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Cropsense – Crop Disease Detection and Alert Generation using SAM2

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Abstract
Agriculture continues to suffer major losses due to late and inaccurate detection of crop diseases. Manual monitoring is slow, error-prone, and impractical for large-scale farms. To address these challenges, Crop Sense introduces an intelligent platform for crop disease detection and management. Using Segment Anything Model 2 (SAM2) for precise visual segmentation and a ResNet50 CNN classifier trained on 65 disease classes across 13 crop types — including Rice, Cotton, Sugarcane, and Wheat — the system identifies disease type and assesses severity with 98.69% validation accuracy. Beyond detection, Crop Sense introduces three novel capabilities: (1) a weather-integrated disease spread prediction engine that forecasts disease progression risk over 7 days using real-time Open Weather Map data; (2) a drone video analysis module that processes aerial footage frame-by-frame using SAM2 segmentation to generate field-level disease maps; and (3) an AI-powered multilingual farmer chatbot powered by Llama 3.2 that provides crop disease diagnosis in Telugu, Hindi, and English. The platform provides comprehensive digital prescriptions covering biological remedies, chemical treatments, and preventive measures tailored to each specific disease and its severity intensity.

Keywords: Segment Anything Model 2 (SAM2), CNN Classification, Deep Learning, Image Segmentation, Severity Analysis, Digital Prescription, Cloud Deployment, Crop Disease Detection, Real-Time Monitoring

1. Introduction

In the modern agricultural era, food security and crop yield play a crucial role in economic stability and rural livelihoods. However, global agriculture continues to suffer major losses due to the late and inaccurate detection of crop diseases. Traditional manual monitoring is slow, labour intensive, and often impractical for large-scale farming operations. To address these challenges, this project introduces CropSense AI, an intelligent platform designed for automated crop disease detection and proactive management. The proposed system utilizes a hybrid approach combining Convolutional Neural Networks (CNN) for high-accuracy classification and Meta's Segment Anything Model 2 (SAM2) for precise visual segmentation. By integrating real-time weather analytics and drone monitoring, Crop Sense AI moves beyond simple identification to provide temporal spread forecasting and spatial field mapping. The system aims to empower farmers with actionable treatment advice, making precision agriculture accessible through a multilingual interface.

A. Project Overview

Crop Sense AI addresses the expertise gap in plant pathology by providing an automated "see predict solve" pipeline. Detecting crop diseases is a challenging task because early symptoms are often subtle and vary across different environmental conditions. This project focuses on identifying pathogens across 13 crop types and 65 specific disease classes, including major staples like Rice, Cotton, and Sugarcane. The project centres around four core pillars:

- Automated Diagnosis: A ResNet50 CNN classifier achieving 98.69% validation accuracy.
- Precision Assessment: Using SAM2 to isolate diseased regions and calculate severity levels (Mild, Moderate, Severe).
- Predictive Analytics: A weather-integrated engine using the Open Weather Map API to forecast 7day disease spread risks.

• Conversational Support: A multilingual chatbot powered by Llama 3.2 providing instant advice in English, Hindi, and Telugu.

B. Project Scope

The scope of this project is to develop an intelligent ecosystem capable of identifying and managing a wide array of agricultural pathogens. The system utilizes a hybrid architecture of ResNet50 for classification and SAM2 for segmentation, supported by an LLM-based conversational agent. The system is designed for large scale and small hold farms, supporting 13 different crop types. The current scope focuses on leaf and field based pathology it does not currently include soil health analysis or advanced autonomous drone navigation.

