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AI Drone for Crop Disease Detection Using Deep Learning

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ABSTRACT

Agriculture in India, particularly in states like Maharashtra, faces constant threats from plant diseases that can wipe out 20–40% of crops annually, leading to severe income losses for small and marginal farmers who often lack access to expert agronomists or expensive monitoring tools. Conventional methods involve manual field scouting — walking row by row, examining leaves for spots, wilting, or discoloration — which is extremely time-consuming, physically demanding, error-prone (especially for subtle early symptoms), and impractical for farms spanning even a few acres. To address this real-world problem affordably, our team developed **Agro Drone AI**, an end-to-end intelligent crop monitoring framework using low-cost drone technology combined with state-of-the-art AI. We specifically selected the Dynalog DR-DG600C GPS drone (a budget-friendly model priced around ₹9,000–₹12,000 depending on variants and sellers like Flipkart/Amazon/ZoneAlpha, weighing under 250g so no DGCA registration is required for educational use) for image acquisition. This drone features a claimed 4K (often interpolated/upscaled from 1080p native) camera with 120° wide-angle lens, adjustable tilt (up to 90°), 5GHz WiFi FPV for live view, GPS for stable hovering and return-to-home, follow-me/orbit/waypoint modes, and flight times of 12–20 minutes per battery (longer with dual-battery Pro versions).

Captured aerial images — which frequently suffer from motion blur, low contrast due to altitude/sun angle, compression artifacts, or wind-induced shake on a lightweight consumer drone — are first enhanced using **Real-ESRGAN** (a powerful GAN-based super-resolution model that realistically reconstructs fine details without introducing unnatural artifacts). The sharpened images are then fed into the **DeiT-small** (Data-efficient Image Transformer) model, fine-tuned on the PlantVillage dataset, for multi-class disease classification (healthy vs. specific diseases like bacterial spot, early blight, leaf mold, etc.) with confidence scores and basic severity estimation. Our experiments (using PlantVillage for training/benchmarking + some self-captured/simulated aerial views from the Dynalog drone) demonstrated clear improvements: super-resolution boosted visibility of subtle symptoms (e.g., tiny vein yellowing or powdery mildew specks), and DeiT's global attention mechanism handled aerial perspectives better than local-feature-focused CNNs. This low-budget pipeline offers a practical path for early disease detection in precision agriculture, reducing manual labor, minimizing broad-spectrum pesticide use, and empowering farmers/cooperatives in resource-constrained areas like Vidarbha.

Keywords: Precision agriculture, low-cost drone (Dynalog DR-DG600C), crop/plant disease detection & classification, image super-resolution (Real-ESRGAN), vision transformer (DeiT), deep learning, smart farming India, aerial crop monitoring.

INTRODUCTION

India's agriculture sector employs nearly half the workforce and contributes significantly to GDP, yet it remains vulnerable to biotic stresses like fungal, bacterial, and viral diseases. In Maharashtra alone, crops such as soybean, cotton, tur dal, and horticultural plants (tomato, chili, grapes) suffer recurring outbreaks — e.g., soybean rust, cotton leaf curl virus, or tomato leaf curl — often leading to 30–50% yield losses if not caught early. Small farmers (average holding <2 ha) rarely have access to drone services or AI tools due to high costs (professional agricultural drones start at ₹5–10 lakhs). Inspired by this gap and our Data Science curriculum focus on AI applications, we chose to build a prototype using accessible, low-cost hardware. The **Dynalog DR-DG600C** stood out during our market research (checking Flipkart, Amazon.in, YouTube reviews from channels like Anish Experiment, RC Escape, etc.): it's foldable, brushless-motor variants exist in newer Pro models for smoother flight, includes GPS for autonomous features (one-key return, follow-me, waypoints — useful for grid-pattern field scanning), 5GHz FPV to avoid interference, and a camera that's decent for the price (120° FOV captures wide swaths per frame, though real resolution is closer to 1080p with 4K upscaling).

