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Harnessing robotics for EU habitat monitoring

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***Abstract*—This paper presents a novel approach to forest habitat monitoring using robotics and advanced data analysis techniques. We introduce a quadrupedal robot with LiDAR and onboard cameras to collect detailed data about forest structure and composition. The data is then processed using a combination of data analysis techniques and machine learning algorithms to perform a comprehensive dendrometric and floristic survey. Our approach provides an efficient and accurate method for assessing the ecological health of forest ecosystems. This work contributes to the ongoing efforts in habitat conservation and offers a promising tool for future environmental monitoring tasks.**

***Index Terms*—robotic monitoring, quadrupedal robots, forestry**

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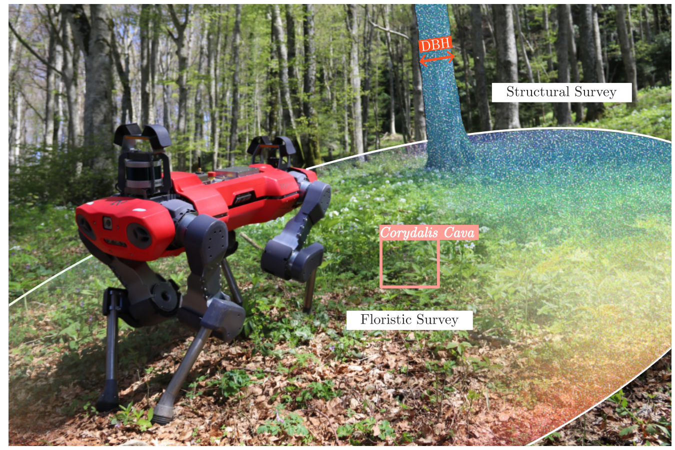

Fig. 1. The quadrupedal Robot ANYmal-C is equipped with a 3D LiDAR, able to create a point cloud of the environment, and a set of cameras. We use these sensors to estimate a series of critical indicators, such as tree Diameters at Breast Height (DBH) and the presence of typical species, that are essential to assess the conservation status of forest habitats.

I. Introduction

The assessment of habitat conservation status is acquiring an increasingly important role in the effort to measure and preserve biodiversity in the Anthropocene. The European Union (EU) aims to tackle this necessity with the Directive 92/43/EEC of the European Council (Habitats Directive, hereafter HD; 1992), which specifies habitats and species of interest. To pursue this fundamental objective, a coordinated network of conservation areas was designed, the Natura 2000 network. According to the HD, all European Countries must carry on the monitoring of Habitats listed in the HD Annex I every six years, periodically evaluating the outcome of conservation efforts and the achievement of conservation goals (HD, Annex I: Arts. 11 and 17). Forests encompass more than 50%, in terms of surface area, of the Special Areas of Conservation (SACs) in the Natura 2000 network. They harbour numerous several species that are of conservation concern [1], and frequently require restoration efforts due to their compromised conservation status [2], [3]. Moreover, the complexity of forest ecosystems poses a challenge for the monitoring, which requires personnel with advanced botanical knowledge and the capacity to move for extended periods of time in rugged environments with steep slopes and slippery terrains [4].

In this perspective, the pressing need for extensive monitoring of forest habitats becomes evident, while finding strategies and methods to reduce time consumption and costs of monitoring activities becomes a priority. According to the Habitats Directive (HD) Annex I, monitoring requires the selection of specific habitat plots of a fixed size and shape [5], [6]. Due to the complexity of the forest ecosystem [7], each plot is analyzed through two primary data collection methods:

- Structural Data, which involves a dendrometric survey

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that measures stem density and tree diameters at breast height (DBH).
- Floristic Data, that requires identifying dominant, typical, or relevant species, which indicate a healthy ecosystem, and detecting alien or synanthropic species, which signal potential degradation [5], [8].

To overcome the growing necessity of habitat monitoring, the H2020 European project Natural Intelligence (NI) aims to empower scientists' activities with robotic technologies. In particular, NI aims to automate the process of data collection, which comprehends most of the physical effort, and to augment the data processing capabilities [9].

In this article, we showcase a framework for robotic-assisted monitoring of EU forest habitats. In particular, we propose to assist plant scientists in data collection and data processing aimed at plot analysis. We showcase a robotic platform used for habitat monitoring, describe the data processing techniques employed to acquire conservation indicators and present the results of the monitoring executed with our method. In particular, we validate our method on habitat 9210(*) Apennine beech forests with *Taxus* and *Ilex*. We compare our results with those obtained with a conventional method carried out by plant scientists, showing that our methodology can act as a valuable tool to assist scientists in the effort required to follow the HD.

