ML for Weed Detection
Project Proposal

Applications of Machine Learning for Remote Sensing

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Abstract:

Weeds in lawns and crop fields spread quickly through underground roots and are difficult to remove without damaging nearby plants. Deep-learning models such as the one talked about in DeepWeeds (Inception-v3 and ResNet-50) can classify species from RGB images, but they do not explain *why* a prediction is made or *where* the physical crown of the weed lies (the point from which roots emerge into the soil below).

This project aims to re-implement the DeepWeeds baseline and extend it with interpretable computer vision methods including Class Activation Maps (Grad-CAM), Segment Anything model (SAM), and other explainable machine learning techniques (SHAP, LIME) to visualize which image regions and features most influence model decisions. CAM highlights discriminative areas for classification, while SAM can generate pseudo-segmentation masks that help locate probable crown centers.

By comparing these approaches, I aim to understand how deep models perceive vegetation patterns, which visual cues drive their predictions, and whether such cues correspond to biologically relevant structures like crowns. The outcome will be an interpretable, hybrid pipeline for crown-based weed mapping from proximal remote-sensing imagery, forming a foundation for future precision weed-management systems.

Introduction:

Weed management has always been one of those problems that never really goes away: whether it's in agriculture, lawns, or small gardens. Weeds spread fast through underground roots and choke out healthy vegetation, but most of the current solutions are either labor-intensive or environmentally harsh. Pulling weeds manually is tedious, herbicide use is undesirable in residential settings, and even existing "automated" weeders are huge, expensive industrial systems designed for ordered crop rows, not irregular lawns.

When I started thinking about this problem, I realized that the real challenge isn't just removing weeds, it's teaching a machine to perceive them the way humans do. For a personal or small-scale robot or drone to work, it would have to map the lawn, spot weeds accurately among normal grass, identify the crown center (the point where the plant meets the soil), and remember those coordinates for precise removal. Essentially, the "brain" of such a robot would be its computer vision and remote sensing system: how it sees, interprets, and decides what to act on. My undergraduate project of building a CNC-gantry based terra-farming robot, which I built ground up, is what exposed me to this problem of identifying weed, and killing it, or notifying the user, at a very cheap cost. But that robot does the planting of seeds in a grid like fashion, hence it is very easy for any kind of cheap camera sensor to spot an "alien" and take action. This is what first drew me into exploring machine learning and deep learning for remote sensing.

The significance of this work goes beyond a single use case. The market for smart, autonomous weed management, currently dominated by large agricultural systems, is estimated to exceed 4 billion dollars globally, yet there is a clear absence of affordable, compact systems designed for individual users. Developing reliable perception models that can classify and localize weeds at the crown level could make personal weed-detection robots feasible. Beyond lawns, this kind of research could extend into several domains I personally find fascinating – archaeology, historical mapping, planetary exploration, or even search-and-rescue robotics – essentially any domain where identifying small, meaningful structures hidden among cluttered backgrounds is critical.

The DeepWeeds project (Olsen, A., Konovalov, D.A., Philippa, B. et al. 2019) provides a strong foundation for this work. It demonstrated that deep convolutional neural networks could classify nine weed species from RGB imagery collected in natural rangelands across Australia. However, while their models achieved strong classification performance, they didn't address why the model made certain predictions or where the weed's biologically meaningful regions were located. That interpretability gap is crucial if we ever want to integrate such models into autonomous systems that physically act on their predictions.

To bridge that, my project focuses on reimplementing and extending the DeepWeeds framework with a focus on interpretability and biological localization. I plan to rebuild the training pipeline from scratch rather than use pre-trained models – training and fine-tuning my own architecture (likely a ResNet or Inception variant similar to the one used in their work) using the labeled images available through the Weed-AI dataset, which is organized in the same format as DeepWeeds.

On top of that, I will explore interpretable machine learning methods – specifically Grad-CAM, SHAP, and LIME – to visualize what parts of the image or what "features" help the model decide a weed's species. In parallel, I will experiment with SAM (Segment Anything) to generate pseudo-segmentation masks, which may help locate the plant's crown center or at least show where a model's visual attention aligns with the biological center. I am still learning these techniques, and part of this project's purpose is exactly that – to understand how explainability tools can help make CV model decisions tangible and useful.

The goal, in short, is to develop an interpretable, crown-aware weed-classification-detection pipeline that does two things:

1. Classifies the weed species from images, and
2. Attempts to locate the crown center using explainable and segmentation-based methods.

By comparing and visualizing the outputs from Grad-CAM, SHAP, and SAM, I hope to understand how deep learning models perceive weeds and whether those learned patterns align with what actually matters biologically - the crown. This understanding could later form the backbone of a real robotic system that performs localized weed removal.

