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In This Issue

EDITORIAL

Dear colleagues:

This Summer/Fall double issue of the *ICUAS Association Unmanned Aviation eMagazine*, the *eUAM*, includes three peer reviewed technical papers. The first paper is entitled "*Assisted Aerial Remote Contact Operations: Field Deployment and Lessons Learned*" and it is co-authored by Manuel J. Fernandez, Riccardo Franceschini, Antonia Hüfner, Hameed Ullah, Fernando Ruiz Vincueria, Anibal Ollero, Lionel Ott, Fabio Ruggiero, Julian Cayero, and Matteo Fumagalli. The reported research is part of an EU-funded AERO-TRAIN project. A hexarotor with a prismatic manipulator, a shared autonomy control strategy, and advanced perception modules for real-time target detection and approach compose the combined system that allows for precise and repeatable aerial surface contact operations with significant implications for cost-effective industrial inspection applications. The second paper is entitled "*Applied AI Technique for Crop Counting and Biomass Estimates using Drones*" and it is co-authored by Stephen Wilkerson and Stephen Andrew Gadsden. The paper presents an AI methodology for crop counting and biomass estimation from drone-acquired datasets. The long-term objective is to provide a foundational framework for integrating AI-driven analysis into small- and large- scale farming operations. Both papers address timely challenges in unmanned aviation that are of interest to our technical society. The third paper is entitled "*Designing Resilient Law for the Rise of UAS-Ready Airports*" and it is co-authored by Kateryna Vodolaskova and Svitlana Holovko. The focus of the paper centers around a phased legal and resilient model for "UAS-ready airports", based on lessons learned, wartime lessons and European regulatory practices.

To help and facilitate authors who wish to submit their research to our *eUAM*, for peer review and publication consideration, we provide a short summary of the steps that need to be followed for online, electronic submission. This double issue, then, concludes with a detailed presentation of the current landscape of the annual conference, ICUAS 2026, which is expected to be very successful.

Last, but certainly not least, we urge you to submit your thoughts, recommendations and proposals to improve our conference, our eUAM, as well submit 'a position paper' to the eUAM addressing any unmanned aviation topic of interest.

We are here to serve you, our readers and authors, and to register the state-of-the-art in unmanned aviation!

ASSISTED AERIAL REMOTE CONTACT OPERATIONS: FIELD DEPLOYMENT AND LESSONS LEARNED

Manuel J. Fernández[1], Riccardo Franceschini[3], Antonia Hüfner[4], Hameed Ullah[2], Fernando Ruiz[5], Anibal Ollero[5], Lionel Ott [4], Fabio Ruggiero[2], Julian Cayero[3], Matteo Fumagalli[1]

Abstract—This paper presents a field test of an approach to assisted aerial remote contact operations, developed as part of the EU-funded AERO-TRAIN project. The project proposed a Grand Challenge event, where teams of PhD students designed and deployed aerial platforms to interact with targets in a GNSS-denied environment. The solution described in this short technical report integrates a hexarotor with a prismatic manipulator, a shared autonomy control strategy, and advanced perception modules for real-time target detection and approach. The system was tested at a decommissioned nuclear reactor facility. Results demonstrate the efficacy of the proposed framework in enabling precise and repeatable aerial surface contact operations with regular multi-rotor platforms, with significant implications for cost-effective industrial inspection applications. However, a lesson learnt exposes the limitation of Commercial Off the Shelf (COTS) technology dealing with precise physical contact.

Keywords: (Aerial Systems, Aerial Physical Interaction, Telemanipulation, Shared Control, Object Detection

I. INTRODUCTION

Recent years have seen increasing interest in contact-based inspection using aerial robots [1]. Commercial systems such as the Flyability Elios 3 UT [2] and Voliro T ([3], [4]) demonstrate practical contact inspections in industrial environments. Meanwhile, research prototypes, including underactuated [5], [6], fully actuated [7], [8] or omnidirectional [9], [10] systems, have shown precise, force-controlled contact on a variety of surfaces. These solutions, however, remain limited by endurance, payload capacity, and contact stability, motivating lightweight and versatile designs like the one proposed here. The EU-funded AEROTRAIN project [11] aims to close the gap between the infrastructure operations and maintenance industry and Industry 4.0 with the ambition to keep our invaluable assets operational and safe. The project, which concluded in December 2024, has taken a unique human-centered direction by developing new drone technologies for collaborative human–machine intelligence for supported evaluation of criticalities, leveraging immersive technologies such as augmented and mixed reality for damage assessment by a remote expert. Among the main goals of the project was a strong focus on developing new approaches for improving the robustness of aerial manipulators under conditions that reflect real applications, as well as leveraging on widely available and cost-effective COTS drone technology. To reach this goal, the project organized a Grand Challenge event as part of its internal activities. The event was held from 6 to 10 May 2024, where 15 PhD students involved in the project were divided into three teams to address an inspection scenario as use-case. The teams were tasked with designing their own solutions based on a common aerial platform, as described in Section III. This short paper presents the technical solution, deployment approach, and results achieved by one of the three competing teams—corresponding to the first five authors and discusses the key lessons learned regarding the limitations and potential of COTS aerial vehicles for physical interaction tasks.

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Fig. 1. Experimental scenario at the decommissioned nuclear reactor tank used for the AERO-TRAIN Grand Challenge.

II. INDUSTRIAL SCENARIO

The industrial infrastructure used was a nuclear reactor tank, nowadays decommissioned [12], located at DTU Risø campus (Fig.1). The objective of the challenge was touch surface operations, inspired by applications in industry for inspection and maintenance activities. The aerial system was expected to touch targets attached around a work location (Fig. 1). The targets were positioned at several elevations and locations to achieve varying difficulty levels. The scenario was deemed a GNSS-denied area, and each team had to develop a solution to accomplish the target interaction and UAV (Unmanned Aerial Vehicle) localization in order to maximize their scoring. A scoring system was defined to evaluate each team's performance based on accuracy, repeatability, target location difficulty, autonomy, and hardware cost. Higher targets received higher scores, as they demanded greater stability and thrust control. The side-pipe target (target 5 in Fig. 1) carried the highest score due to its smaller radius and the higher surface curvature, which made precise contact more difficult. Scores were adjusted by autonomy level (less user involvement yielded higher scores) and by cost overruns in additional COTS components.

III. SYSTEM ARCHITECTURE

A. Aerial Platform

A lightweight and low-cost aerial platform based on a Tarot 690 hexarotor frame constituted a common setup for all teams. This platform included KDE2814XF-775 motors, a PixHawk Cube Orange autopilot and a Lattepanda 3 Delta as companion computer (see Fig. 2).

A RealSense D455 camera provides visual feedback to a remote operator, while a Ubiquiti system ensures low-latency communication with a ground station. The team used a Livox Mid-360 3D LiDAR for onboard GNSS-denied localization as an extra COTS component for localization and planning. The pose estimation relies on the LiDAR-based localization algorithm Fast-LIO [13], as it exploits geometric information fused with Inertial Measurement Unit (IMU) data.

A custom-design 1 d.o.f. prismatic manipulator was installed aligned with the heading of the platform. The manipulator consists of two coaxial sliding carbon fiber rods forming a telescopic joint actuated using a servo motor, allowing an extension from 75 cm to 90 cm from the center of the vehicle, which is a requirement to achieve contact with the target while lowering the risk of damaging the propellers. A ground station comprising a screen and a joypad allows a remote operator to pilot and take high-level decisions over the mission and enable operations.

B. Software Architecture and Modules

The proposed remote-assisted architecture (see Fig. 3) is operator-centered and has the goal of minimizing the need for piloting skills. The humanmachine software interface is responsible for tasks like localizing targets, extracting features from targets, planning autonomously toward targets and Waypoint Control waypoints, and controlling the aerial physical interactions during the contact phase. An operator monitors the processes and modifies mission states using a handheld joypad. The teleoperation framework AeroAssistant [14] is adopted to allow the operator to control the retractable arm, enable and confirm target detection, and approach targets directly from the controller. An augmented reality interface provides visual cues to the operator. This interface is implemented as an overlay rendered directly on the video stream received from the UAV, with all information visualized on a standard monitor at the ground station. The overlay (Fig. 4) provides contextual cues such as target bounding boxes, estimated distance, and alignment indicators to support teleoperation.

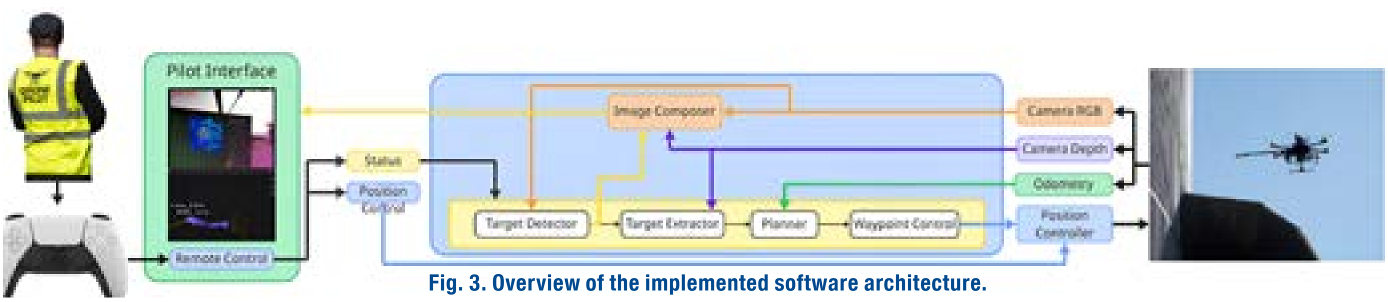

Fig. 3. Overview of the implemented software architecture.

