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INTRODUCTION OF REWEEMAP PROJECT: AI DRIVEN REMOTE-SENSING FOR DATURA STRAMONIUM DETECTING

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Abstract: The ReWeeMap project, co-financed by EIT Food and the European Union, aims to develop an AI-driven, image recognition-based software capable of specifically detecting Datura stramonium (jimsonweed) among selected arable crops using supervised learning. To achieve this, we employed advanced drone technology equipped with multispectral imaging cameras. Field testing and data collection were conducted at two locations in Hungary, focusing on maize, tomato, and pepper crops. Meanwhile, the software development and IT implementation were carried out in Lithuania by BetaVia (formerly ART21). The development was scientificly proved by the University of Szeged. Following nearly one year of data collection and development works, the software now operates with an accuracy exceeding 80%. The project's long-term objective is continuous improvement, a core principle in AI-based software development. The methodology established for this software is scalable and adaptable to detect other hazardous weed species in various crop types. Consequently, the project envisions not only the commercialization of the software but also its expansion based on the developed framework. Ultimately, this initiative contributes to reducing the food industry's exposure to contamination by toxic weeds by enabling early-stage detection and mitigation directly at the source of infestation. Our aim is to present the development steps and methodology we have established, with the hope that it will support the broader adoption of digital solutions designed to mitigate threats to the agri-food sector.

Keywords: multispectral imaging, Datura stramonium, AI, drone technology, UAV, weed management

1. Introduction

In the food industry, numerous regulations and requirements must be met to ensure the population is supplied with safe and reliable food. The sector is significantly exposed to threats, as various infections and hazards may compromise processing operations from multiple sources (Prasad 2008). These risks may arise from poor personal hygiene, physical contaminants, biological and chemical infections, and pollutants. However, effective internal defense mechanisms have been developed within food safety and quality assurance frameworks to mitigate such risks.

Nevertheless, these systems often struggle to manage external threats, such as weed contamination introduced through agricultural raw materials (Soler-Rodríguez et al. 2006). While advanced sorting technologies are capable of filtering out weed seeds in many cases, certain instances still pose serious challenges. One of the most hazardous and toxic weeds is Datura stramonium, commonly known as Jimsonweed, which is particularly difficult to separate from some raw materials. Its presence regularly leads to poisoning incidents and represents a significant food safety risk.

Datura stramonium is a tropical-origin plant belonging to the Solanaceae family (Aćimović 2025), making it closely related to several important horticultural crops, which complicates its identification. Although the plant and its fruit are sometimes utilized for pharmaceutical or chemical purposes—and have even been cultivated in the past—it is generally classified as a dangerous weed. Phytochemical analysis has revealed that its roots, leaves, and fruits contain alkaloids, saponins, tannins, steroids, flavonoids, phenols, and glycosides. Among these, the alkaloids are of particular concern. The tropane alkaloids present in the plant—such as atropine, hyoscyamine, and scopolamine—are especially hazardous to humans (Prasad 2008). While these compounds can be used in controlled settings for antiepileptic, anti-asthmatic, and analgesic purposes, accidental ingestion may induce effects similar to narcotic substances (Al-Snafi 2017).

In most documented cases, symptoms include hallucinations, pupil dilation, dry mouth, rapid heartbeat, speech impairment, aggression, fever, and skin flushing. In severe cases, respiratory arrest, hyperthermia, and seizures may occur. Poisoning can simultaneously affect the stomach, intestines, and central nervous system (Aga & Geyid 1992). Jimsonweed frequently appears among crops such as soybean, flaxseed, wheat, maize, sunflower, open-field tomato, and various bean varieties, posing a significant threat to the food industry (Pérez-Ortiz et al. 2015). Moreover, the alkaloids are heat-stable, meaning the toxic compounds are not eliminated through thermal processing.

Therefore, it is crucial to eliminate such threats as early as possible, ideally at the point of origin. Since the early 2000s, numerous advanced technologies have been available for weed mapping and monitoring (Westwood et al. 2018). Ground-based mechanical or manual inspections have been rapidly replaced by aerial imaging, and with the fast-paced development of technology, multispectral imaging has been used for nearly two decades to generate weed maps and conduct plant health monitoring analyses (Feyaerts & Van Gool 2001).

Today, mapping is conducted using high-performance, long-range, and extended-operation drones—Unmanned Aerial Vehicles (UAVs) - capable of capturing high-quality imagery. In addition to these precision tools, intelligent data processing software and farm management systems—often powered by Artificial Intelligence (AI) - have been developed to support integrated enterprise management and decision-making for farmers (Bajwa et al. 2015, Ma et al. 2023, Naveed et al. 2023, Monteiro & Santos 2022)

These efforts are driven by the growing adoption of ecological farming practices and various EU and national regulations aimed at reducing chemical plant protection and other environmentally harmful interventions, while maintaining or improving efficiency. This objective is also supported by the European Institute of Innovation and Technology’s agrifood division, EIT Food. The innovation funding opportunities provided by EIT Food have enabled the implementation of the ReWeeMap project, which aims to deliver targeted and specific responses to the threats posed by Datura stramonium through the integration of advanced drone technology and agricultural digitalization tools (Hunter et al. 2020, Mutebi et al. 2022).