Ultimately, this project is not only about replicating existing work but also about learning how to see like a model – to interpret, question, and visualize what it "pays attention to." It's about building a bridge between perception and action, between AI and practical problem-solving – one weed (and one crown) at a time.

Methods:

1. Data Source and Study Context:

The dataset I am using originates from the Weed-AI platform, which hosts multiple open datasets for weed detection, including a cleaned and well-organized version of the DeepWeeds dataset. DeepWeeds consists of more than 17,000 RGB images representing nine common weed species from rangeland environments in Australia, collected under natural light and varying weather conditions. Each image is 256×256 pixels and categorized by species, such as parthenium hysterophorus (Parthenium), lantana camara (Lantana), and vachellia nilotica (Prickly Acacia).

The images were originally captured using a FLIR Blackfly 23S6C RGB camera mounted on a tripod at about 1 m height, simulating a proximal remote-sensing setup. I will treat this as a ground-based remote sensing configuration and re-use its annotated WeedCOCO format for supervised training. The dataset provides only species-level labels, not bounding boxes or segmentation masks, which makes it ideal for my plan to experiment with both classification and pseudo-segmentation techniques.

Although DeepWeeds was collected in Australian pastures, the long-term goal is to apply the same perception logic to top-down lawn imagery (or ideally, the logic wouldn't be dependent on the orientation of the object with respect to the sensor on the drone), where weed plants grow intermixed with grass. By starting with this dataset, I can prototype the core perception pipeline – classification and interpretability – before extending it to local, real-world lawn footage later.

2. System Setup:

I will build the project entirely in PyTorch, using pretrained convolutional backbones (ResNet-50, Inception-v3, or a small Vision Transformer) as the base architectures. The training will take place in a GPU-enabled environment such as Google Colab or RIT's local compute cluster (since it is a huge dataset, I cannot use my M1 macbook pro).

The model pipeline will include:

1. Image preprocessing and augmentation – resizing to 224×224, normalization, random rotation, and brightness adjustment to mimic variable lighting.
2. Train/validation split – 80/20 split, stratified by weed species.
3. Model training and fine-tuning – using transfer learning with frozen base layers initially, then unfreezing later for deeper fine-tuning.
4. Evaluation metrics – accuracy, F1-score, and confusion matrix by species.

3. Interpretability and Crown-Center Localization:

After baseline classification is achieved, the next step will be to explore interpretability and biological localization using the following methods:

1. ### Grad-CAM / CAM:

   Generate heatmaps of activations over each image to visualize the regions influencing classification. I will test whether the areas of high activation correspond roughly to the weed's crown or leaf clusters.

2. ### SHAP and LIME (model-agnostic explanations):

   Apply these methods on selected samples to understand pixel-level importance and identify which color-texture patterns contribute most to species recognition. This will help interpret how the model "perceives" weed identity.

3. Segment Anything (SAM):

   Use SAM to create pseudo-masks from point-based prompts (such as a central click within Grad-CAM's highlighted area). This combination may help infer potential crown-center coordinates without needing manual segmentation labels.

4. Comparison and Visualization:

   Overlay Grad-CAM and SAM results to evaluate how consistently the model's discriminative focus aligns with the geometric center of each weed. This qualitative analysis will be complemented by IoU-like overlap measures and visual summaries.

4. Analysis Approach:

The overall workflow can be summarized as follows:

1. Re-implement DeepWeeds baseline classification (PyTorch version of ResNet/Inception).
2. Train and validate on Weed-AI imagery, saving trained weights and visual metrics.
3. Generate interpretability maps (Grad-CAM, SHAP, LIME) for correctly and incorrectly classified samples.
4. Integrate SAM to derive segmentation outlines and potential crown-center points.
5. Compare interpretability outputs to understand which features and regions each method emphasizes.
6. Document insights into how these models perceive weeds and where improvements in data collection or labeling could enhance crown detection.

5. Expected Challenges and Mitigation Strategies:

Challenge	Description	Mitigation Strategy
Viewpoint mismatch	DeepWeeds images are side-angled, while real lawns need top-down (nadir) perception.	Treat this as a learning prototype; later gather small top-down samples to test transferability.
Limited annotations	No bounding boxes or crowns labeled.	Use Grad-CAM and SAM pseudo-masks as weak supervision for region estimation.

Interpretability noise	Grad-CAM and SHAP can produce diffuse or unstable maps.	Smooth maps using Gaussian filters and average across multiple layers or seeds.
Computational cost	SHAP and SAM are heavy to run.	Test on smaller subsets or use lighter surrogates (KernelSHAP, SAM-lite).
Biological ambiguity	"Crown center" can be visually unclear in RGB images.	Collaborate with simple heuristic rules (color, shape) or expert visual judgment to approximate ground truth.

