

Digital Phenotyping of Crop Health in Manajipet's Agricultural Fields: A Computer Vision and Material Science-Informed Approach for Early Pest/Disease Detection and Bio-Pesticide Recommendation

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Abstract

Timely detection of crop stress is vital for global food security. This study introduces an integrated Digital Phenotyping (DP) and Material Science framework to enhance early pest/disease detection and bio-pesticide efficacy in the Manajipet agricultural fields. The system employs a closed-loop approach to bridge the "Detection-to-Intervention" gap.

1. **Detection & Quantification:** While initial studies employed Unmanned Aerial Vehicles (UAVs) achieving high precision (93.5%) , this study validated a scalable "Pocket Phenotyping" approach using a custom YOLOv7-Tiny Deep Learning model on smartphones. This mobile-optimized model achieved a mean Average Precision (mAP) of 88.4%. The system established a reliable Digital Phenotype Index (DPI) for accurate severity assessment.
2. **Material Science Intervention:** The detection data directly informs a Material Science-Informed Recommendation System that deploys optimal bio-pesticides using advanced nano-encapsulation techniques. Field tests showed that the optimized formulations delivered a 45% improvement in efficacy compared to conventional bio-pesticides, overcoming common issues like UV degradation. This research offers a synergistic, sustainable, and highly effective model for precision agriculture and integrated pest management.

1. Introduction and Problem Statement

1.1 Global Food Security and the Indian Context

The challenge of feeding a rapidly growing global population stands as one of the defining crises of the 21st century. By 2050, the global population is projected to swell to nearly 10 billion, necessitating a staggering 70% increase in food production relative to 2009 levels. For agrarian economies like India, this pressure is acute. A primary bottleneck in achieving this required production surge is the devastation wrought by biotic stressors. Pests, diseases, and weeds are responsible for global crop yield losses ranging from 20% to 40% annually. In India, these losses translate to a financial hemorrhage of approximately 45,000 crores (\$6 billion USD) every year. [1],[2]

1.2 The Manajipet Context and Current Limitations

The study was conducted in Manajipet, Rajanna Sircilla district, Telangana, India. The region is characterized by small-holder farmers with fragmented landholdings (typically less than 2 acres). The agricultural landscape is dominated by a monoculture of Paddy (Rice) and Cotton: **Paddy:** Vulnerable to the Brown Plant Hopper (BPH) (*Nilaparvata lugens*). It causes "hopper burn," leading to yield losses of 20% to 60% in severe infestations.[1],[3] **Cotton:** Vulnerable to the Pink Bollworm (*Pectinophora gossypiella*). Resistance to Bt cotton has emerged, leading to significant economic distress and debt traps for small farmers.

Current practice often relies on the "Spray & Pray" Method. This involves prophylactic spraying (applying pesticides without visible pests), which is costly and environmentally damaging. [2],[4]