2. Materials and methods

Numerous scientific sources report on the development of weed monitoring systems based on closed-range spectral imaging technologies. However, most of the known methods generate general weed maps, indicating the presence and extent of weed contamination in a given area. In contrast, the ReWeeMap solution, through its AI-powered image analysis functionality, is capable of directly identifying Datura stramonium (Jimsonweed).

The project consortium includes two test sites in Hungary: AgriCorn and UniverAgro, BetaVia, an agricultural digitalization IT development company from Lithuania, and Campden BRI Hungary, a food industry research institute and based on the advantages of the knowledge triangle, the scientific background was provided by the University of Szeged. During the development of the methodology and the definition of implementation steps, several key factors had to be categorized to establish a coherent work program (Xuan et al. 2025).

To ensure accurate annotation and training, potted Datura plants were placed in the designated test areas. At the time of placement, GPS coordinates were recorded, and the pots were photographed from multiple angles to ensure traceability and identification. Additionally, the pots were marked with signage and colored markers, enabling their precise localization in aerial imagery. The experiment should be carried out in a greenhouse under natural daylight conditions. For each plant species, 5–10 individual plants in separate pots (1 plant per pot), or 2–3 rows of plants, should be used. To simulate the conditions of future field campaigns, natural daylight is the preferred illumination source. Image acquisition should take place around midday (between 11 a.m. and 1 p.m.) to minimize shadows and other unwanted effects. If natural light is insufficient, alternative lighting solutions will be considered (Roberts & Florentine 2024).

To ensure the availability of sufficient and high-quality data for drone operations, Datura stramonium plants were cultivated in pots within a greenhouse facility. The weed seeds were provided by the University of Szeged, a project partner. Cultivation was carried out in multiple stages, with weekly planting intervals, to allow for repeated data collection. During the growth period, multispectral and RGB images were captured according to the methodology provided by the IT development partner. This enabled the inclusion of early-stage weed specimens in the AI model training, ensuring that the software can detect the weed even before flowering.

Flight plans must be synchronized with the growth dynamics of the cultivated crops. It is important to consider that fast-growing crops such as maize or sunflower may quickly outgrow the weeds, making identification more difficult due to increased canopy coverage and height differences. Since the primary goal of the project is early-stage prevention, the software training must emphasize data collection during the early growth phases.

A particular challenge arises with tomato crops, as they belong to the same botanical family (Solanaceae) as Datura stramonium, making visual differentiation difficult (Makuleke & Ngole-Jeme 2020). During the “bush formation” stage typical of open-field tomatoes, the plants become nearly indistinguishable. Once the canopy closes, effective image analysis and labeling become nearly impossible.

Additionally, wild-growing Datura stramonium plants were observed among the cultivated crops, alongside the potted specimens used for experimental purposes. While this supported data collection and confirmed the market relevance of the solution, it also imposed limitations on the experiment. Due to the need to protect the crop yield and comply with legal regulations, weed control operations had to be carried out, which in turn affected the continuity of data acquisition.

To establish the necessary technological conditions, it is essential to define the physical characteristics of the images and recordings required by the AI developers for consistent data collection and processing (Lobo et al. 2000). In addition, the operational parameters of drone flights must also be determined. Several test flights were conducted to define the following technological specifications for data acquisition:

- Optimal flight altitude
- Flight speed
- Image resolution and Ground Sampling Distance (GSD)
- Image overlap rate for orthophoto generation

It is also necessary to ensure and coordinate that the initial data collection flights at both test sites are carried out under identical technological conditions, using the same methodology, and in a reproducible manner. (Gerhards et al. 2022) The availability of suitable environmental conditions is also critical for successful operations, as rain, strong winds, shadow casting, and overcast weather can all negatively affect the quality of data collection.

The multispectral camera should be capable of capturing imagery within the visible and near-infrared spectral ranges. The sensor must include at least four spectral bands (blue, green, red, and near-infrared), and preferably five (blue, green, red, red-edge, and near-infrared). The camera should be operable as a stand-alone unit for close-range indoor image acquisition and should also be mountable on a drone for field applications. Furthermore, the camera must include a GPS module to enable geo-registration of images during field campaigns.

Given that agricultural monitoring drones are typically equipped with multispectral cameras, the required imaging hardware was readily available (*Table 1*). Data acquisition was performed by the project partners using DJI Mavic 3 drones. In this context, the presence of an RTK (Real-Time Kinematic) module is of critical importance, as it ensures precise geolocation. Accurate GPS coordinates are essential for the reliability and precision of the software’s analytical outputs (Centorame et al. 2024).

The drones used were equipped with both multispectral and RGB cameras. The multispectral cameras employed in the project were capable of capturing imagery in the following spectral bands.