In Section I, we introduce the framework for robotic-assisted forest habitat monitoring, discussing its objectives and the necessity of such technology in addressing the challenges of traditional methods. In Section II, we review relevant works, focusing on existing technologies for forest monitoring such as UAVs, LiDAR, and ground robots. We highlight the limitations of these methods and introduce the quadrupedal robotic platform used in our work. In Section III, we describe the methods employed in our approach. This includes details on the study area, the robotic platform, data collection and processing procedures. Finally, in Section IV, we present the results of our monitoring efforts, comparing the robotic method to traditional techniques, and discussing its advantages and challenges.

II. Related Works

The growing need for efficient habitat monitoring has recently driven the research effort into the use of advanced technologies to aid in data collection and analysis. A range of sensing tools and robotic systems have been explored to address the challenges posed by complex environments like forests. Remote sensing has become an increasingly valuable tool in forest habitat monitoring [10]. Uncrewed Aerial Vehicles (UAVs) can be employed in forest monitoring when equipped with hyperspectral or multispectral cameras [11], [12], or with Light Detection and Ranging sensors [13], [14] (LiDARs). However, airborne data acquisition using these tools has limited capabilities for the assessment of Habitat Conservation status, which often requires close-up identification of indicator species located in the understory of the forest habitats and direct measurements of tree DBH. Due to the challenges associated with the acquisition of such data types, recent focus was given on the deployment of Autonomous Grounded Vehicles (AGVs). Pierzchała et al. [15], utilized a LiDAR sensor mounted on a wheeled robot, together with a 3D graph-mapping algorithm, to extract DBH measurements in a flat, semi-structured forest. Tremblay et al. [16] built upon this work, employing a different remotely-controlled wheeled robot with a LiDAR sensor for similar purposes in various forest types.

While UAVs and wheeled robots have shown promise, they are often constrained by terrain or limited in acquiring close-up measurements required for floristic surveys. Moreover, while these works proposed new forest inventory practices, they did not provide a workflow that can adhere to the standardized monitoring protocols outlined in the HD.

The NI project proposes a general workflow for robotic-assisted monitoring of EU habitats using quadrupedal robots [17] (Figure 3). In recent years, the locomotion abilities of quadrupedal robots, which have been mainly used only in human-related environments [18], were applied also to navigate outdoor and unstructured environments [19]. Recent improvements in reinforcement learning-based controllers have enabled quadrupedal robots to overcome stairs, gaps [20], climb obstacles [21] and human-level outdoor hikes [22]. Their high payload capacity makes them capable of localizing and navigating autonomously while acquiring all the data required for monitoring. When equipped with LiDAR sensors, for example, they have been already proven effective in forest structural analysis [23]. However, their deployment so far was focused on offering partial solutions to the challenges of forest habitats monitoring, often focusing on a specific type of analysis and neglecting the whole picture of Conservation Status assessments. To the best of the authors' knowledge, there is no validated solution for integrated habitat monitoring able to adhere to standardized HD protocols. Our work addresses these gaps by proposing a quadrupedal robotic platform that offers a robust, standardized approach for habitat monitoring in challenging forest environments.

III. Methods

We designed a comprehensive methodology (Figure 2) that mirrors conventional habitat assessment practices while exploiting the capabilities of our robotic platform. This section details our study area, the robotic platform used, the mission procedure for data collection, and the data analysis methods for both structural and floristic surveys.

A. Study area

The monitoring fieldwork was performed in the La Verna forest (Tuscany, central Italy), located within the "Foreste Casentinesi" National Park and included in the Special Area of Conservation (SAC) "La Verna - Monte Penna" (IT5180101) within the Natura 2000 Network. In particular, we decided to monitor habitat 9210(*) Apennine beech forests with *Taxus* and *Ilex*, which includes thermophilous beech forests that are considered of priority interest for the European Union, due to their high species richness and presence of taxa of conservation value.