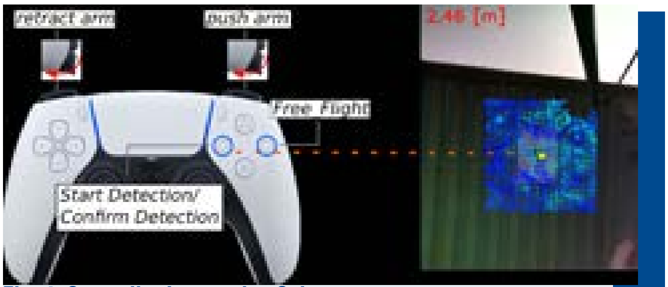

Fig. 4. Controller Interaction Scheme.

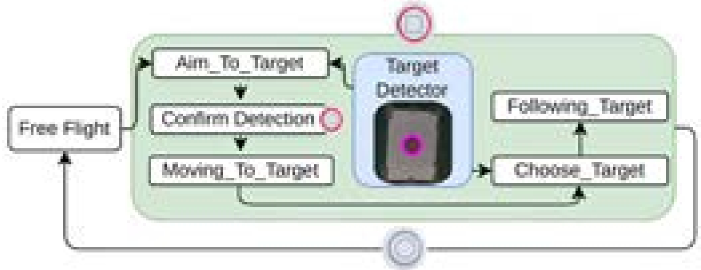

Fig. 5. State Machine Pipeline of the teleoperation process.

The target used in the challenge was an archery target with a circular pattern. Detection was achieved by downscaling the image for computational efficiency and implementing circle detection through the OpenCV library [15] which exploits the Hough transform for circle detection [16] and returns the center and radius of all detected circles in image space. Notice that since computational requirements are critical, the tracking was executed across consecutive frames to speed up computations. This was done by using the previously retrieved detection to define the area to track and by applying a Kernelized Correlation Filters (KCF) [17] approach, which operates on local features and can track the desired target across frames with minimal computational burden.

Once target centers are extracted in the camera plane, we determined the position of the target in world coordinates by utilizing the depth information from the installed depth sensor. The information from the depth sensor is furthermore used to identify the normal components to the surface by relying on information from the surrounding points in a local point cloud. Once the center point and normal direction of a target are detected, the UAV aligns with the target center and its normal direction, and moves towards the target.

The developed approach aims to keep the operator at the core of the decision-making process while assigning the UAV the responsibility of performing detection and planning towards the target. Thus, the operator interacts with the aerial system through a Sony DualSense™ Wireless Controller [18]. Once the UAV is positioned in front of the target, the operator controls the extension of the arm using the trigger button on the controller, as shown in Figure 4. Initially, the operator manually pilots the UAV to approach the target. Once the target is within the line of sight (within the camera frame), pressing the square button initiates the autonomous approach routine, as shown in Figure 5.

In this stage, target detection is started, and the operator is presented with an interface highlighting the detected target along with the retrieved path to approach the target. To confirm the proposed detection, the operator presses the square button again, enabling the moving-to-target routine, which sequentially sends waypoints to the UAV until it reaches the target. Once the target is within the camera's field of view and the UAV is positioned in front of it, detection is further refined. The target is first detected, and then the KCF tracker is initialized, extracting and averaging *n* consecutive target points. These points are used to maintain the UAV's position in front of the target at a desired distance such that the arm can reach the target when it is actuated. During this phase, the operator is kept aware of the tracking process through a visualization on the interface.

IV. SYSTEM DEPLOYMENT

The architecture described in Section III-B was first tested in a simulation before the field tests. The simulation environment consisted of a Software in the Loop (SITL) simulation with PX4 autopilot [19], ROS and Gazebo Simulator. The simulator was developed as part of the AERO-TRAIN project and is available for use [1].

Field trials were conducted at the outdoor facility described in Section II (see Fig. 1). The safety pilot manually performed the take-off and landing steps. A first test of the system was carried out on a container close to the nuclear tank to evaluate the system's performance prior to full-scale deployment (see Fig 1). Figure 6 shows the detection step working in the camera streaming with information available for the remote operator, such as the distance to the target and positioning data from Fast-LIO.

When the operator confirms the detection, the moving-to-target process is engaged to move the aerial vehicle close to the target. After the approaching process, the tracking process (Fig. 7) will ensure the position of the vehicle kept at the desired distance, while the operator controls the manipulator.

The same process was evaluated for touching the targets placed on the tank. Due to issues perceiving the contact while the end effector is in motion during the experiments, reported in Section V, the team was forced to use the manipulator as a fixed rod, while relying on the stability of motion of the aerial platform in its front and sideways directions. Figure 8 shows one of these trials considering a fix manipulator, where the rod was tested withstanding an over-press (third picture) against the surface during the touching process. Figure 8 also shows the qualitative results of the field trial at the bottom picture, where touch precision is clearly degraded. The vertical marks are caused by errors in positioning and the need to pitch the vehicle to approach and touch the target.

V. CONCLUSIONS AND LESSONS LEARNED

This work presents the development and field deployment of an aerial manipulation system designed for the AERO-TRAIN Grand Challenge. The platform integrates shared autonomy and human-inthe-loop control to enable remote contact operations in a realistic outdoor, GNSS-denied environment. Despite limited preparation and challenging conditions, the system successfully demonstrated teleoperated manipulation using only onboard sensing and lightweight communication.

During field tests, the main challenges arose from the manipulation subsystem—particularly the prismatic joint behavior and the operator's limited perception of contact through the video stream.

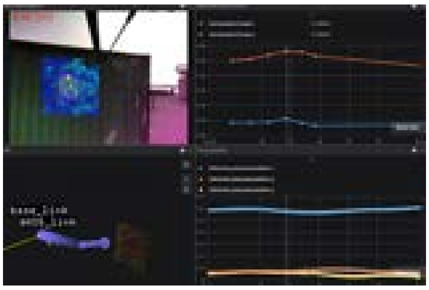

Fig. 6. AR Video stream with detected target and estimated distance.

Fig. 7. Tracking phase following the autonomous approach.

Fig. 8.
Example of contact sequence over the tank surface.

These issues, critical for distant targets, could be mitigated by adding contact sensors, leveraging haptic feedback from the DualSense controller, and integrating clearer visual cues for contact and alignment in the video stream. The platform also showed difficulty maintaining stable position near walls, suggesting the need for further adjustment of the controller or mechanical adjustments based on more representative test surfaces.

Overall, the proposed system proved feasibility through fairly precise and repeatable interactions. It also provided significant insights into practical aerial manipulation under communication limitations, highlighting its potential for industrial inspection applications.

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APPLIED AI TECHNIQUE FOR CROP COUNTING AND BIOMASS ESTIMATES USING DRONES

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Abstract—This paper presents a generic Artificial Intelligence (AI) methodology for crop counting and biomass estimation from drone-acquired datasets. Leveraging Convolutional Neural Networks (CNNs) using MATLAB's Deep Learning Toolbox, we develop a scalable approach for processing large agricultural datasets, including GeoTIFF mosaicked images. The methodology includes an efficient pipeline for generating broad training datasets, enabling clearcut object detection and quantification. Initial results demonstrate that the CNN-based approach achieves robust performance in identifying and counting crops, highlighting its potential for precision agriculture applications, such as yield estimation and crop monitoring. This work provides a foundational framework for integrating AI-driven analysis into small and large-scale farming operations.

Keywords: (Multispectral Analysis, Drone Multispectral Data sets, Artificial Intelligence (AI), GeoTIFF, MATLAB, Convolutional Neural Networks (CNN))

I. INTRODUCTION

The integration of Artificial Intelligence (AI) into precision agriculture has evolved significantly over the past decade, particularly with the adoption of Convolutional Neural Networks (CNNs) for image analysis and object detection. Early work in the domain predominantly relied on deterministic image processing techniques, such as edge detection [1], to identify crop boundaries and features in aerial images. While these methods provided a useful starting point, they often struggled with real-world challenges like variable lighting, occlusions, and the complex backgrounds present in large-scale agricultural settings.

MATLAB's Deep Learning Toolbox [2-5] has played a key role in bridging these gaps by enabling rapid prototyping and deployment of CNN-based models. Studies leveraging these tools have demonstrated that CNNs can automatically learn intricate features from high-dimensional data, overcoming many of the limitations posed by traditional methods. Works such as [6-9] have underscored the potential of CNNs in capturing subtle variations in object shapes and textures, leading to superior performance in classification and detection tasks. These advancements are particularly pertinent to tasks like crop counting, where precision is critical.

In addition to architecture innovations, the literature also highlights the practical challenges inherent in agricultural applications. Factors such as non-uniform planting densities, irregular growth patterns, and the influence of environmental conditions complicate the detection process. Deterministic approaches, which might rely on manually tuned parameters, are often sensitive to these variations. In contrast, deep learning models can be trained on large, diverse datasets to learn robust features that generalize across different conditions. The integration of multispectral indices such as NDVI [10-12] further enriches the available information, enhancing the accuracy of crop quantification by combining spectral and spatial data.

Another important debate in the literature revolves around the choice of computational platforms. While Python has gained traction for its open-source ecosystem and flexibility [13], MATLAB's established suite of tools has maintained a strong presence, especially in academic and applied research contexts, due to its user-friendly interface and comprehensive support for rapid code development [2-5]. The current approach leverages MATLAB's capabilities to integrate extensive droneacquired GeoTIFF datasets with robust CNN methodologies, providing a scalable solution for both yield estimation and crop monitoring.