Table 1.: Different spectra and their corresponding wavelength ranges

Green (G)	560 ± 16 nm
Red (R)	650 ± 16 nm
Red Edge (RE)	730± 16 nm
Near Infrared (NIR)	860 ± 26 mn

The physical characteristics of the image sensor used in the multispectral camera are as follows:
Sensor type: 1/2.8-inch CMOS
Effective pixels: 5 megapixels
Maximum image resolution: 2592 × 1944 pixels
The lens specifications include:
Field of View (FOV): 73.91 (horizontal: 61.2°, vertical: 48.10°)
Equivalent focal length: 25 mm
Aperture: f/2.0
Focus: Fixed focus

With these parameters, the multispectral camera is capable of capturing high-resolution imagery suitable for both field and controlled-environment applications.

Due to the specific requirements of greenhouse imaging and other controlled conditions, a custom multispectral camera was also procured specifically for the project (*Table 2*). This device was selected to ensure optimal performance under artificial or filtered lighting conditions and to support close-range imaging tasks critical for early-stage weed detection and AI model training (Piron et al. 2009).

Table 2.: Physical specifications of aerial imaging

Dimensions:	9.4 cm x 6.3 cm x 4.6 cm
Spectral bands:	blue, green, red, red edge, and NIR (global shutter, narrow band)
Ground sample distance	8 cm per pixel at 120 m above the ground
Capture rate	1 image per s

This stand-alone camera can also be mounted on a drone, making it suitable for executing specialized operations within the project. As such, the equipment used in the project is capable of supporting both close-range and aerial multispectral imaging tasks.

The essence of multispectral imaging in agricultural applications lies in the interaction between electromagnetic radiation and chemical bonds at various wavelengths. Radiation emitted along the electromagnetic spectrum resonates with specific chemical bonds, allowing spectral signatures to be associated with chemical phenomena or symptoms through the absorption of vibrational energy. The resulting series of grayscale images enables the visualization of plant structures at different depths and reveals features in non-visible spectral ranges.

To determine the optimal flight altitude, test flights were conducted by drone pilots at both project sites. The initial test altitude was 50 meters, from which the following results were obtained using both RGB and multispectral imaging methods (*Figure 1-14*).

Figure 1.: Aerial image captured at 50 meters altitude using an RGB camera.

Figure 2.: Aerial image captured at 50 meters altitude using a multispectral camera in the Near-Infrared (NIR) spectral band.

The images clearly demonstrate that an altitude of 50 meters is not suitable for training the image analysis software. The curvature of the camera lens causes distortion at the edges of the image, necessitating a higher degree of overlap for accurate orthophoto generation. Additionally, due to the distance, ground-level vegetation is not clearly visible.

However, what is effectively illustrated by the two figures is that in the Near-Infrared (NIR) spectral band, the potted Datura plants marked with identification signs reflect much more distinctly. This indicates that certain multispectral bands - particularly NIR - are more suitable for the localization of Datura stramonium.

The next test flight was conducted at an altitude of 40 meters. At this stage, the vegetation was more developed, which also influenced the applicability of multispectral imaging. Since the NIR band operates at higher wavelengths and is primarily used for monitoring biomass and leaf area, it was more appropriate in earlier stages. For this flight, however, it became more relevant to utilize the green spectral band, which operates at lower wavelengths and is commonly used for calculating vegetation indices. This band provided better visibility of the placed Datura plants under the denser canopy conditions.

Figure 3.: Aerial image captured at 40 meters altitude using an RGB camera

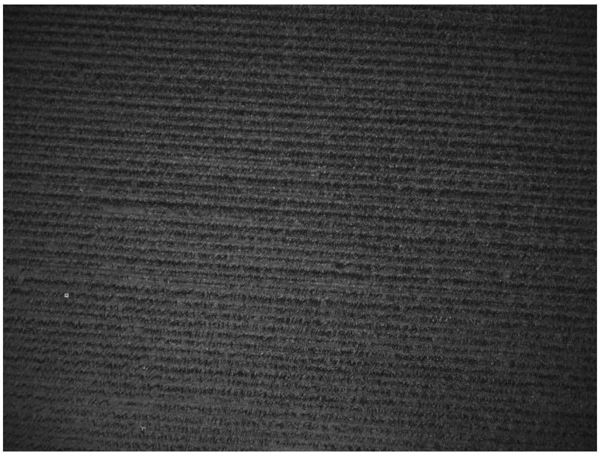

Figure 4.: Aerial image captured at 40 meters altitude using a multispectral camera in the Green (G) spectral band.

It is evident that as the cultivated crops enter their growth phase, canopy coverage becomes an increasing challenge. In the RGB image, the identification marker is barely visible, whereas in the multispectral image, the reflectance remains more pronounced, particularly in the relevant spectral bands (Gaikwad & Tidke 2022)

Despite this, the 40-meter flight altitude still proved to be too high for effective manual annotation and AI model training. The distance limits the visibility of fine details necessary for accurate labeling, and noticeable distortion is still present at the edges of the images due to lens curvature.