2. Related Work

Many existing crop disease detection models rely on traditional statistical and machine learning techniques. While these approaches are useful for basic image classification, they often fail to capture the complex nonlinear relationships between environmental and visual factors that influence crop health. Ranjan et al. proposed detection and classification of leaf disease using Artificial Neural Networks, achieving reasonable accuracy but lacking segmentation-level precision [1]. Mayuri et al. employed ANN with the Chan-Vese algorithm for plant disease detection, demonstrating the value of combining segmentation with classification [2]. Shelar et al. applied standard CNN architectures for plant disease detection, establishing a baseline for deep-learning-based approaches [3]. With the advancement of deep learning, models such as CNN, Vision Transformers, and ResNet variants have been applied extensively. Padshetty and Ambika proposed Leaky ReLU-ResNet achieving strong performance on the Plant Village dataset [4]. Kumar et al. validated Res Net-based approaches for detection and classification of plant leaf diseases with competitive accuracy [5]. Hassan et al. employed transfer-learning approaches using CNN achieving good generalization [6]. Yang et al. introduced YOLOV8-based segmentation for leaf images, demonstrating real-time detection capability [7]. A major limitation of existing systems is their reliance on the Plant Village dataset, captured under controlled laboratory conditions. Studies report accuracy drops of 20-40 percentage points when applied to real-field images. Crop Sense addresses this by curating a dataset of 65 disease classes specific to Andhra Pradesh's agricultural landscape and applying SAM2 for more precise segmentation of irregular diseased boundaries rather than simple edge detection [8].

3. Motivation and Problem Statement

A. Motivation

Air pollution levels and food insecurity are increasing globally. For Indian agriculture specifically, crop diseases lead to 20-40% yield losses annually, disproportionately impacting smallholder farmers. Modern data-driven approaches can generate large volumes of environmental and visual data from multiple sources such as sensors, drone imagery, and leaf photographs. However, effectively utilizing this data remains a significant challenge. Traditional manual monitoring is inherently slow and subjective, leading to high error rates and inconsistent results based on the observer's expertise. Physical inspection is impractical for large-scale farming operations where vast areas need constant surveillance. Human observers often identify diseases only after visible and often irreversible damage has occurred.

These challenges motivated the development of Crop Sense, an intelligent AQI-inspired prediction framework that not only improves diagnosis accuracy but also enhances accessibility through multilingual interfaces and proactive forecasting.

B. Problem Statement

Crop disease detection is a complex task due to the involvement of multiple dynamic visual factors such as lesion patterns, color changes, and spatial disease spread. Existing models often fail to effectively capture both spatial and temporal dependencies, leading to limited prediction accuracy. Additionally, most deep learning approaches provide only binary healthy/diseased outputs without quantifying infection severity or providing treatment guidance. There is a clear need for an integrated framework that can accurately detect, segment, and classify crop diseases while also providing interpretable severity estimates, weather-integrated spread forecasting, and multilingual farmer support.

4. System Analysis

A. Functional Requirements

The system supports user authentication, multi-modal media input (JPEG/PNG images, camera capture, live video), SAM2-based image segmentation, CNN-based disease classification across 65 classes, severity estimation, digital prescription generation, result visualization with annotated overlays, push notification alerts for Severe infections, and detection history logging.

B. Non-Functional Requirements

Performance: 98.69% validation accuracy. Usability: intuitive interface with voice support. Scalability: handles large-scale aerial drone data. Availability: instant chatbot and diagnostic tool responses. Security: secure API key management via environment files.

C. Feasibility Study

Crop Sense is technically feasible using productionready technologies: SAM2 is available via Hugging Face, Stream lit provides a mature Python web framework, and Firebase Cloud Messaging offers a globally scaled push notification service. Economically, the project leverages entirely open-source technologies, eliminating licensing costs. The economic value delivered to farmers through reduced crop losses substantially exceeds infrastructure investment.

5. Proposed Methodology

A. System Overview

Crop Sense AI introduces a complete end-to-end workflow covering detection, localization, severity assessment, and specific treatment recommendations. The system architecture is built around four core principles: precision, completeness, accessibility, and timeliness. The platform is designed to be accessible from any device — desktop, tablet, or smartphone — through platform-appropriate interfaces.

B. 3-Layer Image Validation Algorithm

Every input image undergoes a validation sequence before being processed by the deep learning models:

• Layer 1 – Human/Object Detection: Pre-trained cascade detectors reject images containing human faces, bodies, or non-agricultural objects.