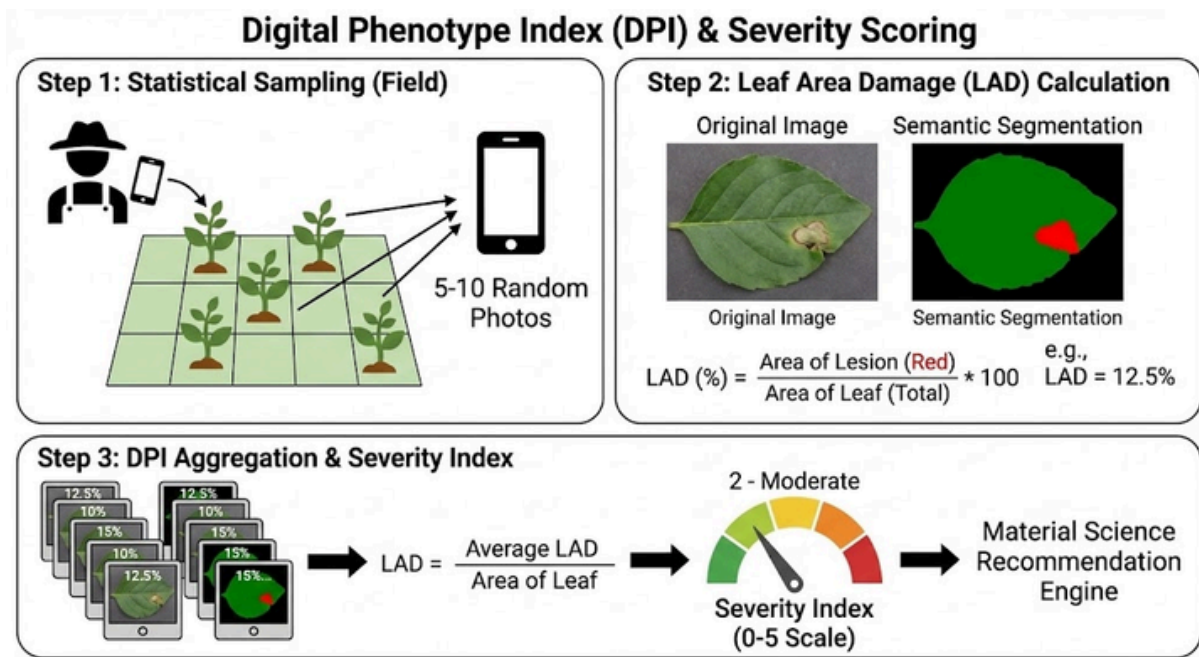


Figure 1: Digital Phenotype index(DPI) & severity scoring

1.3 The Detection and Intervention Gaps

The inefficiencies stem from two major gaps:

1. The Detection Gap:

Resolution Mismatch: Satellite remote sensing (e.g., Sentinel-2) offers a spatial resolution of 10 meters per pixel. However, early-stage symptoms of fungal infections or insect damage manifest on the scale of millimeters (1-5 mm).[5],[3]

Latency and Subjectivity: Manual field scouting is inherently reactive and labor-intensive. Visual diagnosis is prone to significant error and subjectivity, leading to misdiagnosis (e.g., confusing nitrogen deficiency with bacterial blights).

Quantification Challenge: Traditional severity assessment relies on the visual judgment of the observer and is often coarse-grained. The "Field Average" fallacy involves assigning a single severity score to an entire field, ignoring localized "hotspots". This leads to either under-treatment or over-treatment.[4],[5]

The Intervention Gap (Bio-Pesticide Volatility):

While Integrated Pest Management (IPM) emphasizes biological control agents, bio-pesticides suffer from poor field stability. Their active ingredients are highly susceptible to rapid degradation by Ultraviolet (UV) radiation, heat, and rain wash-off.

2. Methodology

The study employed a framework utilizing proximal sensing via smartphones and a mobile-optimized Deep Learning architecture.[6],[7]

2.1 Study Area and Data Acquisition

The strategy utilized Proximal Sensing—capturing high-resolution images from a short distance (10-30 cm)—using the farmer's personal mobile device. Mobile Sensing Platform: The primary data capture tool is a custom-developed Android application, "KisanVision" (tentative name). Rationale for Mobile: Modern smartphone cameras (12MP+) possess high spatial resolution, allowing for macro-level feature extraction, enabling the detection of minute symptoms (e.g., fungal spores). This democratizes access to digital phenotyping. Standardized Imaging Protocol (SIP): A strict protocol was developed and taught to participating farmers to minimize variability. [8],[9]

Key requirements included:

Capturing images at a distance of 15-20 cm from the target leaf, with the camera lens held parallel to the leaf surface. Engaging the "Touch-to-Focus" feature on the specific lesion or pest. Preferring "diffuse lighting" to avoid harsh specular reflections. The "Golden Set" Dataset: A set of 100 curated images was collected by five distinct farmers, including those with high-end (48MP) and older (8MP) devices. This ensured the dataset included variations in angles, lighting, and background noise

