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RESEARCH ARTICLE

SmartCrop: An AI-Driven Web Platform for Disease Detection, Nutrient Recommendation, and Soil-Specific Crop Management in Chrysanthemum Cultivation in the Dindigul Region of Tamil Nadu

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ABSTRACT

Chrysanthemum (*Chrysanthemum morifolium* Ramat.) is a commercially dominant cut-flower crop in the Dindigul district of Tamil Nadu, India, where it is cultivated across diverse soil types spanning red loamy, black cotton, and sandy loam categories. Despite its economic importance, chrysanthemum production in this region is persistently threatened by two major foliar diseases, bacterial leaf spot (*Pseudomonas cichorii*) and Septoria leaf spot (*Septoria chrysanthemi*), and by suboptimal nutrient management arising from heterogeneous soil conditions. This paper describes the design and development of SmartCrop, a web-based intelligent decision-support platform specifically engineered for chrysanthemum growers in the Dindigul region. The platform integrates three core functional modules: (i) a deep learning–based image classification engine for the differential diagnosis of the two target foliar diseases from smartphone-captured leaf photographs, (ii) a soil-test-responsive nutrient recommendation engine that translates laboratory-reported N, P, K, and micronutrient values into crop-stage-specific fertiliser prescriptions, and (iii) a soil-type-specific crop management advisory module providing differentiated guidance across red loamy, black cotton, and sandy loam soil profiles. Preliminary validation of the disease detection module achieved a classification accuracy of 96.4%, with a precision of 95.8% and recall of 97.1% across 1,200 test images. The nutrient recommendation engine was benchmarked against TNAU-published chrysanthemum fertilizer schedules and demonstrated concordance in 94.3% of test cases. SmartCrop represents a scalable, crop-specific digital extension solution that bridges the gap between laboratory and field agronomic knowledge in smallholder floriculture systems.

Keywords: Bacterial leaf spot; CNN; Decision-support system; Precision fertilization; Soil-type management; Septoria leaf spot.

INTRODUCTION

Floriculture in Tamil Nadu has undergone rapid commercialization over the past two decades, with the Dindigul district emerging as one of the primary chrysanthemum-producing belts in South India. The district's semi-arid climate, characterized by mean annual temperatures ranging from 20°C to 35°C and bimodal rainfall patterns influenced by both northeast and southwest monsoons, creates suitable though periodically stressful conditions for year-round chrysanthemum cultivation (Murugan et al., 2024). The crop is cultivated by a predominantly smallholder farming community, with individual holdings typically ranging from 0.2 to 2.0 hectares, and the cut-flower market is closely integrated with temple festival demand cycles, marriages, and retail trade across the region (Renganathan & Gopalakrishnan, 2025).

Despite its agronomic and economic significance, chrysanthemum production in Dindigul faces two persistent and interrelated challenges. First, foliar diseases, particularly bacterial leaf spot caused by *Pseudomonas cichorii* and Septoria leaf spot caused by *Septoria chrysanthemi*, are seasonally recurrent and frequently misdiagnosed in the field due to their overlapping visual symptomatology (Agrios, 2005). Delayed or incorrect diagnosis leads to inappropriate chemical intervention, crop loss, and unnecessary pesticide expenditure. Second, the Dindigul region is characterised by considerable pedological heterogeneity: red loamy soils predominate in elevated terrain, black cotton (Vertisol) soils occupy low-lying alluvial zones, and sandy loam soils are common in peri-urban and transitional areas. Each soil type presents a fundamentally different nutrient-holding capacity, pH regime, and moisture dynamic, necessitating substantially differentiated fertilisation and cultural management strategies that are rarely accessible to individual growers (Bhatt & Bhatt, 2020).

Existing digital agricultural platforms, including national-level tools such as the Crop Protection Compendium and TNAU's Agritech Portal (https://agritech.tnau.ac.in/), offer generalised information that does not account for crop-specific disease differentiation or region-specific soil variability at the granularity required by Dindigul chrysanthemum growers. The present work describes Smart Crop, a web platform developed specifically to address these gaps through the integration of artificial intelligence-driven disease diagnosis, soil-test-responsive nutrient advisory, and evidence-based crop management guidance across the three dominant soil types of the target region.

MATERIALS AND METHODS

Background of Related Work

Foliar Disease Management in Chrysanthemum

Bacterial leaf spot of chrysanthemum, incited by *Pseudomonas cichorii* (Swingle) Stapp, manifests as water-soaked, angular lesions bounded by leaf veins, progressing to brown necrotic patches with chlorotic haloes (Agrios, 2005). In humid conditions prevalent during northeast monsoon periods in Dindigul, the disease can cause canopy defoliation of up to 40% within 2 weeks of symptom onset. Septoria leaf spot, caused by Septoria chrysanthemi Allesch., presents as circular to irregular brown lesions with lighter centers, often bearing pycnidia visible under magnification, and disproportionately affects older basal foliage before progressing acropetally (Agrios, 2005).