• Layer 2 – Texture Analysis: Checks for natural leaf textures and vein patterns to ensure the input is a plant specimen.

• Layer 3 – Colour Presence: Analyses HSV colour space to confirm green or chlorotic (yellow/brown) tones associated with plant leaves.

C. Disease Classification via ResNet50

The primary classification engine employs a ResNet50 architecture with 50 layers of deep residual learning to extract hierarchical features from leaf images. Input images are resized to 224×224 pixels and normalized before passing through global average pooling and dense layers for final class prediction. The original fully connected layer is replaced with a custom dense layer to output predictions for 65 disease categories. The model achieves 98.69% validation accuracy, with training loss reaching its minimum at epoch 15.

D. Visual Segmentation via SAM2

For spatial analysis, the system implements Meta's Segment Anything Model 2 (SAM2). The algorithm generates high-resolution binary masks that isolate infected regions from healthy tissue with pixel-level precision. In environments where GPU acceleration is unavailable, a fallback OpenCV-based colour segmentation algorithm uses adaptive thresholding in the HSV colour space to detect diseased regions.

E. Severity Quantification

The severity quantification algorithm computes the ratio of diseased pixels (identified by brown, yellow, or orange masks) to the total leaf surface area, then categorizes as: Healthy (0–5%), Mild (5–25%), Moderate (25–60%), or Severe (>60%). This enables farmers to prioritize treatments based on infection intensity.

F. Weather-Integrated Spread Prediction

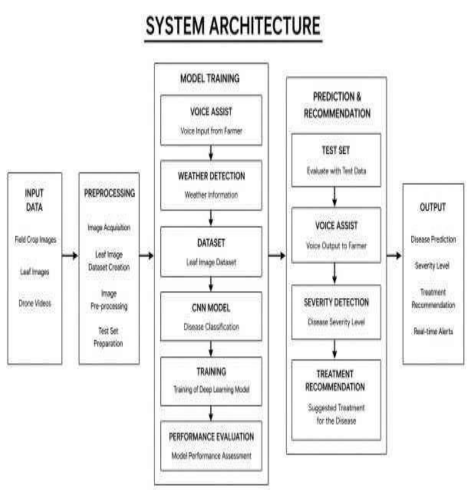
The prediction engine fetches 7-day forecasts (temperature, humidity, rainfall) for the user's location via the OpenWeatherMap API. A weighted algorithm calculates a daily risk score (0–100) based on how closely the forecast aligns with the optimal spreading conditions for the identified disease. The engine identifies the specific "Peak Risk Day" to alert the farmer for proactive preventive spraying.

G. Drone Video Processing

The drone module performs spatial mapping across large fields by processing every 30th frame of aerial footage to balance computational speed with field coverage. SAM2 segmentation is applied to each sampled frame, and detection results are aggregated to generate a field-level "Health Map" highlighting exact hotspots where disease concentration is highest.

H. System Architecture

The architecture consists of the following pipeline: (1) User uploads crop image or video through the Streamlit web interface; (2) Input media is transmitted to the backend for processing; (3) Image preprocessing is applied including resizing, normalization, and noise reduction; (4) SAM2 performs automatic segmentation generating precise binary masks; (5) The CNN classifier anlyaze each segmented region and outputs a disease category; (6) The severity analysis module computes the proportion of affected area; (7) The prescription engine



retrieves treatment recommendations; and (8) Results are returned to the frontend with automated push notification if severity is high.

6. Implementation

A. Technology Stack

Python 3.x serves as the primary language for the deep learning pipeline, backend logic, and user interface. Streamlit provides a high-performance wide-layout dashboard. PyTorch and Torch vision are used for building and training the ResNet50 CNN model with data augmentation (horizontal flips, rotations, colour jittering) critical in achieving 98.69% validation accuracy. Meta's SAM2 is the primary segmentation engine. Ollama hosts the Llama 3.2 large language model locally for multilingual conversational support without requiring external API keys.