As a result, the next test flight was conducted at an altitude of 30 meters. At this height, all multispectral bands provided sufficient reflectance of the identification markers, making them clearly distinguishable. However, the distance was still suboptimal for detailed manual image analysis, and edge distortion remained a limiting factor for precise annotation.

Figure 5.: Aerial image captured at 30 meters altitude using an RGB camera

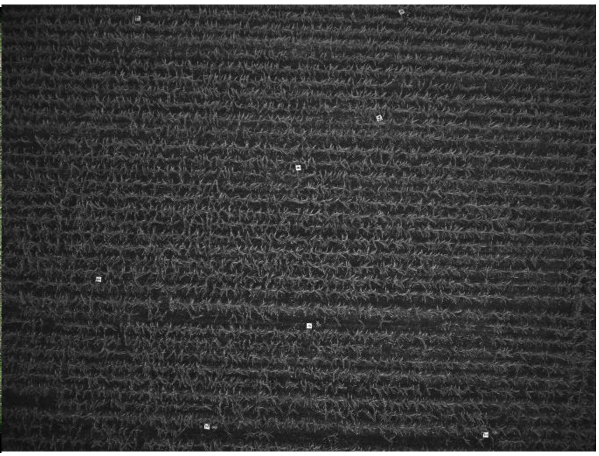

Figure 6.: Aerial image captured at 30 meters altitude using a multispectral camera in the Green (G) spectral band.

As a final step, three additional flight altitudes were tested. Drone operations were carried out at 20 meters, 15 meters, and 12 meters by the drone pilots. All three altitudes proved to be suitable for manual image analysis, while each offered distinct advantages:

- 20 meters: Provided a broader overview of the area, ideal for general field coverage.
- 15 meters: Enabled effective analysis of maize (corn) crops.
- 12 meters: Offered improved visibility for pepper and tomato crops; in cases of dense canopy coverage in maize, this lower altitude was also necessary for accurate detection.

Based on these findings, the data collection methodology was finalized to include these three flight altitudes, which were subsequently used for further data acquisition across the pilot sites.

For the flight altitudes established during the experimental phase, a flight speed of 1.3 m/s was configured. To ensure sharp image capture, the shutter speed was set to 1/2000. The resulting Ground Sample Distance (GSD) - which defines the spatial resolution of the images—was 0.69 cm/pixel.

To minimize image distortion at the edges and ensure high-quality orthophoto generation, the image overlap was configured as follows:

- 80% front overlap
- 70% side overlap

These parameters ensured consistent image quality and reliable data acquisition across all test flights.

Figure 7.: Aerial image captured at 12 meters altitude using an RGB camera

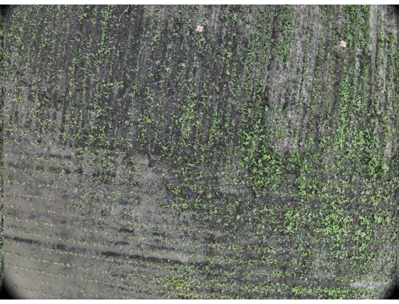

Figure 8.: Aerial image captured at 15 meters altitude using an RGB camera

Figure 9.: Aerial image captured at 20 meters altitude using an RGB camera

To support visual comparison, the following section presents multispectral images captured at 15 meters altitude across different spectral bands, taken over a more developed crop canopy. These images illustrate the varying reflectance characteristics of the vegetation and identification markers under each spectral condition.

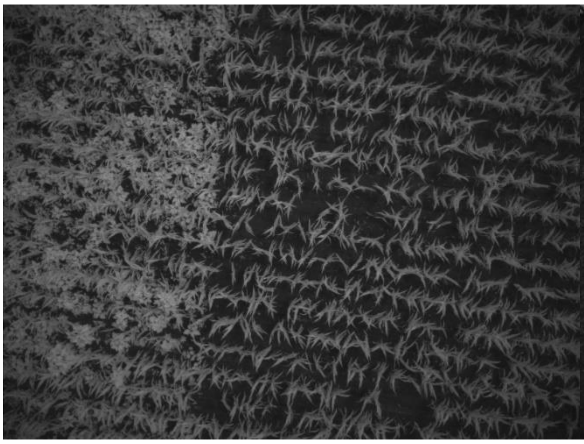

Figure 10.: Aerial image captured at 15 meters altitude using a multispectral camera in the Red spectral band.

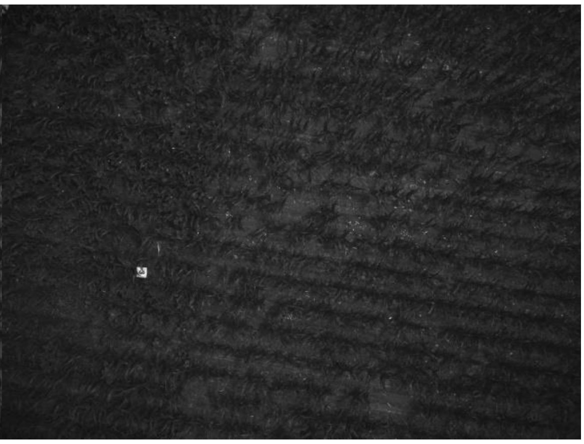

Figure 11.: Aerial image captured at 15 meters altitude using a multispectral camera in the Near-Infrared (NIR) spectral band.