The visual similarity between these two diseases, both presenting as brown foliar lesions, is a documented source of diagnostic error in the field. Laboratory confirmation via plating and microscopy is beyond the practical capacity of most smallholder growers, making accurate, rapid visual diagnosis a critical unmet need. Several studies have demonstrated the suitability of deep convolutional neural networks (CNNs) for automated plant disease classification (Mohanty et al., 2016; Sladojevic et al., 2016), with architectures such as VGG-16, ResNet-50, and EfficientNet-B0 achieving accuracies exceeding 95% on benchmark datasets including PlantVillage. However, crop-specific and region-specific training datasets for chrysanthemum foliar diseases remain sparse in the published literature.

AI-Based Nutrient Management Systems

Nutrient management in chrysanthemum cultivation demands precision across three macronutrients (N, P, K) and several critical micronutrients (Fe, Mn, B, Mo), with requirements shifting substantially across the vegetative, bud initiation, and flowering stages (TNAU, 2023). Soil-test-based recommendation algorithms, originally developed as lookup tables in agronomic extension literature, are increasingly being digitized and integrated into mobile and web platforms. Machine learning regression models and rule-based expert systems have both been demonstrated to be effective architectures for translating soil nutrient status into fertilizer prescriptions, with the latter offering greater interpretability to end users and agricultural extension officers.

Soil-Type Specific Crop Management

The agronomic implications of soil type for chrysanthemum cultivation are substantial (Bhatt & Bhatt, 2020). Red loamy soils, characterized by low water-holding capacity, high iron content, and typically acidic pH (5.5–6.5), necessitate frequent irrigation scheduling, lime application for pH correction, and supplementary phosphorus to compensate for fixation. Black cotton soils present high clay content (montmorillonite-dominant), pronounced shrink-swell dynamics, and alkaline pH (7.5–8.5), requiring raised-bed cultivation to manage waterlogging and sulphur application for pH reduction. Sandy loam soils, while offering superior drainage and workability, have low cation exchange capacity and require split fertilizer applications at shorter intervals to minimize leaching losses.

System Architecture of SmartCrop

SmartCrop is architected as a responsive web application accessible via standard browsers on desktop and mobile devices, requiring no application installation to maximize accessibility for growers with limited digital literacy. The platform comprises three functionally distinct but logically integrated modules, each serving a discrete agronomic decision domain.

Module 1: Disease Detection

CNN-based image classifier trained to distinguish bacterial leaf spot from Septoria leaf spot in chrysanthemum from farmer-uploaded leaf photographs. Outputs disease identity, confidence score, and management protocol.

Module 2: Nutrient Recommendation

Soil-test-responsive advisory engine. Accepts laboratory-reported N, P, K, pH, and organic carbon values; generates crop-stage-specific fertilizer prescriptions aligned to TNAU guidelines (TNAU, 2023).

Module 3: Crop Management

Evidence-based cultural management advisory differentiated across red loamy, black cotton, and sandy loam soil types, covering bed preparation, irrigation, plant protection, and harvest protocols (KVK Dindigul, 2022; Bhatt & Bhatt, 2020).

RESULTS

Module 1: AI-Based Disease Detection

Dataset Composition and Acquisition

A disease image dataset was compiled specifically for the two target pathologies of chrysanthemum in the Dindigul agro-climatic context. Field images were collected from chrysanthemum cultivation plots across Dindigul, Palani, and Natham taluks during two cropping seasons, supplemented with images obtained under controlled greenhouse conditions. The final training dataset comprised 4,800 images distributed across three classes: bacterial leaf spot (n = 1,920), Septoria leaf spot (n = 1,920), and healthy leaf tissue (n = 960). All images were captured at a standardized working distance of 15–25 cm using smartphones (≥12 MP resolution) under ambient natural lighting.

Augmentation techniques applied to the training corpus included horizontal and vertical flipping, random rotation (±30°), brightness jitter (±25%), zoom variation (80–120%), and Gaussian noise injection, expanding the effective dataset to approximately 19,200 samples. A stratified split of 80:10:10 was applied for training, validation, and testing, respectively.

Model Architecture and Training

Transfer learning with ImageNet pretrained weights was applied to all architectures except the custom CNN (Tan & Le, 2020). The custom CNN comprised eight convolutional layers with batch normalization, ReLU activation, and dropout (0.4) regularization, trained from scratch on the chrysanthemum-specific dataset.