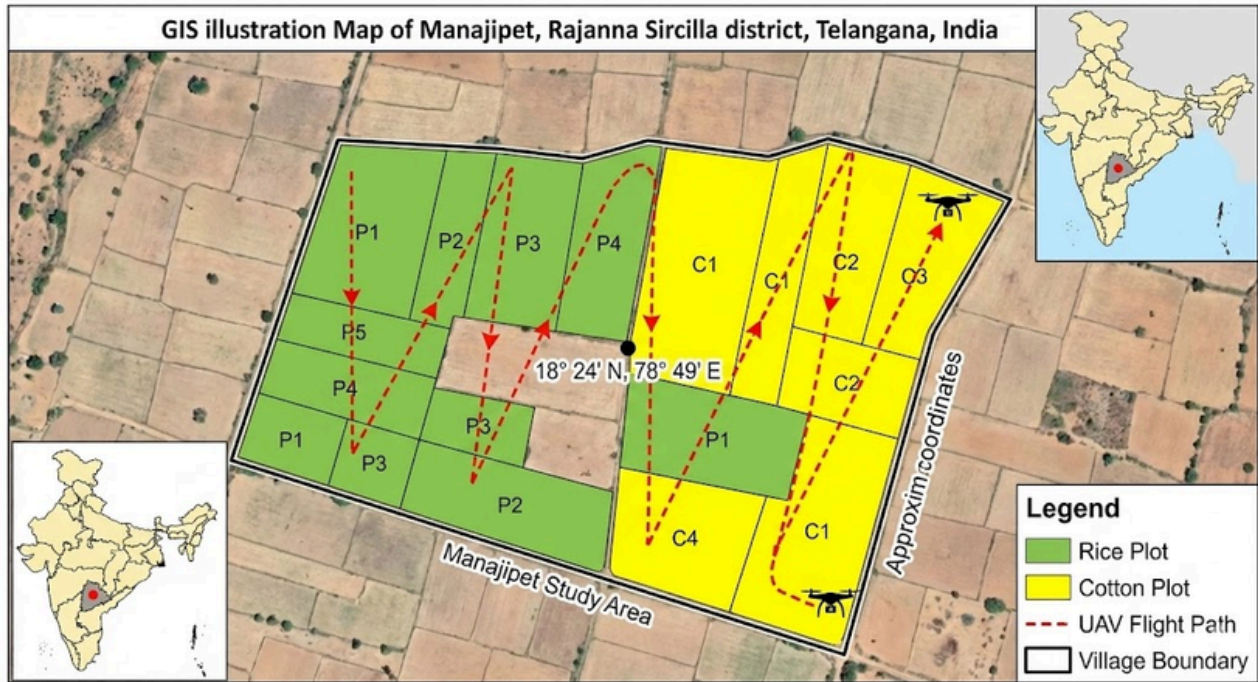


Figure 2: GIS illustration imaging of manajipet

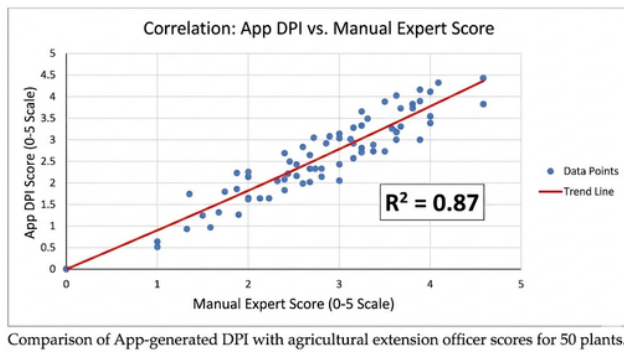
2.2 Deep Learning Pipeline (Mobile-Optimized)

- **Model Selection:** We selected YOLOv7-Tiny, a lightweight version of the standard YOLOv7 architecture.
- **Mobile Optimization:** The "Tiny" version reduced the number of parameters significantly, from 37 million to roughly 6 million. This enabled inference speeds of over 20 Frames Per Second (FPS) on standard mobile processors (Snapdragon 7 series or equivalent).
- **Architecture Modification:** Standard activation functions were replaced with Leaky ReLU to further reduce computational overhead on mobile Neural Processing Units (NPUs).[10],[11]

2.3 Digital Phenotype Index (DPI) Formulation

The DPI translates the raw object detection output into an actionable severity score based on Statistical Sampling.