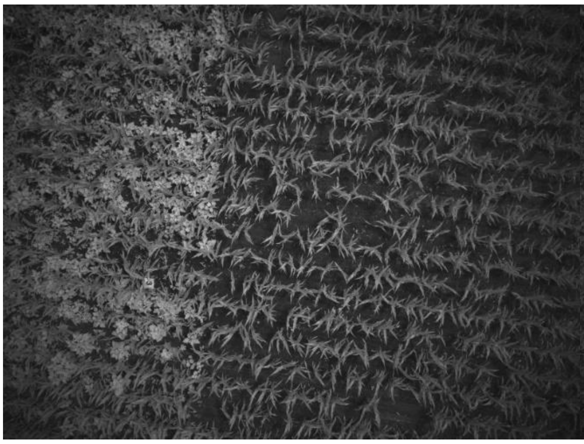

Figure 12.: Aerial image captured at 15 meters altitude using a multispectral camera in the Green spectral band

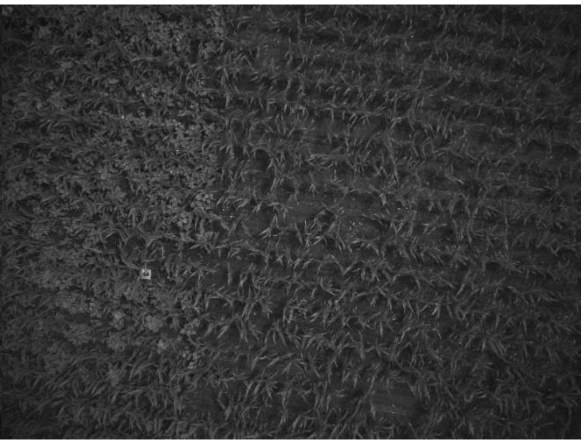

Figure 13.: Aerial image captured at 15 meters altitude using a multispectral camera in the Red Edge spectral band.

Figure 14.: Aerial image captured at 15 meters altitude using an RGB camera.

Each spectral band demonstrated distinct advantages in the captured images. Although RGB images were used for manual annotation and AI training, as they are the most intuitive for the human eye to distinguish and label key features, it became evident that other spectral bands provided valuable complementary information.

For instance, in the Green spectral band, the weed species exhibited noticeably different color intensities compared to the cultivated crops, indicating that this wavelength is reflected differently by weeds and crops. In the Near-Infrared (NIR) band, the identification markers were significantly more visible, suggesting that this spectral range is capable of penetrating canopy cover and distinguishing between plant structures, leaf surfaces, and other objects. This is particularly important, as the GPS coordinates of the marked Datura plants were recorded during placement, allowing the software to cross-reference and validate results using the drone's geolocation data.

The Red and Red Edge bands provided valuable insights into the overall health status of the crop canopy, especially in cases where weed infestation had already begun to inhibit crop development. This functionality is highly beneficial for future applications, such as targeted nutrient and pesticide application planning.

Following the drone-based data collection flights, the captured images were immediately uploaded by the pilot site operators to a shared server developed by the IT partner. Due to the large file sizes, the upload process took approximately 12 hours to complete. The IT development company then imported the images into a custom AI training platform, where manual image annotation was performed.

This methodology proved to be highly automatable, and the dataset was continuously expanded until a sufficient volume of data was available to begin the labeling process. Approximately 3,000 manual annotations were required to initiate effective supervised training of the AI model. Labels were assigned to distinguish between crop plants, soil, weeds, and other vegetation. While the primary focus was on weed annotation, it was also essential to label the surrounding environment to reduce background noise and improve the model's ability to differentiate and identify the target species.

During annotation, it was crucial to label different plant parts, enabling the AI to later distinguish between them automatically. This included marking leaves, stems, and flowers at various sizes and developmental stages.

In total, 47 drone-based data collection operations were conducted across the two test sites:

- 26 missions at the UniverAgro site
- 21 missions at the AgriCorn site

Once the annotation guidelines were finalized in a dedicated instruction document, the task was easily distributed among the consortium partners.

After data collection, a curated selection of 175 images was uploaded to an online annotation platform called Labelling Studio (*Figure 15*). These images represented a balanced and high-quality sample set from all three tested crops - maize, pepper, and tomato - and served as the basis for initiating supervised AI training. The online accessibility of the platform allowed all consortium members to participate in the annotation process collaboratively.

Figure 15.: User interface of AI model training software

During the annotation process, users could select from the following label categories: Datura, Other, Area, Corn, Pepper, and Tomato. These labels were applied to specific plant parts or other relevant features (e.g., Area for background or non-vegetative zones). This labeling system made the task simple and straightforward, allowing for efficient and consistent annotation.