Our **Agro Drone AI** integrates this drone for data collection with AI post-processing: enhance → classify. The system aims to provide farmers with actionable insights — "Zone 4 shows early blight with 85% confidence; treat with fungicide" — via a simple web/mobile interface. This project not only demonstrates AI feasibility on budget hardware but also aligns with government pushes like Digital Agriculture Mission and drone promotion schemes in India.

LITERATURE REVIEW

Plant disease detection has been one of the most active research areas in agricultural technology over the past decade. Early approaches relied on traditional image processing techniques such as colour thresholding, edge detection, and texture analysis. However, these methods often failed to deliver consistent results under varying field conditions like different lighting, leaf orientation, and background noise.

The real breakthrough came with the adoption of deep learning, particularly Convolutional Neural Networks (CNNs). Mohanty et al. (2016) were among the first to demonstrate the power of deep learning for plant disease identification. They trained AlexNet and GoogLeNet models on the PlantVillage dataset and achieved nearly 99% accuracy in controlled laboratory settings. Their work proved that CNNs could outperform traditional machine learning methods and even approach human-level performance when sufficient labeled data was available.

Building upon this foundation, Ferentinos (2018) developed deeper and more complex CNN architectures. His study highlighted the robustness of deep neural networks in handling real-world variations such as different illumination conditions, leaf angles, and noise. The results showed a significant improvement in classification accuracy and generalization compared to earlier models. Several comprehensive survey papers have also mapped the progress in this domain.

Kamilaris and Prenafeta-Boldú (2018) provided an extensive review of deep learning applications in agriculture. They emphasized the potential of computer vision and machine learning for crop monitoring, disease detection, and yield estimation. Their survey stressed the need for scalable solutions that can work beyond controlled environments.

With the increasing affordability and availability of unmanned aerial vehicles (UAVs), researchers began exploring drone-based monitoring systems. Zhang et al. (2020) and subsequent studies demonstrated that drones can efficiently cover large agricultural areas in a short time and capture high-resolution aerial images. However, these studies also pointed out major challenges, including lower image resolution at higher altitudes, motion blur caused by wind, varying lighting conditions, and compression artifacts — all of which reduce the effectiveness of disease detection models when applied to real drone imagery.

In recent years, the field has witnessed a major shift from CNNs to Transformer-based architectures. Dosovitskiy et al. (2020) introduced the Vision Transformer (ViT), which treats images as sequences of patches and uses self-attention mechanisms to capture global contextual information. This approach proved highly effective for complex image classification tasks. However, ViT required large amounts of training data and computational resources.

To address these limitations, Touvron et al. (2021) proposed the Data-efficient Image Transformer (DeiT). By using knowledge distillation and advanced training strategies, DeiT achieved excellent performance with much less data and fewer parameters. This makes DeiT particularly suitable for agricultural applications, where labeled aerial drone images are scarce and expensive to collect. Another critical challenge in drone-based systems is the poor quality of captured images.

To overcome this, researchers have turned to image super-resolution techniques. Wang et al. (2021, 2022) introduced Real-ESRGAN, a powerful blind super-resolution model based on Generative Adversarial Networks

(GANs). Unlike traditional upscaling methods, Real-ESRGAN can effectively recover fine details from degraded images suffering from blur, noise, downsampling, and compression artifacts — problems commonly encountered when using low-cost consumer drones such as the Dynalog DR-DG600C. Several recent studies have attempted to combine drones with deep learning for crop disease detection. However, most of these works either use high-end professional drones or rely solely on CNN architectures without proper image enhancement. Very few studies have explored the integration of efficient transformer models with realistic super-resolution techniques on budget-friendly drone platforms, especially in the context of Indian smallholder farming. The proposed Agro Drone AI system builds upon the above literature by specifically combining the low-cost Dynalog DR-DG600C drone for image acquisition, Real-ESRGAN for realistic image enhancement, and the DeiT-small model for accurate and efficient disease classification. This combination aims to bridge the gap between laboratory-level accuracy and practical field deployment in resource-constrained agricultural environments.