6. Remote Sensing Perspective:

Even though this project primarily uses close-range imagery, it aligns with remote sensing principles. The weed-detection process involves sensing, interpretation, and mapping – all central to remote sensing workflows. By identifying the weed's location and crown center from RGB data, the method can later be scaled to UAV or robotic platforms, integrating GPS and mapping components to remember spatial coordinates for autonomous revisits.

7. Summary:

In essence, the methodology focuses on rebuilding a deep-learning classifier for weeds, then layering explainable AI and segmentation to visualize how the model "sees." The analysis aims to connect machine-perceived features to real, biological plant structures. While the initial scope remains experimental, the interpretability insights gained will directly inform the design of the vision component of a future crown-targeting weed-removal robot or drone.

Outlook:

1. Timeline and Milestones:

Given the semester's schedule and my current internship workload, I have designed a clear, staged plan that is achievable yet exploratory enough to build a foundation for future work. If I begin active development around October 18, I expect to have about 120 or more working hours until December 7. My plan is to break that down as follows:

Phase	Timeframe	Milestones / Deliverables
Phase 1 – Setup & Data Understanding	Oct 18 – Oct 27	Download and inspect Weed-AI/DeepWeeds dataset; understand WeedCOCO structure; write small script to query/filter classes; review baseline models (ResNet/Inception).
Phase 2 – Model Re-implementation (Classification Baseline)	Oct 28 – Nov 10	Rebuild DeepWeeds classifier in PyTorch; train and validate; report accuracy and F1; reproduce paper's results; prepare Grad-CAM visualizations.
Phase 3 – Interpretability & Crown Localization	Nov 11 – Nov 25	Implement Grad-CAM and CAM; run SHAP/LIME on select samples; integrate Segment Anything (SAM) for pseudo-masks; overlay and compare results to estimate crown centers.
Phase 4 – Documentation & Final Presentation	Nov 26 – Dec 7	Finalize visual summaries (Grad-CAM vs SAM overlays); draft report with discussion on model behavior and interpretability; record a short demo video of the pipeline running on real or sample lawn footage (which is yet to be collected, probably of daffodils weeds, or some other common type of weed found here in the US).

Each stage is intended to be modular: even if training or interpretability proves difficult, I will have tangible partial deliverables (such as Grad-CAM heatmaps or SAM segmentations) that demonstrate progress and learning.

2. Key Deliverables:

- A PyTorch-based re-implementation of the DeepWeeds classification pipeline.
- A mini-dataset subset (possibly binary "weed vs none" or US-analog weeds if time permits).
- Grad-CAM, SHAP/LIME, and SAM visualizations comparing interpretability methods.
- A short demo video showing inference and visualization on sample footage.
- A technical report summarizing performance metrics, interpretability findings, and lessons learned.

3. Vision and Future Work:

This project is the first step toward a larger vision that I like to think of as a “seeing machine for the soil.”
In the short term (Track A), my focus is on surface-level perception: teaching a model to detect and classify weeds accurately, interpret its own decisions, and locate the visible crown centers that mark where the roots begin. The ultimate goal is to understand how AI “sees” plants, not just whether it classifies them correctly.

In the longer term (Track B), I want to extend this research into spectral and subsurface sensing. That means experimenting with higher-wavelength bands (NIR, SWIR, thermal) and low-frequency ground sensors (GPR/ERT) to detect soil-moisture patterns or root structures beneath the surface. If the surface perception pipeline succeeds, it could be fused with these modalities to create multi-modal 3D root-mapping systems for affordable, non-invasive plant monitoring.

I also see several interdisciplinary extensions:

- Agricultural and horticultural robotics – using the crown-detection model to guide precision laser or heat-based weed removal.
- Urban green-space management – deploying small drones or rovers for autonomous weed surveys in residential lawns and parks.
- Environmental sensing & archaeology – adapting the same principles to detect buried structures, roots, or artifacts using cross-spectral and subsurface fusion.
- Education & data engineering – treating this as a case study in designing reproducible ML pipelines for multi-modal remote-sensing data.

4. Personal Research and Career Trajectory:

While the current project is scoped for this course, I intend to continue refining it. The combination of computer vision, explainable AI, and remote sensing directly connects to the domains I want to work in long-term – environmental robotics, sustainability analytics, and data-driven perception systems.
If the results are promising, I would like to extend this as a capstone or a publishing-worthy research paper or PhD-level research direction, focusing on affordable, interpretable, and sustainable sensing for lawn-scale or small-farm environments. Collaborating with Professor Amir and Professor Abu Islam or any other interested individual could help integrate sustainable design perspectives with AI-based sensing and make the work both academically and practically meaningful.

5. Impact:

Even a small success here – say, a working demo that shows how CAM or SAM can reveal a weed's crown – would demonstrate how interpretable AI can bridge the gap between machine perception and real-world action. In a broader sense, it's a study of how to teach machines to look at the world meaningfully – and that's a skill that carries value far beyond weed detection: from robotics and conservation to archaeology and space exploration.