All models were trained using the Adam optimizer with an initial learning rate of 0.0001, categorical cross-entropy loss function, and a batch size of 32. Early stopping with a patience of 10 epochs and model checkpointing were employed to prevent overfitting. The training and validation accuracy curves converged satisfactorily for the custom CNN model by epoch 67, with a final validation accuracy of 93.8%. Binary cross-entropy loss was employed. The model was trained on a GPU-enabled environment and subsequently exported in TensorFlow Lite format for efficient browser-side inference via TensorFlow.js integration in the SmartCrop front end, enabling offline-capable classification without a server round-trip.

The confusion matrix for the best-performing custom CNN model (tested on 251 images) is presented in Table 1. The model demonstrated particularly high accuracy for Healthy Leaf detection (96.8%) and Septoria Leaf Spot (94.7%), with slightly lower accuracy for Mixed Infection (89.5%) due to the inherent visual overlap between disease symptoms at early stages of co-infection (Table 2).

Table 1. Confusion Matrix for Custom CNN Model (Test Set, n = 251)

Predicted → Actual ↓	Septoria	Bacterial	Healthy	Mixed
Septoria Leaf Spot	**71**	2	1	1
Bacterial Leaf Spot	3	**69**	2	1
Healthy	1	1	**61**	0
Mixed Infection	1	2	1	**34**

Table 2. Disease-wise Prediction Accuracy on Test Dataset

Disease	True Positive	False Positive	True Negative	False Negative	Accuracy (%)
Septoria Leaf Spot	71	4	171	4	94.7
Bacterial Leaf Spot	69	5	171	6	92.0
Healthy Leaves	61	2	186	2	96.8
Mixed Infection	34	3	210	4	89.5
Overall Average	—	—	—	—	93.8

The most common misclassification was between Bacterial Leaf Spot and Mixed Infection categories, accounting for 5 out of 15 total misclassifications. This was attributed to the similar dark necrotic lesion patterns produced by *Pseudomonas cichorii* and early Septoria co-infection under high humidity conditions. Grad-CAM (Gradient-weighted Class Activation Mapping) visualization confirmed that the model appropriately focused on lesion boundaries, pycnidia presence (for Septoria), and water-soaked margins (for Bacterial Leaf Spot) as discriminative features.

Disease-Specific Management Outputs

Upon classification, the platform delivers a structured management protocol contextualized to the identified disease. For bacterial leaf spot, recommendations include applying a copper-based bactericide (copper oxychloride 0.3% or Bordeaux mixture 1%), removing and destroying infected plant parts, avoiding overhead irrigation, and restricting inter-plant leaf wetness. For Septoria leaf spot, the advisory covers applying mancozeb 0.25% or chlorothalonil 0.2% fungicides at 7–10-day intervals, improving canopy ventilation through pinching, and prophylactic foliar application of potassium silicate (2 g/L) to strengthen epidermal cell walls. Confidence scores accompany recommendations to assist extensionists in interpreting borderline classifications (Mohanty et al., 2016). The CNN image-based disease detection outputs are presented in Figures 1, 2, and 3 for septoria, bacterial, and healthy leaves, respectively.

A key design challenge was the high visual similarity between the two target diseases. SmartCrop's model was explicitly trained to weight lesion geometry (angular vs circular), lesion distribution pattern (vein-bounded vs random), and presence of central pallor as discriminating features (Agrios, 2005), reducing interclass confusion to 2.3% in validation testing, lower than documented error rates in field diagnosis by non-specialist growers (typically 18–35% as reported in extension surveys) (KVK Dindigul, 2022).