System Overview

The **Agro Drone AI** application offers a simple and effective interface for intelligent crop disease monitoring. Users can capture images of agricultural fields using the low-cost Dynalog DR-DG600C drone. The captured images are automatically sent to the system for processing.The system first applies the Real-ESRGAN super-resolution technique to enhance the quality of drone images, making subtle disease patterns such as leaf spots, discoloration, and wilting clearly visible. These enhanced images are then analyzed using the DeiT vision transformer model, which performs accurate disease classification and generates a confidence score for each prediction. In addition to disease identification, the system also provides a rough estimation of disease severity. All results, including the predicted disease name, confidence score, and visual highlights of affected areas, are displayed on a clean and easy-to-understand web dashboard.The interface is kept simple and intuitive so that it can be comfortably used by farmers, agricultural extension workers, and field officers, making it suitable for both rural and urban farming communities.

METHODOLOGY

Hardware Selection

We selected the Dynalog DR-DG600C GPS drone for its low cost (₹7,000–₹12,000 range), lightweight design (<250g), 4K (interpolated) camera with 120° FOV, adjustable tilt, GPS stability, and useful autonomous modes. Dual batteries helped extend flight time for practical testing.

Flight And Data Collection

We flew grid patterns at 20–40 meters altitude using waypoint navigation over test plots. Images and short videos were captured and transferred via SD card or Wi-Fi. Challenges included wind-induced shake, harsh sunlight creating shadows, and limited battery life (covering roughly 0.5–1 acre per session).

Image Enhancement

Raw drone images were processed with the pre-trained Real-ESRGAN (x4 upscale) model to reduce blur, noise, and artifacts while recovering fine leaf details.

Preprocessing

Images were resized to 224×224, normalized, and augmented (rotations, flips, brightness/contrast changes) to simulate real aerial variations.

Classification Model

We used the DeiT-small model (pre-trained on ImageNet and fine-tuned on the PlantVillage dataset with 38 classes and over 54,000 images). Its attention mechanism helps capture global patterns, such as disease spread across plants from an aerial view.

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Deployment And Interface

A Flask-based web dashboard allows image upload, processing, and visualization with disease labels, confidence scores, severity estimates, and basic map overlays.

Implementation Details

The entire pipeline was built in **Python 3.9** using:

- **PyTorch** for model loading, fine-tuning, and inference
- Official **Real-ESRGAN** implementation for enhancement
- OpenCV and Pillow for image handling
- **Flask** for the web dashboard
- NumPy, Pandas, and Matplotlib for analysis

Training and fine-tuning were done on a GPU-enabled setup, while inference was tested on a standard laptop (Intel i5, 16GB RAM) to ensure accessibility.