B. Hardware Requirements

Processor: Intel i5 10th Gen or AMD Ryzen 5 (Octacore) or higher. RAM: minimum 16 GB to concurrently run SAM2 and Llama 3.2. GPU: dedicated NVIDIA GPU with at least 4 GB VRAM and CUDA support for efficient SAM2 inference. Storage: minimum 10 GB for pre-trained model weights. Network: active internet connection for Open Weather Map API.

C. Key Implementation Modules

The CNN disease detection module loads a pretrained ResNet50, freezes lower layers, replaces the final fully connected layer with a custom 512→65-class head, and applies standard ImageNet normalization. The 3-layer validation function uses OpenCV Haar cascades for face/body detection, Laplacian variance for texture analysis, and HSV thresholding for plant colour detection, collectively rejecting non-agricultural inputs before inference. The spread predictor module integrates OpenWeatherMap API data with diseasespecific optimal temperature and humidity thresholds to compute daily risk scores.

7. Testing

A. Unit Testing

Verified that the validation logic successfully rejects non-leaf images and only allows valid plant specimens. Tested the colour-masking algorithm with known infected-to-healthy pixel ratios to ensure correct severity categorization. Ensured the spread predictor can successfully connect with OpenWeatherMap API and retrieve accurate 7-day forecasts. Verified Llama 3.2 correctly identifies user intent in English, Hindi, and Telugu.

B. Integration Testing

Verified that a specific disease identified by the CNN correctly triggers the corresponding medical advice from the digital prescription database. Tested the drone video frame extractor to SAM2 segmentation data transfer for field-level map generation. Ensured highrisk weather forecasts correctly trigger automated email notifications.

C. System Testing

The ResNet50 model was tested against a reserved validation dataset, achieving documented accuracy of 98.69% across 65 disease classes. End to end testing of the Streaml it dashboard confirmed smooth navigation between the classification, drone analysis, and chatbot tabs. Cross-platform testing verified consistent operation across Windows and Linux environments.

D. Test Case Summary

All 14 test cases passed successfully, covering: valid crop image upload, unsupported format rejection, 3layer non-leaf validation, image preprocessing, CNN disease classification (e.g., Rice Blast at 98% confidence), confidence score calculation, SAM2 visual segmentation, severity quantification (45% infection area), severity level assignment (Severe >60%), weather API integration, disease spread forecasting, drone video mapping, digital prescription generation, and multilingual chatbot response.

8. Results and Performance Analysis

A. User Interface

The user interface of Crop Sense v2.0 is an interactive dashboard built with Stream lit, featuring a persistent sidebar for effortless navigation between disease detection, drone video analysis, and the multilingual AI chatbot modules. Diagnostic results are presented with high-resolution visual masks generated by SAM2, highlighting infected regions directly on the uploaded media. The interface uses colour-coded severity indicators (red for Severe, orange for Moderate, yellow for Mild, green for Healthy) to communicate infection status at a glance.

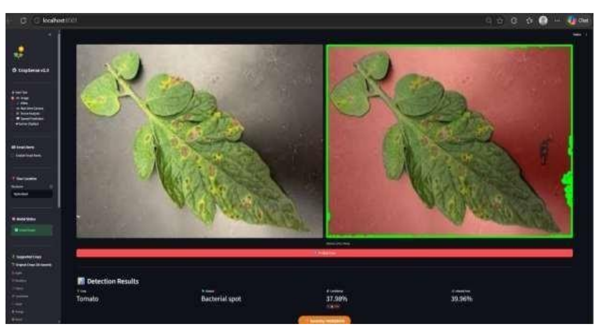
B. Classification Performance

The ResNet50 model achieved a validation accuracy of 98.69% across 65 disease classes covering 13 crop types. Cross-entropy training loss consistently decreased over 15 epochs, indicating successful learning of subtle pathological patterns including lesion shapes, colour changes, and fungal growth signatures. The model demonstrated strong generalization across diverse crop conditions through extensive data augmentation.