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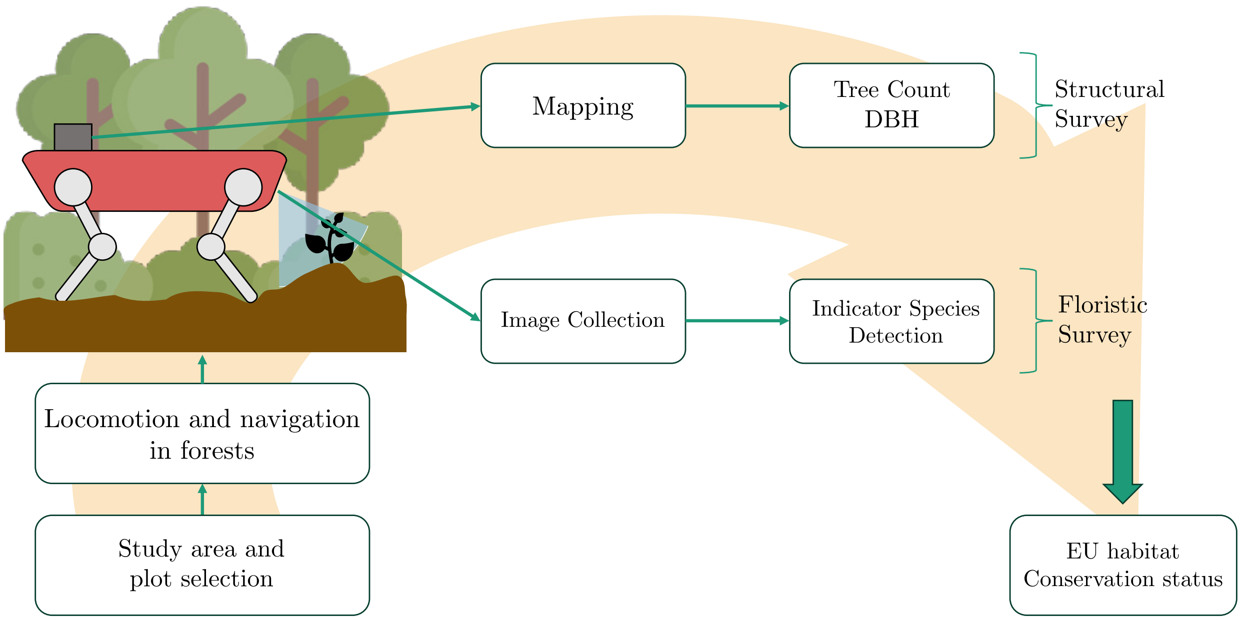

Fig. 2. Our workflow starts from a selected study area, in which the robotic platform performs mapping and image collection. These data are used by our framework for both structural and floristic surveys, with the structural survey focusing on tree count and DBH measurements and the floristic survey on identifying key indicator species. These insights ultimately inform the assessment of EU habitat conservation status.

We selected dates for the field work to coincide with the flowering season of nemoral (mainly geophytic) understory taxa, which are indicator species of the Habitat 9210*. We performed data acquisiton campaign in the last week of April 2022 and monitoring work in the first week of May 2023.

We selected five plots in the area. Three smaller plots were chosen in areas clean of obstacles, with clear ground, even terrain, and no trees, where we performed floristic surveys. These acted as a testbench to verify the feasibility of the robot deployment. Two larger plots with highly cluttered and uneven terrain, were then selected to perform a full structural survey. Table I reports the date, location and size of the selected plots.

These two larger plots also served as a benchmark for the locomotion performance of the robot. In particular, the robot needs to overcome high obstacles ($\geq$ 20cm), compliant and slippery terrains, which pose a challenge on quadrupedal locomotion.

Fig. 3. ANYmal-C is a quadrupedal robot equipped with cameras, depth sensors and a LiDAR, enabling it to autonomously locomote in rugged, unstructured environments.

B. Robotic platform

The robotic platform used for the survey is the quadrupedal robot ANYmal-C [24] built by ANYbotics AG (Zurich, Switzerland). This robot (Figure 3) has four legs, each with three actuated joints, enabling hip abduction/adduction, hip flexion/extension, and knee flexion/extension. The robot is powered by a 932.4 Wh lithium-ion battery, which gives it an autonomy of 2-4 hours on a single charge.

Plot	Date	Location (EPSG: 4326)	Size
1	03/05/2023	43.706862° N, 11.9355950° E	25 m^2
2	05/05/2023	43.70642° N, 11.928057° E	25 m^2
3	05/05/2023	43.70644° N, 11.928262° E	25 m^2
4	04/05/2023	43.708695° N, 11.9281201° E	200 m^2
5	04/05/2023	43.7075053° N, 11.935148° E	200 m^2

TABLE I
PLOT DATES, LOCATIONS AND SIZES.