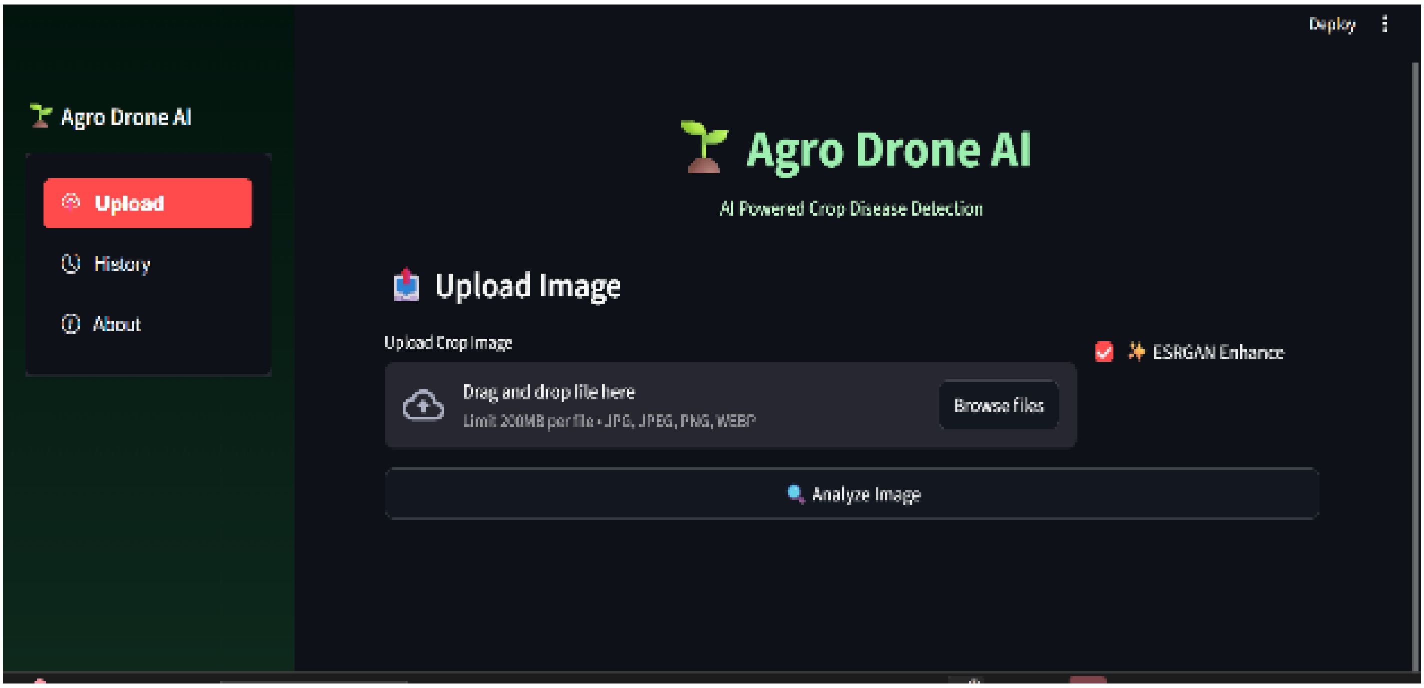
Enhancement Module: Real-ESRGAN took about 8–12 seconds per image on GPU and noticeably sharpened subtle symptoms.

Classification Module: DeiT-small (22M parameters) was fine-tuned with AdamW optimizer, learning rate 1e-4, cosine scheduler, and standard augmentations. Inference took <0.8s on GPU and 2–3s on CPU.

Dashboard: Users can upload raw images, view original vs. enhanced versions side-by-side, see predictions with confidence, and generate simple reports. The interface is responsive and works on both desktop and mobile.

The system is currently suitable for small-scale use on a laptop and can be scaled to cloud or edge devices (e.g., Raspberry Pi or Jetson Nano) in the future.