The software interface was user-friendly and intuitive, significantly facilitating the development of AI applications. Its clear structure and ease of use enabled contributors to focus on accurate labeling, thereby improving the quality and reliability of the training data (*Figure 16*).

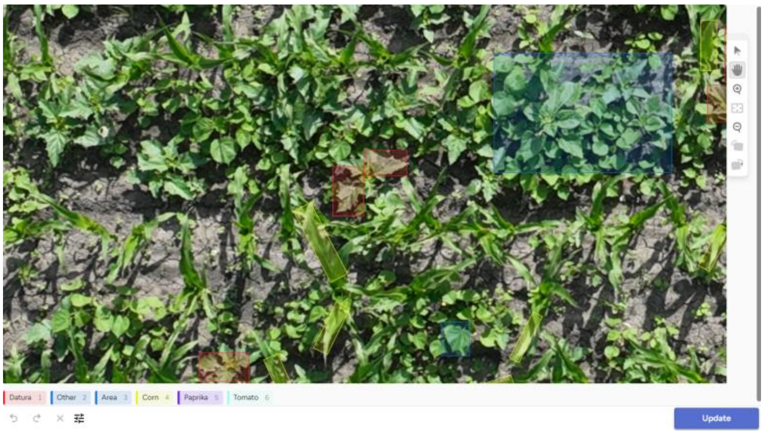

Figure 16.: User interface of AI model training software

The image clearly illustrates the level of precision required for accurate label placement. Based on this, the following color-coded labeling scheme was applied:

- Red labels were used to mark the leaves of Datura stramonium, ensuring high visibility and precise identification of the target weed species.
- Yellow labels were assigned to the characteristic elongated leaves of maize, enabling clear differentiation from other vegetation.

- Blue labels were used to indicate the presence of other weed species, supporting the development of a general weed mapping function in addition to the specific detection of Datura stramonium.

This labeling strategy ensures that the developed software can support both specific weed identification and general weed distribution mapping.

In the case of tomato crops, the annotated Datura plants served as reliable reference points (*Figure 17*). This allowed for the use of larger, homogeneous label areas to mark the cultivated plants, facilitating efficient annotation of the crop canopy.

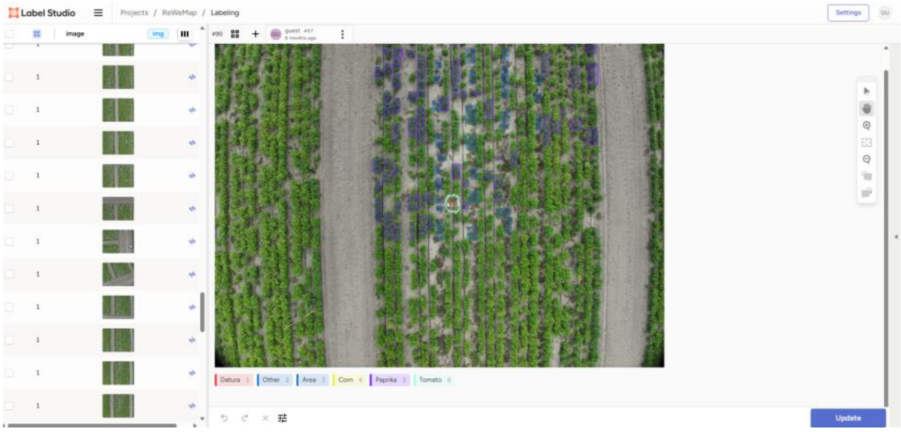

Figure 17.: User interface of AI model training software shwing a placed label

Although manual annotation in open-field tomato crops presents certain challenges, a well-labeled and accurately geolocated weed specimen can provide a reliable spectral signature that the software can later recognize. This means that even a small number of precisely annotated weeds can be sufficient for the model to detect distinct spectral patterns, which can then be used to correlate RGB imagery with multispectral data.

By learning to associate the unique spectral response of Datura stramonium with its corresponding appearance in RGB images, the software gains the ability to generalize and identify similar patterns across larger datasets. This cross-referencing capability is essential for enhancing the model’s accuracy and robustness in real-world field conditions.

3. Results

We utilise the YOLOv8n model, a lightweight member of the YOLOv8 family, which has demonstrated strong performance in weed detection tasks using RGB images (Ding et al. 2024, Liu et al. 2024, Wang et al. 2025). The nano version is chosen for proof-of-concept purposes due to its smaller number of trainable parameters, enabling faster iteration and efficient deployment. While larger models may offer improved accuracy (Liu et al. 2024), the nano model is sufficient for initial validation.

Data augmentation techniques—including translation, scaling, and rotation—were applied during training to improve model robustness and introduce variability in the dataset. Colour augmentations were disabled for this experiment.

The dataset was split into training and testing using the 80/20 rule. Images were split into batches of 16. AdamW optimiser was used with a learning rate of 0.001 and momentum 0.9.

Training was performed on an NVIDIA RTX A5000 GPU.