While previous studies have primarily focused on object classification [12], fewer have directly addressed the challenges of scalable and accurate crop counting in complex field environments. The methodology presented here differentiates itself by focusing on the systematic generation of training datasets and the specific tuning of network parameters to handle the inherent variability in agricultural imagery. This work thereby addresses the gap between theoretical advancements in deep learning and the practical demands of precision agriculture.

By synthesizing insights from deterministic methods, multispectral analysis, and deep learning, this literature review not only contextualizes the evolution of AI-based agricultural research but also highlights the contributions and innovations of the present work. The proposed approach aims to improve upon earlier methods by providing enhanced accuracy, robustness, and scalability in detecting and counting crops, thereby offering a practical tool for modern farm management.

The York College of Pennsylvania (YCP) drone program has applied multispectral imaging technology to detect unhealthy plants, invasive weeds, and other agricultural anomalies in fruit trees and crop fields across York County. Coupled with soil and tissue testing, this approach provides valuable insights into the root causes of local crop damage, which can significantly impact farm productivity and profitability. A key component of this initiative is the incorporation of Artificial Intelligence (AI) to enhance analytical capabilities. By utilizing AI-driven models and engaging students in the research process, this program aims to improve the detection and classification of agricultural challenges, thereby extending its application to additional farms in the greater York area.

To complement multispectral imaging, this project integrates AI techniques to systematically analyze farm fields. While some anomalies, such as sick or missing trees, may be visually detectable, tracking their progression over time presents a challenge. Convolutional Neural Networks (CNNs) are employed to train models to detect and classify these issues within the collected data. This technology has the potential to provide farmers with actionable insights, such as tracking the progression of sick or missing trees to enable data-driven decisions about removal, treatment, or replacement. In field crops like corn and soybeans, AI can detect planting or application errors, such as over-spraying, and help assess damage extent to mitigate yield losses.

This paper focuses on the use of CNNs, developed using MATLAB's AI Toolbox, to count and estimate crop quantities. Specifically, it presents a generic AI algorithm to detect and quantify specific round objects, such as pumpkins, tomatoes, and other fruits and vegetables, in agricultural fields.

MATLAB Inc. has played a significant role in advancing the integration of AI into practical applications by offering specialized toolboxes tailored for deep learning [2-5]. The field of deep learning itself has seen a surge in published research, with CNNs being extensively documented for their versatility and effectiveness in vision-based tasks [6-9]. While the broader implications of AI are explored in numerous texts, CNNs remain a prominent focus for their applicability in visual and image-based analyses.

For this project, MATLAB was selected over Python due to its established Deep Learning Toolbox, which simplifies the development of neural networks through pre-built components and efficient workflows. Additionally, MATLAB's widespread use among the research team ensured a smoother implementation process.

The objective of this work is not to advance AI itself, but rather to utilize existing methodologies to evaluate drone data in an efficient and practical manner. The following sections outline the methodology and logical framework applied in this study.

II. METHODOLOGY

A) Drone-Based Data Collection and Image Processing

To gather high-quality, multispectral data, drones equipped with specialized cameras are flown over the target farmland in a crisscross pattern. During flight, the drones capture numerous overlapping images while recording essential metadata such as the geolocation (GPS coordinates), camera orientation, and pitch or roll angles. This structured approach ensures comprehensive coverage of the field, allowing for detailed analysis of crop health and spatial distributions.

Once the flight is complete, the individual images and their associated metadata are imported into Pix4D Fields [10]. This software automatically stitches together the large number of overlapping images to create a georeferenced Ortho-mosaic, typically exported as a GeoTIFF. Each pixel in this file carries multispectral information, revealing plant health indicators (e.g., NDVI) and other crop characteristics. Because the resulting dataset can be extremely large, effective organization and processing methods are essential. Figure. 1 depicts this process below.

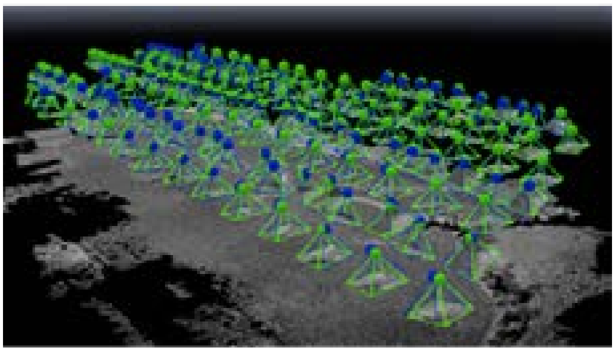

Figure 1. Drone Images Stitched together with Pix4D Fields

Building on this rich, spatially aligned dataset, the next step is to apply Artificial Intelligence (AI) techniques for efficient information extraction. In this paper, we focus on how Convolutional Neural Networks (CNNs) can be trained to count specific crops quickly and accurately. By first developing a generic training procedure on synthetic or simplified data, we lay the groundwork for applying the same methodology to realworld multispectral drone imagery. This approach demonstrates the potential to transform vast aerial datasets into actionable insights for farmers, such as plant density estimates and early detection of anomalies in the field.

B) Preparation of Training Data

To train the CNN, synthetic datasets were generated, consisting of 512x512-pixel RGB images with dots of interest on a uniform green background. Each image was paired with a CSV file containing the *x,y* coordinates of the center of each dot. Positive and negative sample extraction as follows. Positive samples consisted of square patches of size *nxn* was extracted around the labeled dot centers. Each patch captured the local pixel values around the dot. The size of the patch, n, was determined such that the radius of the dot region, r = (n – 1)/2 encompassed the dot and its surrounding pixels. To ensure balanced training data negative samples not near any labeled dot were extracted. Negative patches were required to satisfy the condition:

$$\min\ (\mathrm{xiyi}) \in \mathcal{D}\sqrt{}(x - xi)2 + (y - yi)2 > 2r$$

where (x,y) is the center of the candidate negative patch. The resulting dataset consisted of normalized RGB patches with corresponding labels: 1 for a positive patch and 0 for a negative patch.

C) CNN Architecture

A convolutional neural network (CNN) was designed to process the extracted patches and classify them as dots or nondots. The architecture consisted of layers accepts patches of size $n \times n \times 3$, where n is the patch size and 3 corresponds to the RGB channels. No additional normalization was applied, as pixel values were pre-scaled to the range [0,1].

The feature extraction layers or convolutional layers consist of two 2D convolutional layers (3×3 filters) with 16 and 32 filters, respectively, each followed by ReLU activation. The pooling layers, (i.e. =max-pooling layers) were a (2×2 windows, stride = 2) interspersed to reduce the spatial dimensions while retaining the most salient features. The fully connected layers were a 64-node fully connected layer followed by ReLU activation mapped the extracted features to a latent representation. Another fully connected layer reduced the output to two neurons representing the probability of each class. The softmax and classification were used to convert the network outputs into probabilities. Finally, a classification layer assigned the most likely label to each input. This architecture enables efficient feature extraction, dimensionality reduction, and binary classification. The use of small filters (3×3) and max pooling ensures computational efficiency and a compact model. This was needed so that the computations could be handled on a typical laptop computer. D) Model Training The CNN was trained using the extracted patches and their associated labels. The categorical cross-entropy loss function was used to optimize the network's parameters:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k}\log(\hat{p}_{i,k})$$

where yi,k and $\hat{y}i,k$ are the true and predicted probabilities for class k of sample i, N is the total number of samples, and K=2 (dot and non-dot classes). The optimization process used the Adam optimizer with an initial learning rate of 10-4. Training was conducted for 30 epochs with a mini-batch size of 16. The model was validated using a separate subset of patches to monitor overfitting and convergence.

E) Model Evaluation and Testing

The trained model was evaluated on a separate test image. Predictions were made using a sliding window approach. Patch- Wise predictions were used for every pixel (x,y) in the test image, a patch of size n×n centered at (x,y) was extracted. The patch was classified using the trained CNN, generating a binary prediction map prediction Map(x,y) = {1, if classified as a dot, 0, otherwise} The cluster analysis reduced false positives, connected-component analysis was applied to the prediction map. Neighboring pixels classified as dots were grouped into clusters. Clusters with fewer than a specified number of pixels with a min Cluster Size of 8 were discarded. The centroids of the remaining clusters were identified as the predicted dot locations. This four-step process provided a systematic approach to developing and testing a CNN for dot detection. The combination of synthetic data generation, compact CNN architecture, and cluster-based post-processing ensured robust performance, making the methodology suitable for adaptation to other similar tasks.

III. RESULTS

The end goal is to apply this methodology directly to a farmer's field. Figure 2. shows a typical farmer field for pumpkins in northern Maryland. The images were taken from a DJI Mavic 3 multispectral drone. The drone was flown at an altitude of approximately ~40m feet resulting in a pixel size of roughly 4.56x4.56mm. Images are stitched together using the *PIX4D Fields* application. Final images are typically in the gigabytes in size. The image shown in Figure 2 below is a GeoTiff that has pumpkins that have not been completely picked. To give the reader an approximate scale to the field, the length of the field below was about 0.4 miles.

As can be seen in this zoomed in image the pumpkins are easily identified once we zoom in on a section. In the current year we manually counted pumpkins as a baseline". However, if we could do it easily *(it only took us 20 minutes to count this partially picked field)* then a CNN algorithm should be able to do it more accurately and efficiently. Once trained the CNN should be able to accurately predict pumpkin numbers and biomass estimates. Both estimates are of value to the farmer. Figure 2. Drone Stitched Images of Pumpkin Patch.