ANYmal-C is equipped with a variety of sensors, including a Velodyne VLP-16 LiDAR, four depth cameras, two wide-angle cameras, an Inertial Measurement Unit (IMU), and joint encoders. An on-board state estimator algorithm fuses the angular rates and linear accelerations measured from the IMU with the joint encoder measurements and the feet contact state to estimate the robot's state, which includes position, orientation and velocity of the robot.

Exteroceptive sensors such as cameras and LiDAR are used to perceive the environment. The LiDAR sensor creates a three-dimensional model of the environment by measuring the

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time-of-flight of emitted laser pulses (Figure 1) The depth cameras use stereo vision to provide both colour images and range information.

The robot's locomotion controller is based on reinforcement learning [19]. This controller employs a neural network policy that modulates the leg trajectory generators [25] based on a history of proprioceptive information, such as feet and legs position and velocities, joint tracking errors, base orientation and estimated velocity [26].

The robot can be teleoperated wirelessly with a dedicated remote controller or with a laptop, and the onboard sensors enable it to work autonomously even in an unstructured environment like a forest. The computing power required to perform autonomously in these environments is satisfied by three on-board computers. Of these, two are dedicated to the locomotion and navigation of the robot, while a third is tasked with task-specific processing.

C. Mission Procedure

We designed the procedure of the monitoring to mirror typical botanist fieldwork practices. In particular, we performed monitoring on selected circular plots of around 200 m^2 (radius = 8 m), a size and shape commonly used to monitor forest habitats [7]. Each plot survey was carried out in two phases. In the first phase, the robot was teleoperated by a human operator to move around the area while acquiring LiDAR scans. During this phase, we use the *Simultaneous Localization and Mapping* (SLAM) algorithm of the robot, which merges measurements coming from the on-board LiDAR, a Velodyne VLP-16, which is mounted on the robot's back, together with the front RGB-D camera, an Intel RealSense D435i, and the on-board state estimator algorithms. The result is a 3D Point Cloud of the surroundings that is used by the robot to navigate and localise itself. The same point cloud is later used in the in the structural analysis to compute the number of trees and their DBHs. The second phase consisted of image acquisition. In this phase, the robot moved in a predefined grid pattern and systematically captured images and videos of the plant species at regular intervals. The grid consisted of waypoints arranged in a bottom-right to top-left pattern with a spacing of 1 m. Each waypoint consists of position and orientation of the robot's base in the map frame, with the orientation constant with respect to the initial robot's pose. At each waypoint, the robot oriented itself consistently before taking four photographs utilizing its four RGB-D cameras. Additionally, a video is continuously recorded during the mission from the four cameras. The resulting data, for each mission, consists of 4 images for each waypoint and a video.

Due to the highly unstructured nature of forest habitats, obstacle detection, and consequently avoidance, is a non-trivial problem in research. The presence of small branches, high grass and the foliage renders unsuitable most traditional approaches which are often suitable for clean environments where boxes, humans, walls or other furniture can be easily recognized from exteroceptive data. For all these reasons, we decided for safety purposes to remotely control the robot in the case of presence of obstacles, and operate autonomously when the area is clear of obstacles.

D. Structural Analysis

Estimating the structural vegetation properties of a forest habitat includes counting the number of trees and measuring their DBH. In traditional field surveys, scientists can measure directly the DBH using callipers, by taking two readings at right angles to take into account elliptical stems, or can derive this value from the circumferences measured from a tape measure at a height of 1.2 meters above the ground (Fig. 4). The data on tree location is primarily gathered through close-range traversals, which entail utilising a compass and a 100-meter tape measure to determine the tree's position accurately [27]. Our approach employs the data coming from the SLAM algorithm of the robot. The acquired point cloud is used by the robot to navigate and localise itself in the environment when moving autonomously. We employed the data processing pipeline described in [23]. As suggested by these authors, the parameters of the processing algorithm were hand-tuned for each plot, optimising the extraction of DBH_E to better fit the specific vegetation structural characteristics of each plot.

Fig. 4. Diameter at Breast Height (DBH) is commonly measured by expert personnel at 1.2 meters above the ground using a common tape measure.