The model was trained using images of individual plants or small groups of plants. This approach reduces labelling effort, as it does not require annotating every plant in a field image. The model performs well in identifying individual plants and accurately distinguishes between species such as corn, paprika, and datura, which have distinct appearances and are not densely clustered (*Figure 18*).

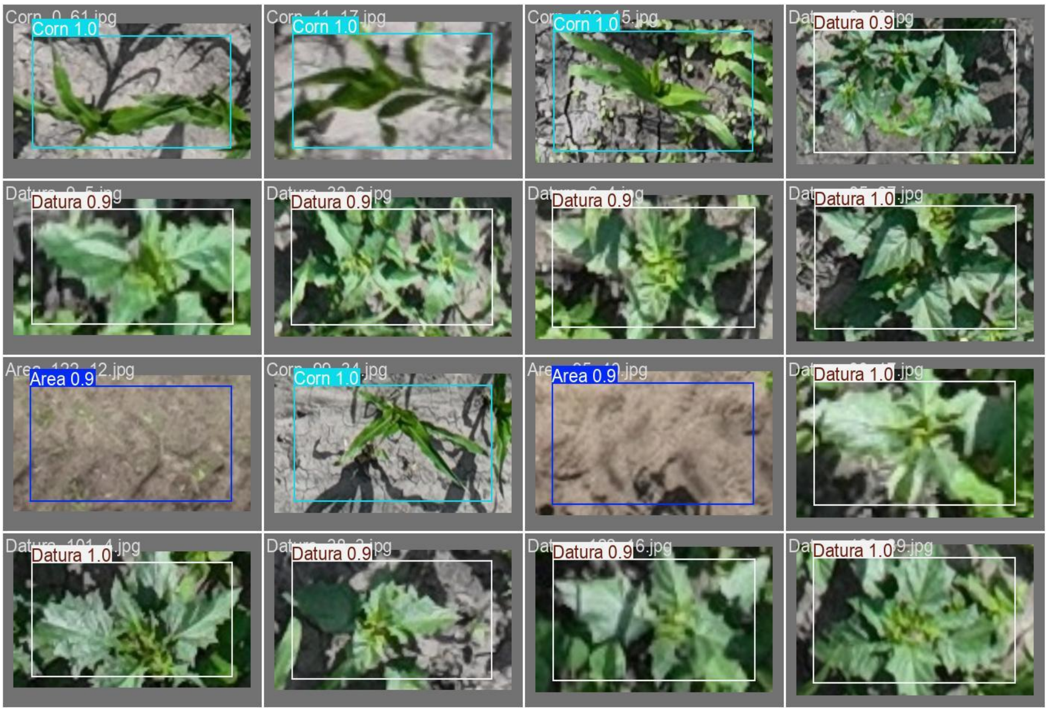

Figure 18.: User interface of AI training validation software

The picture shows inference of the validation dataset after model training. The added number indicates the model's confidence in the prediction.

Training was stopped after 50 epochs, as the loss curve began to plateau, indicating it was approaching a minimum.

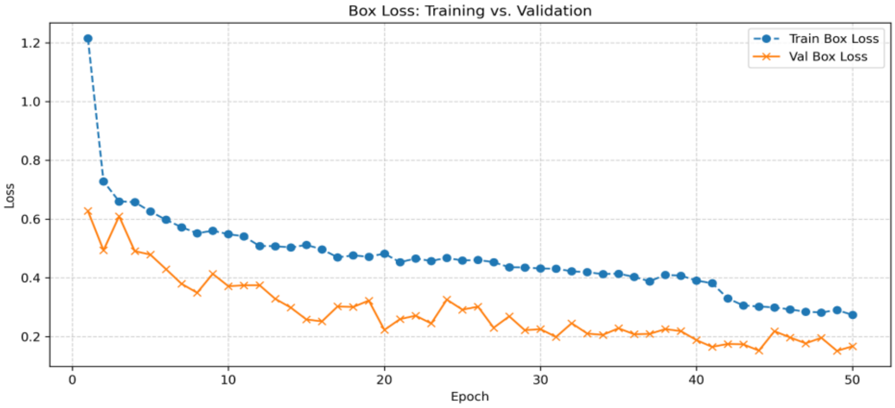

Figure 19.: Box loss comparison of AI model training and validation results

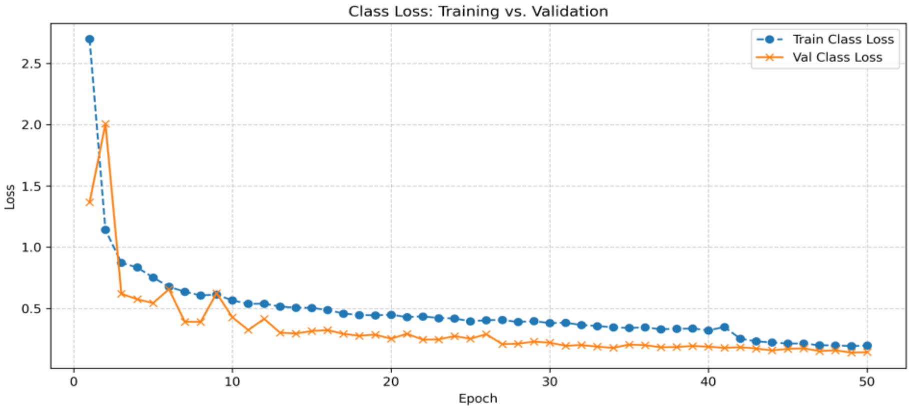

Figure 20.: Class loss comparison of AI model training and validation results

The accuracy graph shows that the model can effectively distinguish between plant types, even during the early stages of training.