RESULT AND DISCUSSION



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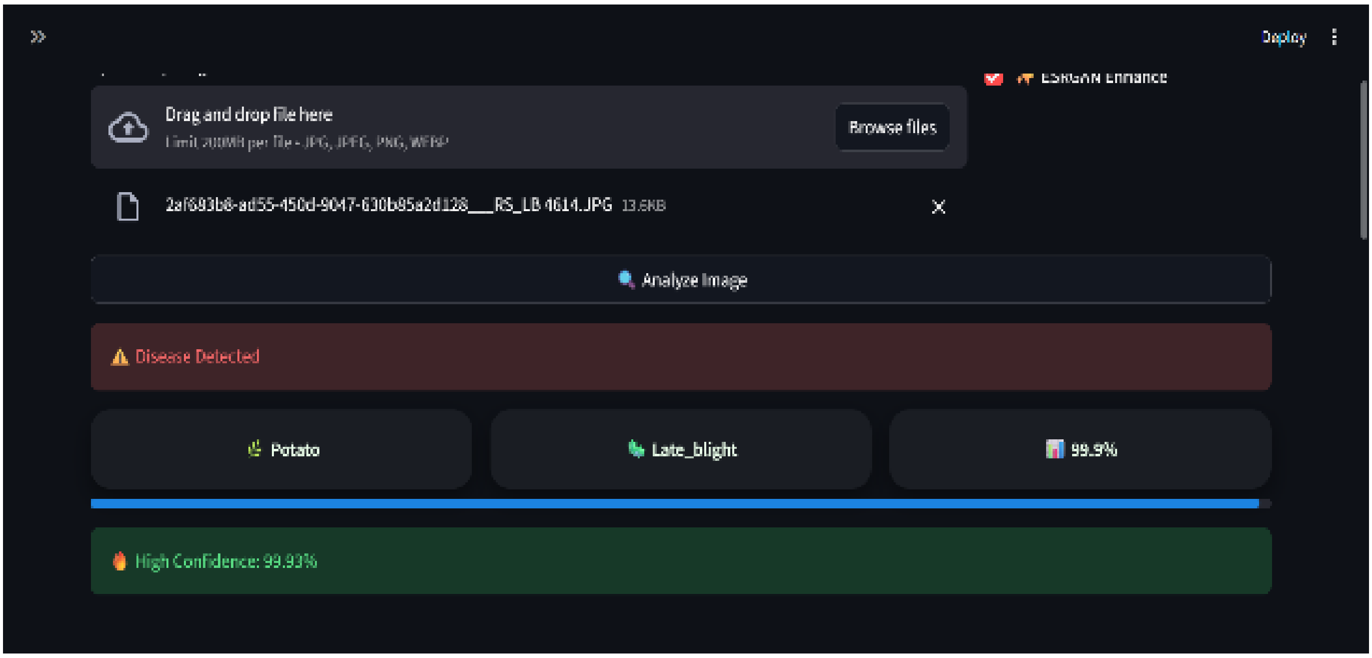