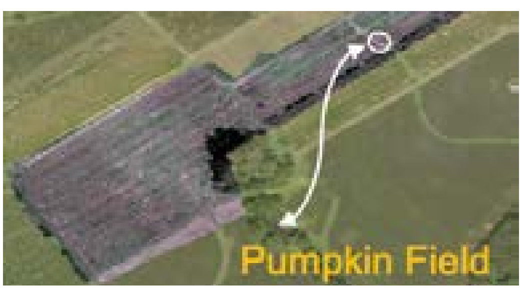

Figure 2. Drone Stitched Images of Pumpkin Patch.

In this particular example the pumpkins are traditionally colored and it is rather easy to pick pumpkins out from the farmers' fields. Moreover, by flying the drones at set altitudes over the field the s size give good estimates of the actual size and therefore mass of the pumpkins. When developing algorithms it was tempting to start with the actual field and go from there but that could prove problematic by over simplifying the process. Therefore, we develop a generic algorithm that is not easily accomplished by a human knowing that it would be more robust than one based on the field shown. In Figure 3, we show a series of round filled circles of random dimension and color on a uniform background with the correct dots on the left with a black circle around them and the predicted set with red circles around each dot.

In this figure the control dots are marked by black circles. As can be seen, a human will not be able to determine which dots qualify and which do not. We do not tell the AI algorithm what the criterion is, rather want to examine how much training is required for the CNN to learn the criteria based on the image and location of the center point. We started with 100 training sets and increased the number of training data sets, until a reasonable amount of accuracy was acquired (~ 99%). For this particular challenge, ~5000 training sets were required to train the algorithm to a reasonable amount of accuracy. In this case two false positives were identified out of the 100 or more colored dot objects on the screen. However, and important to note, in most of the cases tried so far; the colored dots that were correct are usually found with the errors being skewed toward over predicting. Upon further examination the AI algorithm was only off by one RGB value from the unknown criteria, hence it had learned the criteria without a priori knowledge *(in other words if we had a RGB of 212,40,41 then the error was for example 212,40,42*).

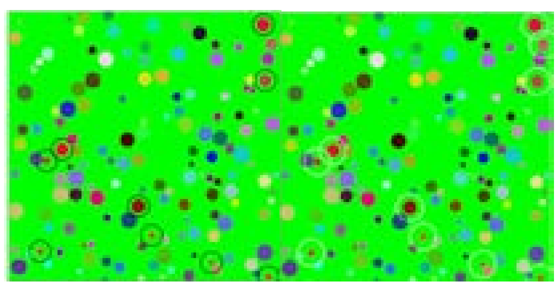

Figure 3. Dots exact and predicted w/5000 T.S.

When we tested the technique on a simpler set of color values (10 different colors rather than 256x256x256 colors) with 100 training sets. The same process as used in the generic algorithm easily achieve near perfect accuracy every time. This example is given in Figure 4. When we

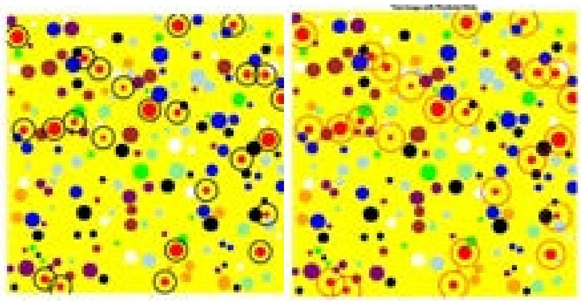

Figure 4. Dots exact and predicted w/100 training sets.

reduced the number of training sets to 20 the accuracy was still the same. From this experiment we concluded that we will not need as many training sets for the pumpkins as in our generic example.

Our pumpkin patch should lie somewhere between these two examples. When the number of training sets is reduced to 20 in the above example, the same results are obtained. This is a testament to the robust nature of the technique. In the first example we made the criteria more difficult. This allowed us to experiment with many of the input parameters that affect the results and obtain a good combination. For this particular problem a radius of 3 and a patch size of 7 proved the best combination for all of the examples given here.

Turning our attention from the generic examples to the project of pumpkin identification requires us to generate new training sets specifically for pumpkins. Figure 5 shows how the pumpkin patch in Figure 1 was broken into 9 reasonably sized segments. Figure 6 below show the process for taking that segment breaking it into 512x512 images. These are selected and writing a training set file as shown on the left. The sliders allow the position of the training segments to be adjusted in x and y locations. Below Figure 7 shows the process that allows the user to select the pumpkins by clicking on them. Then those data points are written to a csv file as a training set.

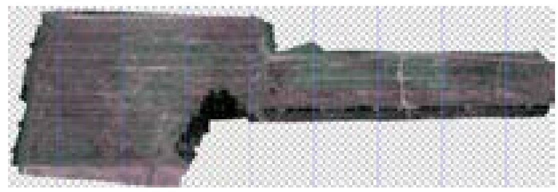

Figure 5. Segmented pumpkin patch.

In this example we produce data sets from the 21 images in Figure 6 and use them to train our generic AI algorithm. Using this training set we had a ~90% accuracy. In order to increase the accuracy we need only include more training sets. However, the methodology is now proven to work for this particular application. Seen below in Figure 8 is a random patch of the field not used in the training and the predictions. As can be seen, the algorithm captures every pumpkin in the field with 3 misses where there were no pumpkins. This was done using only 21 training sets.

The downside of this method versus a deterministic approach is the initial time it takes to set up a system of training data. Nonetheless, once trained the approach seems to work well for specific applications.

IV. WHAT'S NEXT?

Many fruits, vegetables, and other agricultural products can be estimated and monitored during the growing season using existing techniques. Numerous crop-counting and monitoring tools, many of which rely on deterministic methods such as edge detection, have already proven useful for these purposes [12- 13]. However, the advent of AI techniques presents a transformative opportunity for advancing farm crop prediction, detection, and monitoring. AI methods, particularly those employing deep learning algorithms, have the potential to overcome the limitations of traditional deterministic techniques by adapting to variations in environmental conditions, crop shapes, and growth stages.

Our approach focuses on addressing the most accessible applications first, gradually refining and scaling these techniques to enhance farm productivity and operational efficiency. For example, Figure 9 shows a field full of corn early in the growing season. One critical question is: of the approximately 33,000 seeds planted per acre in this field, how many corn plants actually grew? Current estimation methods often rely on sampling a 10x10-foot section and extrapolating

Figure 8. Algorithm with only 21 training sets.

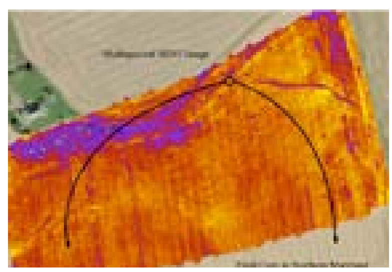

Figure 9. Northern Maryland Field Corn.

the average for the entire field. As shown in Figure 10, variations due to the planter and other factors are large enough to be of significant concern. The inclusion of an NDVI multispectral image provides an additional layer of analysis. By integrating multispectral and visual data, AI routines can generate more accurate estimates for the entire field.

Figure 10 highlights a zoomed-in region, indicated by a circle in Figure 9, showing both the NDVI multispectral image and a corresponding visual RGB image for the

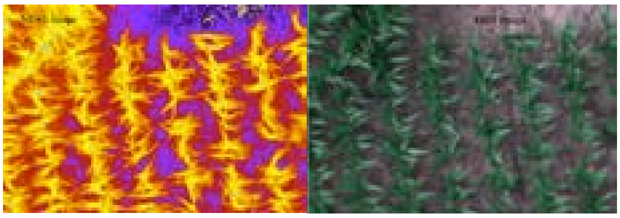

Figure 10. Zoomed in Image from Figure 10 NDVI and Multispectral.

same location. This combination of data types enables more nuanced assessments and actionable insights.

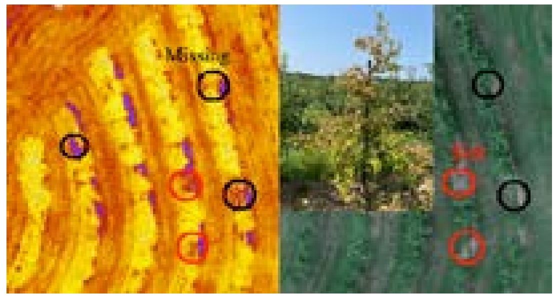

Figure 11. Fuji Apple Trees in August.

Another example of actionable data is shown in Figure 11. Here, in a small subset of a farmer's Fuji apple orchard, sick trees and open spaces are easily identified using multispectral analysis. A typical farm in Northern Maryland or Southern Pennsylvania might have 30 to 50 fields of various tree and fruit bush types. Within these fields, missing and sick trees or bushes often go unnoticed by the farmer, leading to potential crop losses. AI techniques, similar to those presented in this study, can estimate the extent of such losses and provide guidance on corrective actions.

Interestingly, the tree highlighted in Figure 12 was healthy at the beginning of the season but had died by the end of it. NDVI and other spectral analyses identified this tree as having issues early in the season, long before visual signs of decline became apparent. Moving forward, we plan to sample soil and leaf tissues for testing and correlate these findings with other multispectral research. Such integrative approaches hold promise for enhancing the predictive power of AI models and improving overall farm management.

V. CONCLUSIONS

In conclusion, this study successfully implemented a generic AI-based approach for developing a crop-counting algorithm from drone datasets. By employing Convolutional Neural Networks (CNNs) within MATLAB and the AI Toolbox, we established a generalized methodology for identifying and estimating crop counts and biomass. We demonstrated the effectiveness of the proposed process in managing large-scale agricultural datasets, including mosaicked GeoTIFF composite images. Additionally, we developed an efficient pipeline for generating extensive training datasets, which were used to train the AI model for accurate object detection and quantification. The results confirm that CNN-based approaches are highly effective for precision agriculture, offering reliable tools for yield estimation and crop monitoring.