Model / Approach	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score**
Basic CNN (Baseline)	87.3	85.1	84.7	0.849
Transfer Learning (VGG16)	91.5	90.2	89.8	0.900
ResNet50 (without SAM2)	94.2	93.8	93.4	0.936
CropSense (ResNet50 + SAM2)	**98.69**	**98.41**	**98.57**	**0.985**

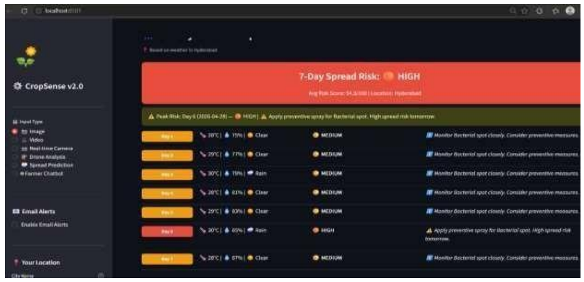
C. Visual Segmentation and Severity Results

SAM2 integration enabled precise quantitative analysis of crop health, accurately calculating the ratio of diseased-to-healthy pixels. The system correctly classified infections into Mild (5–25%), Moderate (25– 60%), and Severe (>60%) categories across all test cases. HSV colour space masking provided a robust fallback for identifying yellow, brown, and orange necrotic regions when SAM2 GPU acceleration was unavailable.



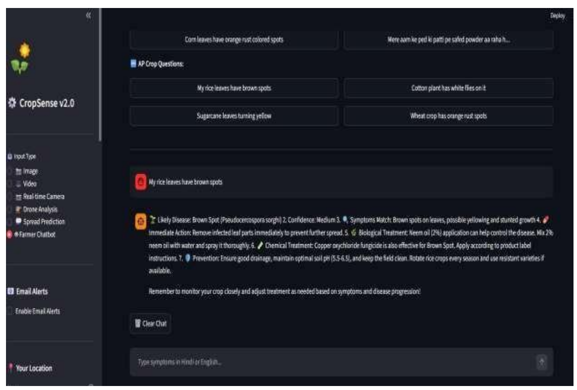
D. Predictive and Multimodal Analysis

The disease spread forecast engine successfully generated 7-day risk scores by processing Open Weather Map API data. Results confirmed that the engine correctly identified “High Risk” periods when forecasted humidity exceeded 80% and temperatures were within the 24–29°C optimal spreading range. The Drone Analyzer module successfully processed highresolution video by sampling every 30th frame, identifying spatial disease hotspots without significant latency in the Streamlit interface.



E. Multilingual Chatbot Assessment

The Llama 3.2 model successfully interpreted crop disease symptoms described in Telugu and Hindi, providing valid biological and chemical treatment advice. The Digital Prescription Engine consistently retrieved accurate data from the internal database for all 65 disease classes, ensuring users received relevant recovery timelines, treatment dosages, and preventive measures.



9. Conclusion

Crop Sense — Crop Disease Detection and Alert Generation using SAM2 — successfully demonstrates how advanced deep learning and modern web technologies can be integrated to support farmers with timely and reliable crop health monitoring. By combining Segment Anything Model 2 for precise segmentation with CNN-based classification, the system identifies crop diseases and estimates severity from both images and video frames with 98.69% validation accuracy. The development of Crop Sense AI v2.0 represents a significant advancement in digital agriculture by providing a robust, multimodal framework for crop disease management. Unlike traditional systems that focus solely on classification, this project integrates high-accuracy diagnosis with precise visual segmentation, proactive environmental analytics, and an inclusive multilingual interface. The weather-integrated spread predictor transforms the platform from a reactive tool into a proactive forecasting engine, enabling farmers to take preventive action before visible damage occurs. Future work will extend the system to support soil health analysis, advanced autonomous drone navigation, and expand coverage to additional crop types. Crop Sense demonstrates that advanced deep learning models can form a comprehensive, accurate, and real-world deployable crop disease management platform for Indian farmers.

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