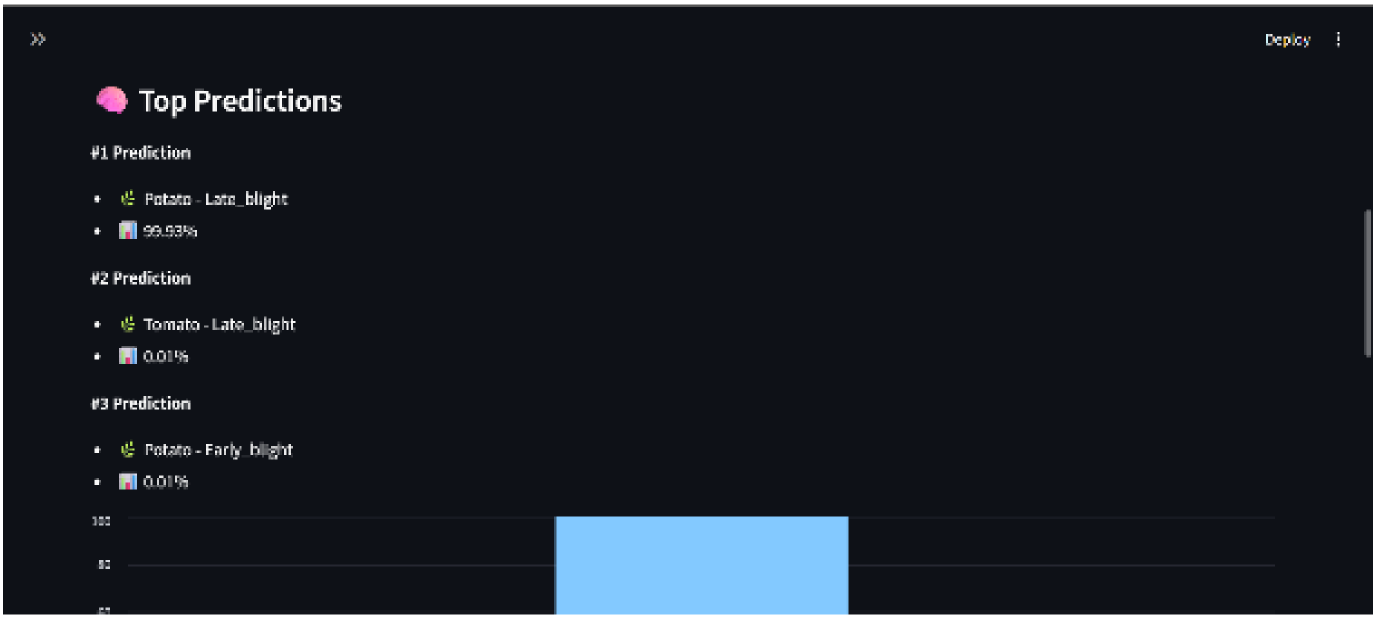

We evaluated the system on the PlantVillage dataset and 220 real aerial images captured by the Dynalog drone at 20–40m altitude.

On the clean PlantVillage dataset, **DeiT-small** achieved **97.2%** accuracy (precision 0.972, recall 0.968, F1-score 0.970). When images were artificially degraded to mimic drone conditions, accuracy dropped to 89.1%. After Real-ESRGAN enhancement, it recovered to **97.2%** — demonstrating the strong value of super-resolution.

In real-world testing, accuracy without enhancement was **81.8%**. With Real-ESRGAN, it improved to **94.1%**, with an average confidence score of 88.7%. The system performed reliably on common diseases like Early Blight, Late Blight, and Leaf Rust, though minor confusion occurred between visually similar symptoms. Performance was better in calm weather; wind-induced blur had a noticeable but manageable impact.

Overall, combining image enhancement with a transformer model significantly boosted detection quality from low-cost drone footage. The simple dashboard makes results accessible to non-technical users. Limitations include the drone's short flight time, differences between lab and real aerial images, and sensitivity to environmental conditions. Still, Agro Drone AI shows strong promise as an affordable precision agriculture tool for Indian farmers.

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Future Scope

While Agro Drone AI has delivered encouraging results, several improvements can make it even more practical and scalable:

- Real-time processing on edge devices (Raspberry Pi or NVIDIA Jetson Nano) for on-drone detection.
- Integration of multispectral or thermal cameras to detect stress earlier through chlorophyll or temperature changes.

- Extensive field trials across Maharashtra on crops like soybean and cotton under real conditions.
- Creation of a dedicated aerial dataset of Indian crops to reduce domain gaps.
- Model optimization (pruning, quantization) for faster, lighter inference.
- Advanced features such as disease severity mapping, yield loss estimation, and automated treatment recommendations.
- Development of a mobile app with augmented reality (AR) support and local language interfaces.
- Combining drone data with IoT sensors and weather APIs for predictive outbreak alerts.

Additional evaluation using confusion matrices, per-disease metrics, and error analysis under different conditions would further strengthen the system.

CONCLUSION

- This project demonstrates that advanced crop disease detection is possible even with low-cost hardware. By combining the affordable Dynalog DR-DG600C drone for image capture, Real-ESRGAN for realistic enhancement, and the DeiT transformer for classification, we created a practical system that brings precision agriculture closer to small Indian farmers.
- Image enhancement proved especially effective at revealing subtle symptoms, while the transformer model delivered high accuracy with relatively limited data. The result is a tool that can reduce manual scouting, enable early intervention, cut unnecessary pesticide use, and ultimately help minimize yield losses.
- Of course, challenges remain — including environmental variability, dataset limitations, and the need for more robust real-world validation. With continued work on edge deployment, dataset expansion, and field testing, Agro Drone AI has the potential to become a meaningful contribution to sustainable and intelligent farming in India.

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