E. Floristic Analysis

In addition to the dendrometric survey, we conducted a floristic survey to assess the presence of key species that are indicative of a good or bad conservation status of the habitat. Plant scientists typically perform this task by manually identifying all species present in the surveyed plots, often removing and collecting samples for further analyses. We focused on four species, shown in Figure 5 which are among the most indicative of the good conservation status of EU Habitat.

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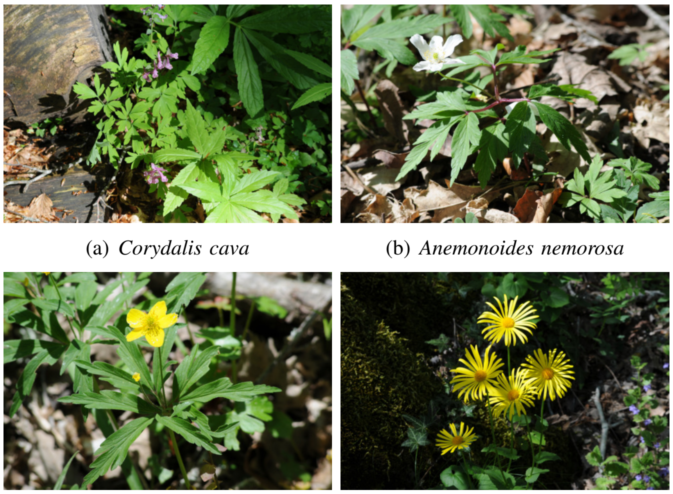
TABLE II
THE DATASET COMPOSITION IN NUMBER OF INSTANCES, AND THE DETECTION ACCURACY REACHED DURING TESTING.

Species	**Family**	**Ecological Role**	**Total Instances**	**mAP 50-95**
Anemonoides nemorosa	Ranunculaceae	Typical species	2882	0.51
Corydalis cava	Papaveraceae	Typical species	1182	0.409
Anemonoides ranunculoides	Ranunculaceae	Typical species	6544	0.547
Doronicum columnae	Asteraceae	Early warning	2867	0.735



(a) *Corydalis cava* (b) *Anemonoides nemorosa*

(c) *Anemonoides ranunculoides* (d) *Doronicum columnae*

Fig. 5. We selected as species of interest *Corydalis cava*, *Anemonoides nemorosa*, *Anemonoides ranunculoides*, and *Doronicum columnae*.

To automate the species identification process, we employed a Convolutional Neural Network (CNN). In particular, we adopted Ultralytics YOLOv9 [28]. Once trained on a sufficiently large dataset of labelled images, this model is able to detect and localise classes of objects in the input RGB image. As with any supervised learning task, the quality of the training data is crucial to the performance of the model. To this end, we collected a large dataset of images in the habitat of interest, including both images taken by the robot [9] and images taken by scientists during fieldwork. Table II reports the composition of the training dataset, together with the accuracy obtained in the validation dataset on every species. All the images were labelled by plant scientists, who identified and localised the species present in the image.

IV. RESULTS

In this section, we present the results of our framework in habitat 9210* Apennine beech forests with *Taxus* and *Ilex*. Table III shows the data relevant for conservation status assessment, acquired by our methods and by expert personnel on five plots of two different sizes, that represent two different monitoring efforts. We report two values for each measurement, the first refers to our robotic monitoring approach, and the second refers to the traditional expert-based methods. Time, in particular, refers to the total execution time for all the procedures, i.e. mapping and data collection for our framework, study area setup and surveys for the expert-based method.

We report the results of the structural analysis in the form of Tree detection error and estimated DBH error and bias. For the floristic survey, we report the results of the validation performed against scientists by counting the number of detected instances on four selected species of interest. In the following sections we explain in detail the results of the two analyses.

A. Robotic performance benchmark

Steep slopes, tree branches and slippery terrains make legged locomotion in forests a challenging task. Despite this, the locomotion controller of the robot, based on reinforcement learning [19], was able to successfully navigate the forest environment, overcoming branches and slopes up to 35° incline. Figure 6 shows the robot locomoting in forests despite challenging terrains. Table III reports the total power consumption of the robot for each plot.

Fig. 6. The forest of *Chiusi della Verna* (Arezzo, Italy) represents an unstructured and harsh environment, with steep hills, branches and uneven terrain. Despite this, the quadrupedal robot ANYmal-C is able to locomote safely in this scenario.

