provides, among other things, the capability to visualize an overview near the plants of the planting date, the harvesting date, and which plants are currently in the need of care. Once all the plants in the greenhouse have been detected, all the detections could be displayed based on their 3D coordinates, including the associated plant information mentioned previously. In this way, only the initial plant detection process would be somewhat limited.

5.2.2 Limitations of the Perspective Test Results

A limitation of the results of the perspective test is the composition of the dataset on which the model was trained for the plant detection of arugula selvatica and its impact on the evaluation.

The two camera models used are wide-angle cameras. The lens of the HIKVISION DS-2CD2542FWD-I 4MP has a focal length of 2.8 mm with a 106° angle of view and the lens of the HIKVISION DS-2CD2185FWD-I(S) 8 MP has the same focal length with a 102° angle of view. The wide angle of view results in slight distortions of the image at its edges, which could also have a negative effect

on the plant detection results, since the focal length of HoloLens 2's photo/video camera is 4.87 mm +/- 5% and the angle of view is 64.69°.

The nature of the annotation, within the training dataset, may have contributed to the poorer plant detection results from a higher distance. During the annotation process, a bounding box was put around each arugula selvatica plant as accurately as possible. If the plants overlapped too much, so that a clear assignment was no longer possible, several plants were annotated together within one bounding box, following the plant annotation recommendations of Zheng *et al.* [61]. By annotating each plant, the option was kept open to indicate procedures to be performed, such as pruning, precisely on a specific plant. This resulted in many very small annotations of plants and a low number of pixels within the bounding boxes. If all overlying arugula selvatica plants had been combined into one bounding box, regardless of whether individual arugula selvatica plants were detectable, then the bounding boxes for training would have been correspondingly larger. As a result, the arugula model (320x192 pixels) would also have had access to a larger number of pixels from which features could have been formed, which could result in better plant detection results.

5.3 Plant Detection Accuracy

The arugula model achieved a mAP@[0.5:0.95] value of 0.5368. The mAP@[0.5] value of the arugula model is 0.8731. Zheng *et al.* [61] reported a similar mAP@[0.5] value of 0.9144 for their YOLOv3 CropDeep model, which has a similar size (300x300 pixels) to the arugula model (320x192 pixels). Despite the slightly higher mAP@[0.5], it should be noted that the YOLOv3 CropDeep model considers different crops, which limits the comparison of mAP@[0.5]. The previously described mAP@[0.5] values are in a similar range to the RetNet crop detection network's mAP@[0.5] value of 0.9279, which is described as excellent accuracy [61].

6 CONCLUSION AND OUTLOOK

In this paper, we reported on the concept of an AR interface that supports operational tasks to maintain future planetary surface greenhouses. In particular, the implementation and performance of its plant detection module that runs locally on the AR headset for arugula selvatica plant detection and augmentation was presented. Plant detection is feasible with an average frame rate of 48 FPS and an inference time of approximately 602 ms at a height of 110 cm up to a horizontal distance of 50 cm. The AR interface prototype demonstrated proof of concept that plant detection processes can be performed directly on an AR headset. Measurements of frame rates and inference times provide benchmarks for future research in that area. Moreover, the prototype could be used in terrestrial greenhouses or vertical farms.

Furthermore, the approach could be used analogously to detect additional plant species. To implement this, further and more extensive datasets for additional plants need to be created and annotated, as there is a deficit in the agricultural context for this [61]. Such datasets could also improve the model generalizability of our prototype in terms of detecting various plant varieties through additional training. In addition, the impact of the image quality of training datasets on plant detection performance and accuracy could be examined.

The literature review has shown that there is still a huge demand for research in the field of AR applications for terrestrial greenhouses, but especially for lunar surface greenhouses. We will continue to work on the ARCHIE² AR interface to expand its features and improve its practical use. We are planning to conduct a user study for the interface under space analog conditions with different types of plants to evaluate further the effectiveness and performance of the proposed AR technology.

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