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DESIGNING RESILIENT LAW FOR THE RISE OF UAS-READY AIRPORTS

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Abstract — The rapid spread of unmanned aircraft systems is transforming aviation far faster than legal frameworks can adapt. Yet, the same technologies that have shown destructive power in wartime also hold the potential to modernise civil aviation, improve logistics, and strengthen humanitarian resilience. This paper argues that aviation law must evolve from a reactive to an anticipatory discipline, capable of guiding airports through the safe and legitimate integration of UAS. Drawing on both wartime lessons from Ukraine and emerging European regulatory practice, it proposes a phased legal model for "UAS-ready airports". The goal is not only regulatory compliance but resilience – a legal architecture that channels innovation toward human and civil purposes.

Keywords: Legal Challenges; Regulations; Resilience; Integration into the National Airspace; UAS Operations.

I. INTRODUCTION

Drones have changed the face of war. In Ukraine, the night sky has become a theatre of war and drones have become synonymous with fear – a nightly instrument of destruction. For millions of civilians, they have brought devastation and loss – destroying homes, hospitals, and schools, and taking the lives of thousands of innocent people, including many children. This reality has altered the way society perceives unmanned technology.

For airports, air-traffic controllers, and also lawyers, the transformation is equally stark: the same aircraft that once symbolised innovation and efficiency now cast long shadows over our runways, control towers, and legal frameworks, carrying with them both the memory of destruction and the challenge of preventing its return.

Yet, this same technology holds enormous potential for saving lives, delivering medical supplies, supporting green logistics, and modernising infrastructure. Turning that duality into balance is not just a technical or political task. It is a legal one: to ensure that unmanned systems serve human ends, not replace them. The contrast between destructive and constructive uses of drones exposes a deeper problem: while technology evolves at exponential speed, the law that governs it lags behind. International and European aviation frameworks were designed for piloted aircraft and controlled environments. Airports, the physical and legal nodes of global connectivity, now face a profound transformation – the arrival of unmanned systems into civil airspace and ground operations.

Consider the chaos at Gatwick Airport in December 2018: a few drone sightings triggered the closure of a major runway, stranding over 140,000 passengers and cancelling around 1,000 flights. [1] Since then, similar incidents have multiplied. In Warsaw, unauthorised drone flights near Chopin Airport repeatedly interrupted operations in 2022 – 2023 [2]. Recently, in Copenhagen and Oslo, coordinated drone sightings in September 2025 halted all departures for hours, forcing diversions and heightened police patrols [3]. More recently, in Palma de Mallorca, a drone hovering over Son Sant Joan Airport in October 2025 temporarily suspended landings and departures, delaying flights and diverting eight aircraft [4].

Airports and the systems around them are no longer just physical hubs but frontline hubs inan unmanned-aircraft era. The central question is no longer whether drones will enter airports, but how law can shape that transition to be safe, legitimate, and beneficial. Waiting until unmanned operations become ubiquitous is like building fences after the flood has already broken the dam.

A few years ago, who could have imagined smartphones mapping our steps, or artificial intelligence drafting poetry and symphonies? Today, we are exploring quantum computers, machines that compute with particles instead of bits [5], and studying the mineral ringwoodite deep within the Earth's mantle, whose ability to trap water could one day redefine geology [6]. These discoveries remind us that what seems speculative today becomes standard tomorrow.

So, if we are serious about the future of UAS-ready airports, we must act now, before the runway is already buzzing with unmanned arrivals. Because, just like the technology, the law must be designed ahead of its full flight.

II. LEGAL FRAMEWORKS: THE SURFACE OF A DEEPER PROBLEM

The legal world of aviation was never designed for machines that fly without pilots. While technology races ahead, the law still looks skyward through the lens of crewed aircraft and ground-based control. Even as unmanned systems begin to share the same airspace, the frameworks that govern them remain firmly anchored in the past.

As Dr Benjamyn I. Scott and Prof. Steven Truxal remind us in their recent analysis of EU drone regulation, there is still no dedicated legal regime, no *lex specialis*, that clearly defines liability for unmanned aircraft across international, European, or national levels [7]. Europe has indeed made strides with the U-space regulatory package, which introduces digital traffic management for drones, yet these rules remain largely operational in scope. They tell us how drones may operate, but not who bears responsibility or liability when things go wrong. The deeper questions – how to certify autonomous systems, how to divide responsibilities between operators and airport authorities, how to handle cross-border flights or AI-driven decisions – remain unresolved.

Scott and Truxal identify three intertwined problems that make this legal landscape especially fragile for airports. First is *fragmentation*. Although EU drone rules take the form of directly applicable Regulations and thus apply uniformly across all Member States, practical implementation still diverges. Every country has taken its own path, applying EU law within their own national systems or creating parallel systems. The result is a patchwork where liability, privacy, and enforcement standards still differ from one jurisdiction to another. For an airport operating in a networked, international environment, this lack of coherence turns everyday compliance into a legal obstacle course.

Second is the *ambiguity of responsibility*. When a rogue drone forces a runway closure, who has the authority to act – the police, the military, the air navigation service provider, or the airport operator? If a counter-UAS system damages the drone or delays passengers, who pays compensation? Liability in these cases commonly falls back on general tort or administrative law rather than clear, aviation-specific provisions. In practice, airports are often left to improvise, relying on laws and procedures that were never written for automated machines or split-second digital decisions.

Finally, there is the problem of *reaction instead of anticipation*. Regulation tends to appear after a crisis, treating drones as occasional disruptions rather than as integral components of modern airspace. This reactive pattern leaves institutions exposed: each incident becomes a lesson learned too late, and legal reform follows the damage rather than preventing it.

All three weaknesses converge at airports – complex ecosystems where air-traffic operations, security, data management, and human safety intersect. Without a legal framework designed for the unmanned era, even the most advanced counter-drone systems or U-space technologies risk being undermined by uncertainty over authority, liability, and jurisdiction. The conclusion is clear: airports cannot simply adjust to drones; they must become legally ready for them. Designing that resilience requires re-imagining law's role – shifting it from a passive rulebook that reacts to incidents into an anticipatory framework that guides technology before it reaches the runway.

III. THE IDEA: ANTICIPATORY LAW

If airports are going to be foundations of the unmanned future, then law must stop being the laggard and become a lead actor. Rather than reacting when a drone disrupts a runway, we need legal frameworks that anticipate the arrival of UAS and embed change into the design of airports from the start. Imagine this as a journey in three stages:

Stage 1 – Hybrid Airports: Here, piloted aircraft and drones share space. An airport begins adapting: new fencing, detection systems, enhanced coordination between UAS operators and air traffic control. Legally, the airport must clarify: Who authorises a drone to operate nearby? Who intervenes if a conflict arises? Certification is still traditional– but now layered with UAS rules.

Stage 2 – Drone-Dominant Airports: Drones become the majority of take-off and landing movements. Airports transform: UAS corridors, autonomous ground systems, digital traffic management. The legal pivot: liability regimes widen, operational permissions shift from pilots to remote operators and automated systems. Scholars note the gap in insurance and third-party liability for drones remains acute [8].

Stage 3 – Fully Unmanned Airports: Aircraft arrive without human pilots, ground operations are automated, and decisionmaking embedded in algorithms. The law now governs: AIdriven systems, data governance, autonomous counter-UAS responses, cross-border interoperability. Traditional rules for manned aircraft fail; what fills the void is anticipatory regulation, designed before disruption strikes [9].

The emphasis is not merely on adaptation but on resilience. Anticipatory law means designing legal rules that align with tomorrow's technology, not yesterday's practices. By imagining these three stages, airports and regulators can cocreate a roadmap: from dealing with present behavioural risks (unauthorised drones) to preparing for full-scale structural change in aviation itself.

IV. WHY IT MATTERS TO ENGINEERS AND SYSTEM DESIGNERS

Engineers working on next-generation runway monitoring systems already know the technical complexity of integrating radar, optics, and AI-based detection for rogue drones. Yet, even the most advanced systems depend on more than precision and speed — they depend on the legal scaffolding that gives them authority to act. A sensor may detect a drone in milliseconds, but if no entity is legally empowered to respond, detection alone changes nothing. When an automated counter-measure damages civilian infrastructure, the question of liability becomes immediate: is responsibility borne by the airport operator, the software provider, the hardware vendor, or the engineer who configured the system? As Hartmann et al. emphasise, even state-of-the-art autonomous drones carry "legal uncertainties" that influence both their technical design and operational deployment. [10] From a systems-design perspective, this means engineers must think about liability, certification, cybersecurity, and interoperability. A noise-reduction algorithm is not just a technical choice – it can affect legal risk exposure. As Mekdad et al. show in their survey of UAS security and privacy, vulnerabilities at the software and hardware levels translate into legal and institutional risk. [11] In other words: an engineer designing a UAS corridor within an airport context must collaborate with legal colleagues to ensure the system aligns with liability regimes, data-protection laws, and counter-UAS authorisation protocols.

Moreover, the rise of digital and autonomous systems – sensors, U-space data flows, automated ground vehicles – means that engineers and lawyers are working on the same challenge from different sides. The engineer builds resilience and reliability; the lawyer builds trust and legitimacy. Without both, airports risk deploying technically capable systems that remain legally unusable, or adopting legal frameworks too rigid to keep pace with innovation. In this way, anticipatory law is not just a legal concept – it becomes a design requirement. Engineers must embed legal readiness into the architecture: modular certification, fail-safe protocols that align with liabilitystandards, and data governance built into sensor flows. The system itself becomes legally resilient, not merely technically advanced.