Here, box loss and class loss are two different training metrics used to train the model in multiple ways at the same time (*Figure 19-20*).

Box loss measures how well the model's predicted bounding boxes align with the ground truth information. This helps ensure that YOLOv8 correctly identifies and frames objects.

Class loss measures if the predicted object is of the correct class compared to the ground truth data (*Figure 21*). This ensures that the model will detect the correct object class in addition to the bounding box of the object.

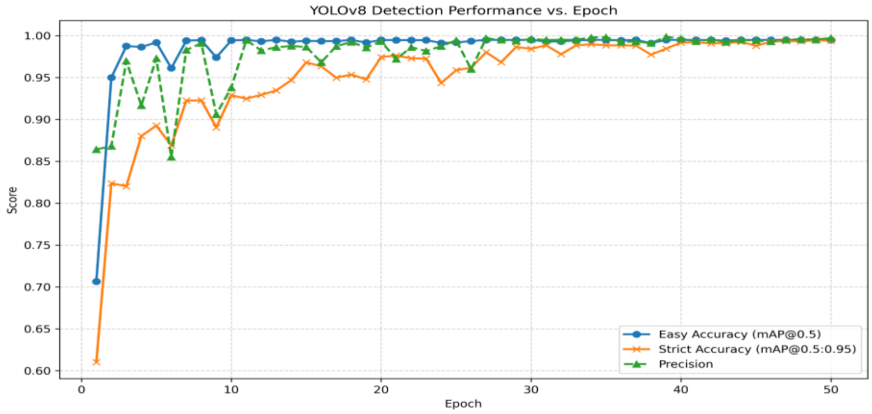

Figure 21.: Comparison of detection performance and epoch

Easy accuracy - Mean Average Precision at IoU = 0.5 — Represents the mean average precision using a relaxed Intersection over Union (IoU) threshold of 0.5, allowing for easier detection success.

Strict Accuracy - Mean Average Precision at IoU 0.5–0.95 — more rigorous and balanced evaluation metric, averaging precision across multiple IoU thresholds (from 0.5 to 0.95), providing a comprehensive measure of detection performance.

To ensure proper validation, we used images with clearly marked daturas that were held out from the training set (*Figure 22*). These samples were excluded to prevent the model from relying too heavily on the markings, which could compromise its ability to detect daturas in unmarked images.

Figure 22.: Datura detected by AI

To accurately determine the geographic location of the detected datura plant, we utilise the drone's telemetry data—including GPS coordinates, altitude above ground level, and orientation (yaw)—alongside camera parameters such as focal length, sensor size, and image dimensions. The centre of the detected bounding box, given in pixel coordinates, serves as the reference point within the image (Sakamoto et al. 2012).

We first calculate the Ground Sampling Distance (GSD), which defines the real-world ground size represented by each image pixel:

$$GSD = \frac{Sensor\ Width \times Altitude}{Focal\ Length \times Image\ Width}$$

Using this value, we compute the ground offset of the bounding box centre relative to the image centre:

$$x_{ground} = (u - W/2) \times GSD$$
$$y_{ground} = (v - H/2) \times GSD$$

where u,v are the pixel coordinates of the bounding box centre, and W, H are the image width and height, respectively. To obtain the final geographic position of the plant, these offsets are rotated according to the drone’s heading (yaw) and then translated into latitude and longitude relative to the drone’s known position.

4. Discussion

In summary, our findings demonstrate that drone technology combined with multispectral imaging is not only suitable for generating weed distribution maps but also effective in detecting individual weed species. However, the creation of a high-quality, task-specific dataset remains a critical factor in the development of AI applications. This requires well-controlled testing environments and data collection over at least two full growing seasons to ensure robustness and generalizability.

A thorough understanding of the target weed species’ phenology and genetic characteristics is essential to minimize development risks. Fortunately, the availability of advanced and accessible AI development tools significantly accelerates the training and implementation process.

Throughout the project, the creation of a high-quality dataset proved to be of paramount importance. It enables the partial automation of labor-intensive tasks such as image annotation, thereby streamlining the development workflow. Advances in drone technology, particularly in localization systems, now allow for centimeter-level mapping accuracy, which further enhances the precision of detection and classification.

The ReWeeMap software offers a practical and scalable solution to a significant challenge in agriculture. It is designed to be understandable, user-friendly, and accessible to end users in the farming sector. Nevertheless, continuous development is essential to ensure increasingly accurate results and to expand the software's applicability to a broader range of crops and weed species.

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