Task 1 — Problem Brief: Precision Agriculture Decision Support

1. What problem is this system trying to solve?

Vegetable growers lose significant revenue when plant diseases spread undetected. Manual scouting by walking crop rows is slow and typically identifies disease only after visible symptoms appear, by which time infections may have already spread to neighboring plants. Laboratory testing can provide accurate diagnoses, but it is too slow to support timely, in-field intervention. This system is designed as an early-warning tool that uses drone-captured RGB imagery to identify potential disease hot spots at the field level. Its purpose is to bridge the gap between ground-level observation and large-scale field monitoring, enabling farmers to treat only affected areas, reduce chemical usage, and prevent widespread crop loss.

2. Who is the end user and what decision are they making?

The primary end user is the farm manager or owner responsible for maintaining crop health and allocating resources. The system supports a recurring operational decision: for example, on a Monday morning the system flags 4% of a field block as potentially diseased—should the farmer ignore the alert, manually verify those specific patches, or immediately apply a targeted fungicide treatment? The system is intended to provide decision support rather than autonomous diagnosis, and it must deliver recommendations quickly, ideally within 30 seconds, so it fits naturally into the farmer's existing workflow.

3. What does success look like in the field (beyond accuracy)?

Success is defined by practical field outcomes rather than model metrics alone. Alerts should be generated several days before symptoms would become obvious through manual inspection, allowing early intervention. Flagged areas should be small and localized enough to enable targeted treatment rather than blanket spraying. The end-to-end process, from image capture to actionable recommendation, should complete within a few hours without relying on cloud connectivity. Over time, the system should lead to measurable reductions in total chemical spray volume compared to calendar-based spraying practices, and it should operate reliably on standard consumer hardware without requiring specialized GPUs.

4. Key assumptions and constraints

The system assumes access to RGB-only imagery captured by drones flying at moderate altitude, without multispectral or thermal sensors. Internet connectivity is assumed to be unavailable during field operations, so all inference must be performed offline on a local machine. Training data is limited to a relatively small and potentially biased dataset of plant-clinic or laboratory-style images that may not fully represent real drone viewpoints. Environmental conditions introduce additional constraints, including motion blur caused by wind, inconsistent lighting due to cloud cover, and visual artifacts such as soil residue, shadows, and overlapping leaves that can partially occlude plant surfaces.

5. Two realistic failure modes

One realistic failure mode is a false positive scenario caused by shadows or low-angle sunlight. Dark, irregular shadow patterns cast by leaves or canopy structures may resemble disease lesions, leading the model to incorrectly flag healthy plants as diseased. This results in wasted time and unnecessary field verification, and repeated false alarms may erode the farmer’s trust in the system.

A second failure mode is a false negative scenario during the earliest stages of disease development. Early infections may appear only as subtle visual cues occupying a very small portion of the image, and if the model has been trained primarily on late-stage symptoms, it may fail to detect these early signs. The consequence is undetected disease spread during a critical window, leading to significant crop loss and undermining the system’s core value as an early-warning tool.