V. UKRAINE AS A LIVING LABORATORY

Nowhere have the legal and operational limits of drone governance been tested as harshly as in Ukraine. Since 2022, the country's airspace has become an unplanned experiment in the coexistence of civilian, military, and humanitarian drones. Airports such as Boryspil and Lviv–once routine nodes of international mobility–have had to adapt to constant unmanned incursions, improvised counter-UAS measures, and emergency coordination between civil and military authorities [12].

These conditions exposed a deeper lesson for global aviation governance. When legal frameworks lag behind technological realities, regulation shifts from prevention to damage control. As researchers in the field have observed, conflict environments accelerate both innovation and norm erosion: drones are deployed faster than laws can respond, and new operational practices emerge without legal validation [13]. Yet, paradoxically, this turbulence also generates insight. Ukraine has become a real-time stress test for anticipatory law–revealing where liability ends, where jurisdiction blurs, and where flexibility enables resilience. For civil airports worldwide, the Ukrainian experience underscores that the boundary between "war" and "peace" in unmanned operations is increasingly porous. Emergency governance–rapid decision-making, adaptive authorisation, distributed accountability–may soon be standard in peacetime airports facing drone disruptions. In this sense, Ukraine functions less as an exception than as a preview of the regulatory future: a proving ground for UAS-ready law under extreme conditions.

VI. OUTLOOK: ENGINEERING THE LAW OF TOMORROW

The future of aviation will not be built by engineers alone. As unmanned systems move from experimental to essential, the law must evolve from a set of static rules into a living design discipline – one that anticipates complexity rather than reacts to crises. The challenge is not only to regulate drones but to engineer legal resilience: to build frameworks that adapt to autonomous decision-making, digital air traffic, and algorithmic accountability. In this sense, law and engineering share the same DNA. Both design systems must work under pressure, fail safely, and recover quickly. Both rely on testing, iteration, and redundancy. What changes is the material: engineers shape code, circuits, and airframes; lawyers shape rights, responsibilities, and governance.

If the 20th century was about engineering machines, the 21st is about engineering trust – between humans and algorithms, between airports and autonomous systems, between innovation and public safety. Building that trust requires collaboration: lawyers who think like system designers, and engineers who see regulation as part of the architecture. Resilient aviation will not emerge from technology alone – it will come from the moment when law, policy, and engineering finally begin to design together.

Because in the unmanned age, the strongest infrastructure is not concrete or code – it is foresight.

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ICUAS 2026: CURRENT STATUS

The 2026 International Conference on Unmanned Aircraft Systems, ICUAS 2026, will take place on June 15-18, in Corfu, Greece. Details can be found at www.uasconferences.com.

As in previous years, the conference is Technically supported by the IEEE Control Systems Society (CSS), the Robotics and Automation Society (RAS), and the Mediterranean Control Association (MCA), while the Conference Proceedings will be acquired by CSS and will be published on IEEE Xplore. Starting with this year's conference, it is a pleasure to report that the European Control Association (EUCA) has unanimously voted to also be a Technical sponsor!

This year's conference includes three Keynote Speakers and an Awards Luncheon Speaker:

- Dr. Antonio Franchi, University of Twente (Netherlands), and Sapienza University of Rome (Italy). The title of the keynote address is "*Flying Robots That Touch the World: Are We There Yet?*"
- Dr. Dimitra Panagou, University of Michigan. The title of the keynote address is "*Resilient Multi-UAS in Complex Missions*".
- Dr. Antonios Tsourdos, Cranfield University. The title of the Keynote address is "*Integrating Advanced UTM Services in a Co-Simulation Environment*".
- Dr. Donald 'Bucket' Costello III, University of Maryland. The title of the talk is "*CAT-A Ground Test to Class-A Miship: Case Study of an Uncrewed Military Helicopter with Lessons Learned for the R&D, T&E, and Academic Community*".

As of now, one Half-Day Tutorial has been secured on the topic of "MODELING NAVIGATION AND CONTROL OF MULTIROTOR UAVs: *A Comprehensive Framework*.

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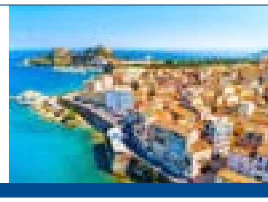
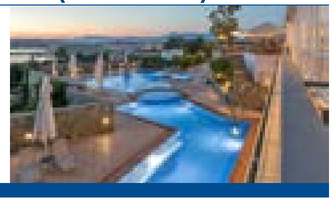




UAV COMPETITION GUIDELINES

The **2026 ICUAS UAV Competition** is organized (as in previous years) by the Laboratory for Robotics and Intelligent Control Systems, **LARICS**, University of Zagreb, Faculty of Electrical Engineering and Computing, Croatia, through the **CBRNe-HERO** project.

The competition will take place in two stages. The first stage is the qualifiers stage. Registered teams will develop their solution in a ROS-Gazebo environment. Submitted solutions will be evaluated and the 'top teams', up to six, will continue to the second and final stage. In the final stage, during the Conference, teams will present and will demonstrate their solution. The UAV Competition timetable is shown below.

OCTOBER 1, 2025	Initial draft of the rulebook published, team registration opens
DECEMBER 19, 2025	Initial submission - team registration closed
JANUARY 16, 2026	Debug submission
JANUARY 23, 2026	Simulation stage submission window opens
FEBRUARY 6, 2026	Simulation stage submission deadline
FEBRUARY 20, 2026	Results of simulation phase announced, finalists announced

- Teams are required to register **via the Google form**, online.

IMPORTANT

- **The Competition Rules along with scenario details are subject to change! Check the official repo and the rulebook for any updates: https://github.com/larics/icuas26_competition. Clarifications and FAQs will be publicly announced.**
- **Communication regarding clarifications on scenario description, rules and scoring will be via the Github discussions: https://github.com/larics/icuas26_competition/discussions.**
- **For the simulation phase, the scoring scheme, including time limits and penalties, will be announced after the first evaluation runs.**
- **The scenario and the scoring scheme for the finals will be announced by the end of the simulation phase.**

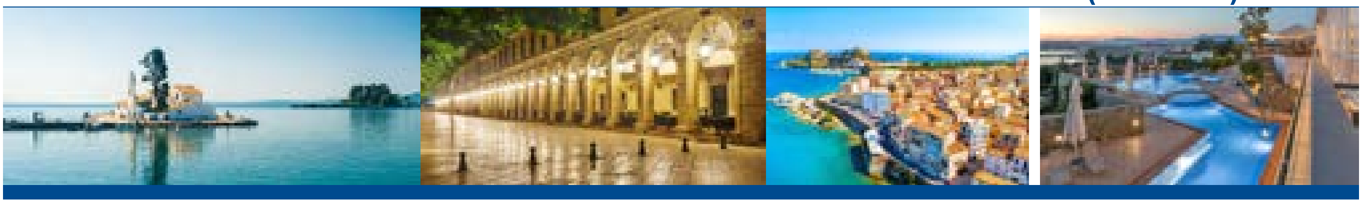
ELIGIBILITY CRITERIA AND TEAM COMPOSITION

The UAV Competition is open to any full-time BSc, MSc and PhD students and/or groups of similar proficiency levels. There is no fee to enter and participate in the qualifier phase of the UAV Competition.

For the first phase, the simulation phase, there is no limit on the number of team members. However, it is strongly recommended that for the second phase, for the finals, the number of team members is four (4). It is mandatory that all team members (up to four) be physically present at the Conference for the UAV Competition; these team members do not need to pay a registration fee for the UAV Competition. However, if team members are authors of accepted papers, or simply wish to also participate in the Technical Conference, then, they should register and pay the Student Registration fee.

Each team must elect a Team Leader (TL) who will be the point of contact for all correspondence with the organizing committee, and referees. Given the dynamic nature of the competition, which may evolve based on received feedback and comments, teams will be given time to 'slightly adjust' the number of team members to tackle all challenges.

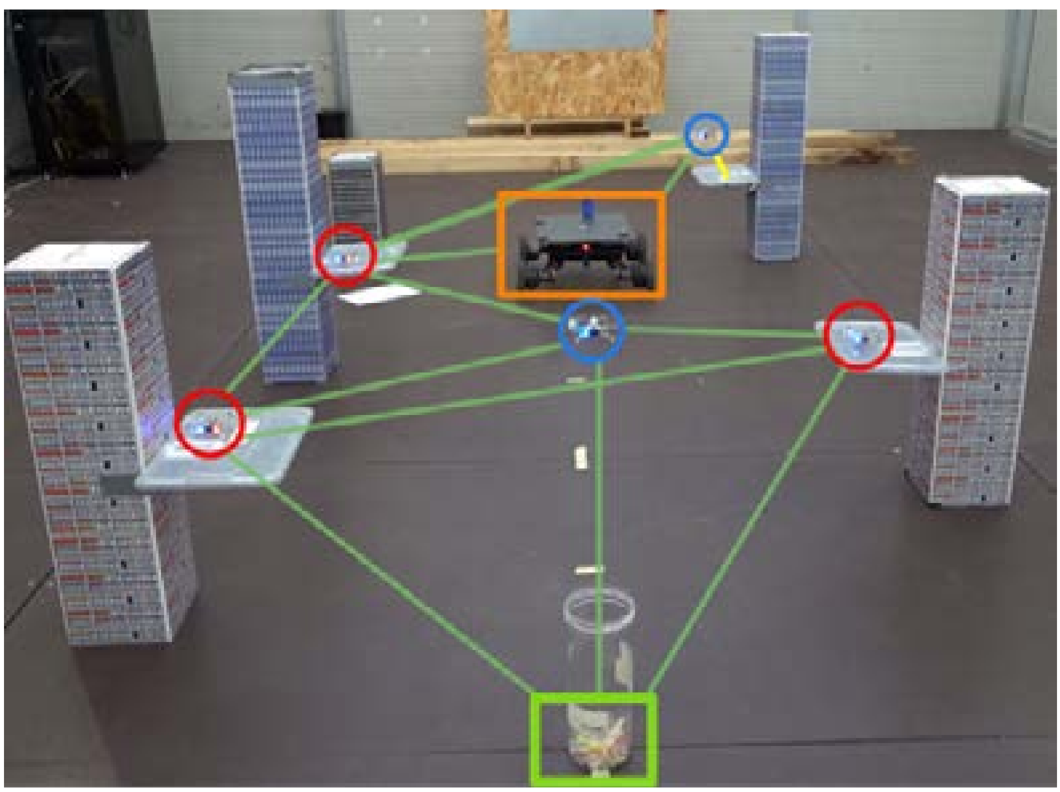
2026 INTERNATIONAL CONFERENCE ON UNMANNED AIRCRAFT SYSTEMS (ICUAS '26)