B. Structural analysis

For each tree, the estimated DBH_E is compared to the experts' measurements DBH_R, and the results in terms of bias DBH_b and root mean square error (DBH_{rmse}) are reported in Table 1. The error was computed with respect to the value measured by the expert botanists. Figure 7 shows the point clouds of two of the plots with the trees detected by the algorithm [23].

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TABLE III
RESULTS OF THE MONITORING. VALUES ARE REPORTED AS (ROBOT/SCIENTIST)

	Plot 1	**Plot 2**	**Plot 3**	**Plot 4**	**Plot 5**
Size	25 m^2	25 m^2	25 m^2	200 m^2	200 m^2
Time	6:44/9:00	3:52/10:00	3:63/15:00	41:23/63:40	63:24/52:34
Tree Detection Error	-	-	-	0 % (8/8)	0 % (3/3)
DBH_{RMSE}	-	-	-	11,28 %	20,36 %
DBH_b	-	-	-	4,63 %	0,61 %
Ind. Species					
Anemonoides ranuncoloides	0 / 0	0 / 0	37 / 43	-	-
Anemonoides nemorosa	12 / 15	0 / 0	0 / 1	-	-
Doronicum columnae	0 / 0	10/12	0 / 0	-	-
Corydalis cava	0 / 0	0 / 0	0 / 0	-	-
Power [Wh]	59,2	35,93	33,54	337,4	518,7
Power [%]	6,35%	3,85%	3,60%	36,19%	55,63%

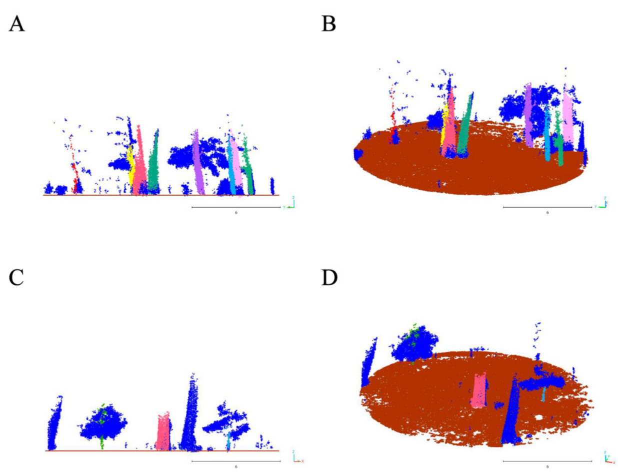

Fig. 7. Height-normalised point clouds of plots 1 and 2. Classified ground points are coloured in red. Each point classified as a detected tree is highlighted in pastel colours. Points classified as shrubs, tree leaves and tree stems occurring on plot boundaries are coloured in blue. A, B: point cloud of plot 4; prospect and oblique view, respectively. C, D: point cloud of plot 5; prospect and oblique view, respectively.

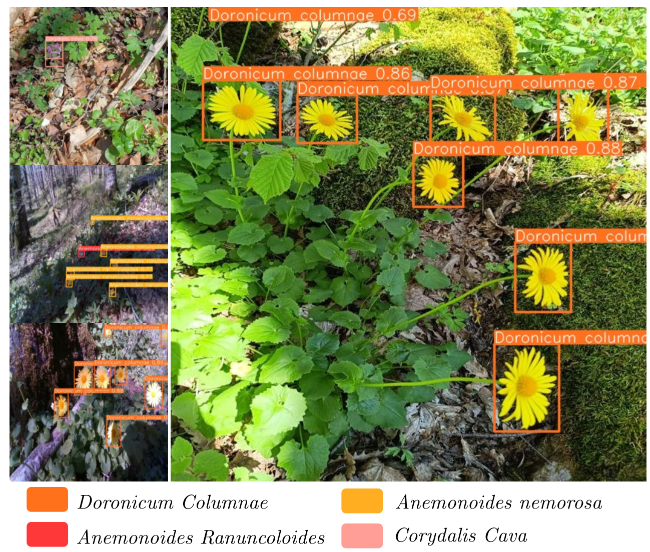

Fig. 8. The Neural Network model was trained to detect instances of the four selected species of interest in input images. The training dataset was built with pictures collected by the robot and by the scientists.

C. Floristic survey

Floristic characterization of habitats is based on the evaluation of the presence of indicator species in the habitat. We selected four species of interest, three typical species and one early warning species. Figure 8 provides examples of species identification performed by our Convolutional Neural Network (CNN) model on pictures taken by the robot during the monitoring.