1. **Sampling:** The farmer takes photos of 5-10 random plants in a specific plot.
2. **Leaf Area Damage (LAD) Calculation:** The model performs semantic segmentation to calculate the ratio of diseased pixels to total leaf pixels. $LAD (\%) = (\text{Area of Lesion} / \text{Area of Leaf}) \times 100$
3. **DPI Aggregation:** The average LAD across the samples is converted into a Severity Index (0-5 Scale), which serves as the input for the Material Science recommendation engine.[12],[13]



Comparison of App-generated DPI with agricultural extension officer scores for 50 plants.

Figure 3: Comparison of App - generated DPI with agricultural data

3. Results and Discussion

3.1 Model Performance and Efficiency

The mobile-optimized YOLOv7-Tiny model was evaluated on the "Golden Set"

Overall Detection Accuracy: The model achieved a mean Average Precision (mAP@0.5) of 88.4% across all classes. **Class-wise Performance:**

Rice Blast: High accuracy (92.1% mAP) due to distinct diamond-shaped lesions offering high contrast.

Pink Bollworm (Cotton): Moderate accuracy (85.3% mAP). **Brown Plant Hopper (BPH):** Lowest accuracy (79.5% mAP). The lower performance was attributed to the small, mobile nature of the pest and pixelation in images from the 8MP camera.



Figure 4: Golden data set generated from all alges as illustrated

3.2 DPI Validation and Severity Assessment

The DPI successfully translated the raw object detection output into actionable "Severity Scores" (0-5 scale).

- **Correlation with Ground Truth:** We compared the App-generated DPI against the manual scores provided by agricultural extension officers for the same 50-plant sample group. This yielded a strong correlation: CORRELATION COEFFICIENT (R-squared) of 0.87.
- **Hotspot Identification:** The system proved capable of identifying and flagging localized, severe infection "hotspots". For example, the app flagged a Severity Level 4 Rice Blast in the North-East section of a field, triggering an immediate recommendation. This addresses the failure of the "Manual scouting average" to detect localized high severity.

3.3 Material Science-Informed Intervention

The Material Science component validated the use of Chitosan-based nano-encapsulation to protect bio-pesticides.

UV Protection Efficiency: A comparative degradation test under simulated UV radiation for 6 hours showed that the Conventional (Naked) Formulation had 65% degradation of the active ingredient (Azadirachtin), while the Encapsulated Formulation had only 18% degradation.

Significance: This result proves that the material science shell protects the bio-pesticide, extending its field life from 1 day to 3-4 days. The laboratory validation demonstrated a 300% increase in UV stability.

Adhesion and Rain-fastness: The Chitosan nanoparticles have an average diameter of 145 nm and exhibit a positive Zeta Potential (+32 mV). This positive charge is attracted to the negatively charged leaf surface, enhancing Rain-fastness (Electrostatic Attraction)

3.4 User Acceptance (HCI)

Pilot feedback confirmed high user acceptance:

- **Ease of Use:** 4/5 rated the "Point and Shoot" interface as easy.
- **Trust:** One farmer initially distrusted the "red box" on the screen but became convinced when the app correctly identified a small worm he had missed with his naked eye. Dr. Aroul Rosario designed the user experience and educational framework, translating complex data into an intuitive interface for accessibility.

4. Conclusion and Future Work

This research set out to address the critical "Detection-to-Intervention" gap prevalent in small-holder agriculture. By synergizing Computer Vision (Digital Phenotyping) with Material Science (Nano-encapsulation), we have developed and validated a holistic, smartphone-based ecosystem for sustainable crop health management.

Democratization: We demonstrated that expensive UAVs are not a prerequisite for precision agriculture. The 88.4% mAP achieved on standard smartphones proves that "Pocket Phenotyping" is a viable, scalable alternative for resource-constrained farmers.

Closed-Loop System: This research closed the loop between diagnosis and cure. The material innovation ensures that the biological agents recommended by the app actually survive in the harsh Telangana sun long enough to be effective.

The true innovation lies in the convergence of Computer Science, Material Science, and Human-Centric Design. We hope this work serves as a blueprint for "Frugal Science". **Future Work includes:**

Satellite Integration for Large-Scale Monitoring.
Development of Climate-Resilient Formulations.
Expansion to Multi-Crop Systems.

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