COMPETITION SCENARIO

Multi-UAV System for Communication Network Establishment and Maintenance during CBRNe Incidents in Urban Environments

A team of UAVs is deployed in an urban environment to track a vehicle, which is tasked with resolving CBRNe threats (chemical, biological, radiological, nuclear, explosive). The UAV team deploys from a (the) base and needs to track a ground vehicle and to maintain its connection with the base station. The ground vehicle is controlled externally, and the UAV team (system)system knows only its current location. Since some threats may interfere with communication links between agents, the UAV team is required to keep constant communication between the base and all agents in the system. The connection between neighboring agents in the system is maintained by keeping line of sight (as shown in the Figure) and by limiting the distance between agents. The team is considered to be in a valid configuration if the underlying graph is connected.
The team of UAVs is also required to locate and identify an unknown number of CBRNe threats, which are simulated with ArUco markers, and to report the location of the threat to the base. While searching, the battery of each UAV is draining and each UAV can go back to the base to recharge, or land on available spots, which are also marked with ArUco markers. There are also decoy markers that do not denote nor CBRNe threat nor landing spot. When going back to the base, or landing, the system needs to remain connected even with one or more UAVs charging or grounded on landing spots. Each UAV can recharge only once but it is allowed to land multiple times on landing spots. The mission ends when the connection of the ground vehicle to the base is lost completely.



■ *Multi-robot team for search, identification and resolving CBRNe threats in urban environments. A team of Crazyflies is tasked with following a ground vehicle to maintain its connection to the base station, while also searching for threats or landing spots to use for energy conservation with the aim of extending the mission time.*

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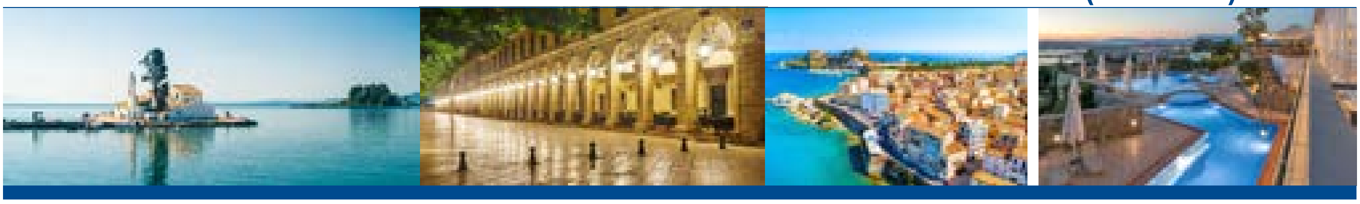

EVALUATION

To evaluate the performance of the team of UAVs in such scenario, three benchmarks will be used:

- **Benchmark 1: Threat localization and identification - The ability of the UAV to correctly identify all existing threats in the environment and report their location accurately.**
- **Benchmark 2: Connectivity - The ability of the team to remain connected throughout the mission.**
- **Benchmark 3: Time - The ability of the team to maximize the mission time of the ground vehicle**

CODE AND DATA STRUCTURES

The simulation phase environment is the Gazebo simulator (**http://gazebosim.org/**), in conjunction with Robot Operating System (ROS, **https://www.ros.org/**). Being realistic and modular, the combination of Gazebo and ROS enables simulations of both actuators and sensors through various plugins. For the UAV Competition, the supported versions for the simulation stage, and the versions that the solutions will be evaluated on, are Gazebo Garden and ROS 2 Humble, running on Linux Ubuntu 22.04 LTS. Teams may opt to use different versions, in which case they take the risk of their code not running on the evaluation machine.

The UAVs to be used are Bitcraze Crazyflies, running through SITL within **CrazySim**. General information about Crazyflies can be found **here**.

For the first phase of the UAV Competition, it is expected that a team's solution will be in the form of one or more ROS nodes. The developed node(s) will interface with the rest of the system via topics and services. List of topics, services and data types will be disseminated to the teams via the technical documentation accompanying the installation files. Subject to feedback from the teams, the organizing committee is open to revise these interfaces to streamline the integration of code developed by the teams. Teams are allowed to use ROS messages and services based on built-in ROS message types to communicate between nodes. The solution is to be submitted through Docker containers. Exact details will be communicated through the **competition repository**.

LARICS **https://larics.fer.hr/**

FER UNIVERSITY OF ZAGREB Faculty of Electrical Engineering and Computing **https://www.fer.unizg.hr/en/**

CBRNE HERO **https://cbrnehero.fer.hr/**

2026 INTERNATIONAL CONFERENCE ON UNMANNED AIRCRAFT SYSTEMS (ICUAS '26)

JUNE 15-18, 2026
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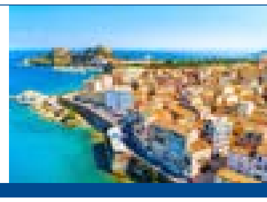

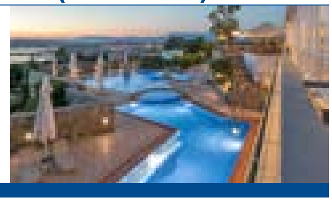

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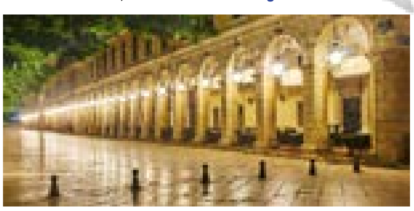

The **2026 International Conference on Unmanned Aircraft Systems**, **ICUAS '26**, will take place in Corfu, Greece, on June 15-18, in the luxurious resort Divani Corfu Palace. Corfu is easily accessible from Athens and Thessaloniki and from many European cities during the tourist season. The location offers the perfect place for business, pleasure and vacations.

ICUAS '26 centers around a wide spectrum of topics. However, emphasis is given to: Soft aerial robots; Cooperative aerial manipulation; Bio-inspired aerial robots; Aerial robot aerodynamics; Reconfigurable UAVs; Multi-mode unmanned platforms; Learning-based perception, navigation and control; Online autonomy; Real-time applications; Human factors and ethical AI for aerial robots; Regulations, policies and safety. Round table discussions will complement the technical sessions.

In addition to the technical sessions, a twofold objective is: i.) Industry and company participation for registrees to find out about the current state of technology and of commercially available products for civil and public domain applications, and ii.) Understanding technical requirements and standards that are prerequisite to UAS full utilization and integration into the national airspace.

Part of **ICUAS '26** is the **UAV Competition**. The Competition is student-focused and student-centered, offering unique opportunities for students to test and compare their skills with those of their peers worldwide. The competition is organized in two stages: simulation qualifiers and in-person finals. The finals will take place during the conference, allowing students to meet and participate in the conference, too. Details on how to participate in the UAV Competition are available on the conference website.

ICUAS '26 offers unique opportunities to meet, interact and shape the future of unmanned aviation, worldwide, bringing together technical, regulatory, and legal communities. Details and logistics about the conference can be found at http://www.uasconferences.com and related links. The conference is fully sponsored by the **ICUAS Association, Inc.**, a non-profit organization, see www.icuas.com.

CONFERENCE STRUCTURE

ICUAS '26 is a 'physical presence only' four-day event. June 15 is reserved for Workshops and Tutorials, while June 16-18 spans the three-day technical conference and the UAV Competition.

IMPORTANT DUE DATES

February 20, 2026:	Full Papers/Invited Sessions /Workshop and Tutorial Proposals, Due
February 6, 2026:	UAV Competition: simulation-based scenario
April 20, 2026:	Acceptance / Rejection Notification
April 20-30, 2026:	Early Registration and Upload Final, Camera-Ready Papers

SUBMISSIONS

All contributions (papers, invited papers, proposals for invited sessions, proposals for workshops and tutorials) must be submitted electronically through https://controls.papercept.net by the due date.

Papers: Paper format (two-column) follows IEEE guidelines. Electronic submission will be handled through PaperCept - details are available on the conference web site. Submitted papers should be classified as Contributed or Invited Session (max. 8 pages) papers. Accepted papers only will be allowed up to two additional pages for an extra charge per additional page.

Invited Sessions: Proposals for invited sessions should contain a summary statement describing the motivation and relevance of the proposed session, the invited paper titles, and the names of the authors. Authors must submit FULL invited papers. Each paper must be marked as "Invited Session Paper".

Workshops and Tutorials: Proposals for workshops and tutorials should contain a title, the list of speakers, and extended summaries (2000 words) of their presentations.