In habitat monitoring, we are interested primarily in the presence of indicator species. To assess the performance of our system in its ability to detect them, we select a set of pictures acquired by the robot and compare the number of instances detected by our network and the number of instances counted by expert scientists in each image. This enables us to focus only on the effectiveness of detection. Results of this comparison are shown in Table III.

V. DISCUSSION

The results of this study demonstrate the feasibility and effectiveness of including a quadrupedal robot in the workflow for conducting EU forest habitat monitoring. In particular, Table III shows that the total elapsed time for our system is comparable with the time taken by expert-based monitoring and, in some plots, even lower. During fieldwork, botanists conduct data collection and analysis directly on-site, a process that, along with plot area setup, is inherently time-intensive. In contrast, on the robot, once mapping is complete, data collection can be initiated simply by defining the plot size and starting point. Moreover, as traditional expert-based monitoring typically requires at least two people for effective data collection, our robotic solution can potentially reduce human resource demands. However, as this is a pilot study, its findings primarily demonstrate feasibility rather than providing a definitive assessment of scalability and long-term performance gains. Further studies are required to evaluate the full impact of automation in forest habitat monitoring.

Structural analysis results show a detection error of 0%, with a DBH_{RMSE} up to 20%. Table III shows a DBH error ranging from 10% to 20%. This aligns with expected error ranges in mobile-laser-scanning measurements [27], where occlusions, sensor placement, and trajectory influence the overall

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precision. The value also meets the general requirements of accuracy for conservation status assessments [29], [30], proving that our method is able to produce meaningful and useful results. Floristic survey was able to correctly identify the selected species of interest in the habitat. Despite proper planning for fieldwork, an unusually hot season caused early blooming, leading to difficulty in collecting and identifying some species that had withered. This is, in particular, the case of *Corydalis cava*, which is underrepresented in our acquisitions and whose transparency makes it more likely to be misclassified, and partly the case of *Anemonoides nemorosa*. As regards the latter species, further difficulty was given by the size and the colour of the floral scape, which may lead to confusion with reflections on the ground. Due to this, the model performed better in detecting the other two species (*Anemonoides ranuncoloides* and *Doronicum columnae*) which were found in abundant and full bloom.

Our results, detailed in Table III, reveal also a clear correlation between power consumption and both plot size and, critically, terrain roughness. The nearly 1.5x increase in power consumption between Plot 4 and Plot 5, both of the same 200 m² size but with differing terrains, emphasizes this point. For typical missions in moderately complex forest habitats, a 2-4 hour battery life allows for efficient monitoring of plots up to 200 m². However, for extensive monitoring programs and for truly long-duration, large-scale deployments, power management becomes a key challenge. This could either require optimizing robot trajectories or working in recharging or battery-swapping infrastructure.

The applicability of this workflow is further limited by the logistic cost of deploying a quadrupedal robot in the areas of interest. Forest habitats are often in remote locations that lack transport infrastructure and readily available power sources, necessitating logistical planning and potentially increasing operational costs. Moreover, for long-term deployments, maintenance needs would also require either in-loco service stations or transportation to and from adequate facilities. Finally, as with any data-driven methodology, the generalization of the method would require the collection of a large amount of labelled data. Despite these issues, these results have significant implications for the field of habitat conservation, showing that our methodology is a promising tool to help human personnel overcome the challenges associated with traditional monitoring methods, such as the need for specialized skills, time consumption, and human resource allocation.

VI. Conclusion

In this work, we presented a novel approach to forest habitat monitoring through the use of quadrupedal robots equipped with advanced sensors, including LiDAR and cameras, for both structural and floristic surveys. The methodology was tested in challenging environments, showing that our system could effectively perform forest monitoring tasks with accuracy comparable to traditional methods. In the structural analysis, the robot achieved precise tree detection and DBH measurement, while the floristic survey utilized machine learning algorithms to identify key species indicating habitat conservation status.

While the results demonstrated the viability of robotic assistance in ecological monitoring, certain challenges—such as the logistical difficulty of deploying the robots in remote areas and the need for extensive training data—limited the overall applicability. Nevertheless, the study provided a promising proof of concept, showing that robotic technologies can significantly contribute to the effort required for habitat monitoring. This work constitutes a potential tool for future environmental monitoring tasks.

Future work will focus on addressing obstacle detection and autonomous navigation in extremely rough environments such as dense forests. This improvement is expected to reduce deployment challenges in remote areas and expand the operational scope of robotic-assisted forest monitoring.

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