Paper Review Process: All submitted papers will undergo a thorough peer review process coordinated by the Program Chairs, IPC members, Associate Editors, and qualified reviewers. Each paper will be reviewed by (at least) three qualified reviewers. Each Associate Editor will make recommendations. The Program Chairs will finalize and announce decisions by the due date. Each submitted paper will be checked for originality through the iThenticate Plagiarism Detection Software. The paper review process will be observed by the supporting technical society representatives.

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ICUAS 2026

VISITING GREECE AND CORFU
GENERAL INFORMATION

LANGUAGE AND CURRENCY

The official and national language of Greece is Greek. It is written in the Greek alphabet. In some tourist areas, you will also find street names and signs transliterated into the Latin script. Most Greeks speak English, French, German or Italian as a foreign language.

Greece uses Euro (EUR) as currency. Major cards are accepted in larger cities and tourist areas in Greece. When shopping, however, you may get better deals with merchants with cash than debit or credit cards. You can withdraw Euros from ATM machines.

If you have a permanent non-EU residence and are planning to do some shopping during your stay in Greece, you may be interested to learn some tips and guidelines for tax free shopping.

ELECTRICITY, PLUGS AND SOCKETS

Electrical supply is 230 V, 50 Hz AC. Greece uses the standard European (round-pronged) plugs and power sockets. In technical terms, sockets are "type C" or "type F" (also known as "Schuko"), and they work with corresponding plugs (type C, E, F).

VISA REQUIREMENTS

Greece is a member of the European Union (EU) and one of the Schengen Area countries – the world's largest visa-free zone, see the list of Schengen area countries for details. Citizens of some countries need an entry visa for Greece. For more information, check out the detailed visa information page. If you need a visa, make sure to apply for one well in advance.

The Greek Ministry of Foreign Affairs provides detailed information on current visa requirements or find the nearest Greek Embassy or Consulate.

DO I NEED A VISA?

To find out whether you need a visa to travel to Greece, check the page on Visas for Foreigners travelling to Greece. If you have trouble opening the link, follow the steps:

1. Go to the Hellenic Republic Ministry of Foreign Affairs web page.
2. In the menu, find *Services*.
3. Click on *Visas*.
4. Click on *Visas for Foreigners travelling to Greece* and follow instructions.

INVITATION LETTERS FOR VISA ASSISTANCE

The Conference Organizers will provide a detailed invitation letter to all registered participants who need to apply for a visa.

TRAVEL TO ATHENS, GREECE

Athens may typically serve as a first stop when traveling to **Corfu** from international and non-Schengen destinations. Check with your local airlines for the most up to date flight schedules.

ARRIVING IN ATHENS BY AIR

The **Athens International Airport** is serviced by all major airlines, offering direct non-stop flights from/to most of the major European cities, Atlanta, Chicago, New York, Philadelphia, Washington, Montreal/Toronto, North Africa, Gulf States, South Africa, and easy connections to the rest of the world. ATH is also serviced by low-cost and/or charter airlines that offer attractive packages.

Visitors arriving by air to Athens will arrive to the Athens International Airport "Eleftherios Venizelos" (IATA code: ATH). This award-winning airport is one of the world's leading airports in overall passenger satisfaction and was first named the Airport of the Year (2014) in the 10-30 million-passenger category by internationally acclaimed web portal Air Transport News. It is being currently innovated and expanded to accommodate more passengers.

CORFU

Corfu is located north of the Ionian Sea, far away from the other Ionian islands. It is named 'the countess of the Ionian Sea', https://greeceinsiders.travel/corfu-the-countess-of-the-ionian-sea/, while others consider the island to be the 'Queen of the Ionian'. Corfu attracts even the most demanding travelers and welcomes everybody with the amazing views it offers, in the middle of the sea and with the sun reflected in the clear blue waters, between the Old and the New Fortress, two of the jewels of the island. Corfu is the "gateway" of Greece to the West. It is a major touristic destination and is worth visiting for many reasons, see https://www.visitgreece.gr/islands/ionian-islands/corfu/ for details.

ARRIVING IN CORFU BY AIR

Corfu Airport (IATA code CFU), https://www.cfu-airport.gr, is located near Corfu Town and has a single terminal building. It operates domestic flights throughout the year, and international seasonal flights during the touristic period (April to end of October). **Aegean Airlines** (www.aegeanair.com) and **SKY Express** (https://www.skyexpress.gr) offer several flights each day from **Athens International Airport** (IATA code **ATH**), https://theathensairport.com/. In addition to these two airlines, the following airlines operate mostly seasonal flights to Corfu: Aer Lingus; Air Baltic; Air France; Air Serbia; Austrian Airlines; British Airways; Brussels Airlines; Condor; EasyJet; Edelweiss Air; Eurowings; Finnair; FlyDubai; Iberia; ITA Airways; Lot Polish Airlines; Lufthansa; LuxAir; Norwegian Air Shuttle; Norwegian Air Sweden; Ryanair; Scandinavia Airlines; Smartlynx Estonia; Smartwings; Sundair; Swiss; Transavia; TUI; TUS Airways; Volotea; Vueling, among several others.

ARRIVING IN CORFU BY FERRY BOAT

Corfu may be reached by Ferry Boat from mainland Greece, mainly from the ports of Igoumenitsa and Patras, as well as from other Greek islands like Paxi and Lefkada. The Ferry Boat from Igoumenitsa takes about 1.5 hours, and it offers the most frequent and shortest daily route to Corfu. The trip from Patras takes about 7.5 hours. Igoumenitsa may be reached by car, driving from Athens, or any other city in Greece.

Ferry Boat services are also available from Italian ports like Bari, Ancona, and Venice. These trips are longer, ranging from about 9 hours to over 25 hours.

Special Issue

Autonomy Challenges in Unmanned Aviation

Message from the Guest Editors

The Special Issue centers around "Autonomy Challenges in Unmanned Aviation" with the aim to register the state-of-the-art and to discuss and/or propose specific autonomy attributes, measures of autonomy, autonomy metrics, levels of autonomy, etc., for unmanned aviation systems, and how they may be implemented and tested to evaluate performance under nominal and detrimental conditions. The goal is to establish the foundations of an autonomous framework that is verified and validated, and is applicable in real-time. As such, submitted papers should focus on both the underlying theoretical methodology for measuring and evaluating autonomy, as well as on its implementation using a real UAV/UAS. Specific interest are articles that emphasize:

- Foundations of Autonomy: Attributes, quantitative metrics and measures of autonomy, levels of autonomy;
- UAV/UAS design for resilience;
- Self-organizing and reconfigurable UAV/UAS controller designs for autonomous functionality;
- Decision-making;
- Real-time applicable and implementable learning based navigation and control techniques for UAV/UAS autonomous functionality;
- Controller design for nonlinear systems with time-varying and unstructured uncertainties.

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Deadline for manuscript submissions

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HERON is in partnership with internationally renowned pioneers in Robotics and AI:

- Athena Research Center, Greece
- Italian Institute of Technology, Italy
- Karlsruhe Institute of Technology, Germany

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Funded by the European Union

GENERAL SECRETARIAT FOR RESEARCH AND INNOVATION

https://heron-robotics-coe.eu

The Hellenic Robotics Center of Excellence – CoE –HERON

Advancing the Science and Technology of Robotics in the AI era

HERON Robotics CoE
for world-class research, innovation, and technology transfer

Research Directions
1. Field & Space Robotics
2. Healthcare Robotics
3. Safety Robotics

Tallent Attraction and Retainment
Fellowships & Scholarships
MSc Programs
Interships
Repatriation programs

Ecosystem Formation
Build national robotics ecosystem, including Research & Technology actors, Higher Education Institutions, Government and policy makers

HERON obotics Excellence

A T H E N S - G R E E C E

The new Hellenic Robotics CoE, "HERON"

Vision: The nascent Hellenic Robotics Center of Excellence, "HERON CoE" aspires to put Robotics empowered with AI in the economic and social well-being map of Greece, by pursuing top level research, both basic and applied, in research areas that reflect current and emerging challenges of national and EU importance.

Goals: Establish HERON as a world-class Robotics Research & Innovation CoE ▪ Build Human Resources and Infrastructure Capacity ▪ Develop strategic collaborations between HERON and Industry towards Innovation ▪ Establish and mobilise the Hellenic Robotics Ecosystem ▪ Welcome and collaborate with the Greek Diaspora in Robotics ▪ Support Education and Training ▪ Drive National Reforms.

Research Directions: HERON research is grouped into 3 Research Directions: (1) Field & Space Robotics (maritime, agricultural, logistics, construction and space), (2) Healthcare Robotics (assistive, social and surgical), and (3) Safety and Security Robotics (aerial, ground and marine for disaster response, search and rescue, and infrastructure inspection).

Partnerships: HERON has already forged partnerships with leading organizations in Robotics, such as the Italian Institute of Technology and the Karlsruhe Institute of Technology, aiming at the enhancement of its scientific, technological, innovation, and educational capacity.

The team: HERON relies on an excellent team of Greek experts in robotics, while researchers from the Greek Diaspora will contribute also. Together, we will strive to develop cutting-edge robots, systems, and research that will not only lead the field in Greece and globally but also have a positive impact on our society by addressing urgent needs, training excellent researchers, and becoming a brain-gain hub. HERON will establish Makerspaces, that will promote a maker hands-on attitude currently so needed in Greece, educating students and researchers in making, exploring, and sharing using high tech and manual tools. Around HERON, a robust ecosystem will be grown and orchestrated comprising both the private and public sectors.

Funding scheme: HERON is funded by (1) the European Commission – HORIZON CSA actions - (15 M€), and (2) the Greek Ministry of Development -General Secretariat for Research & Innovation (15 M€).

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HERON
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ICUAS Association *eUAM*

The Unmanned Aviation eMagazine

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