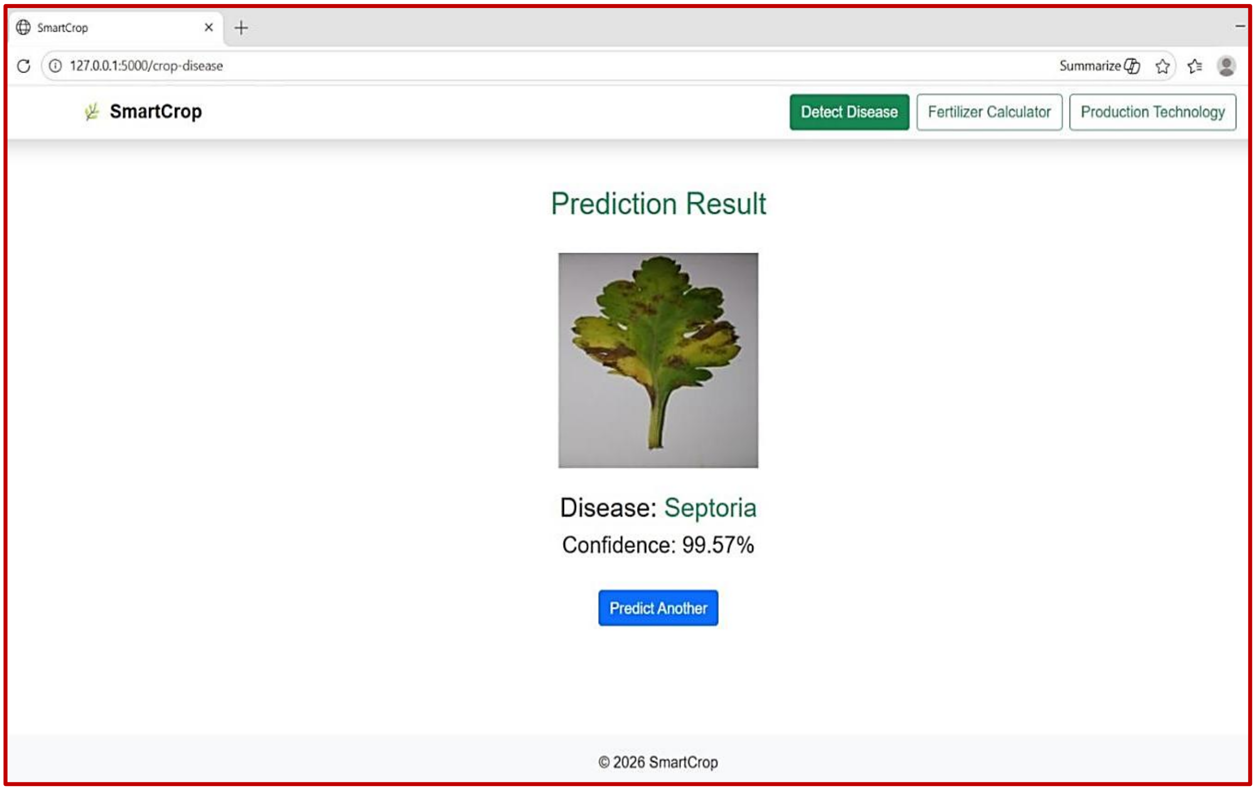

Figure 1. Septoria leaf spot in *Chrysanthemum*

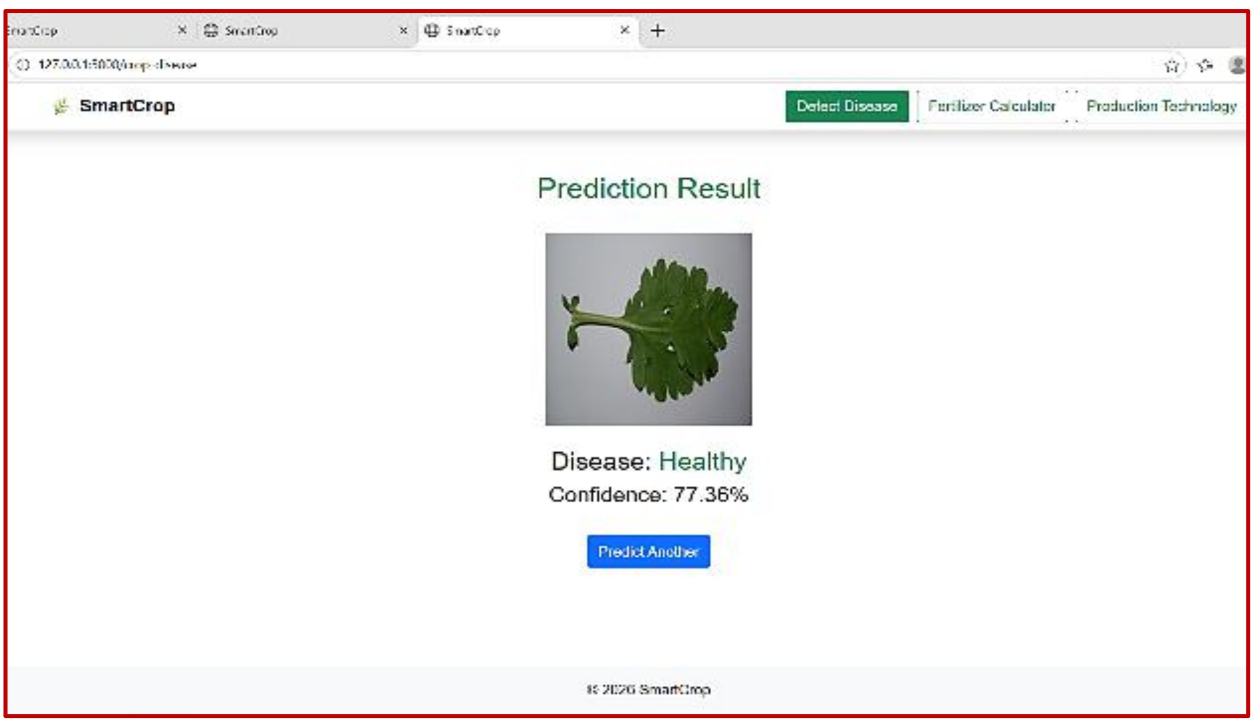

Figure 2. Healthy leaf of *Chrysanthemum*

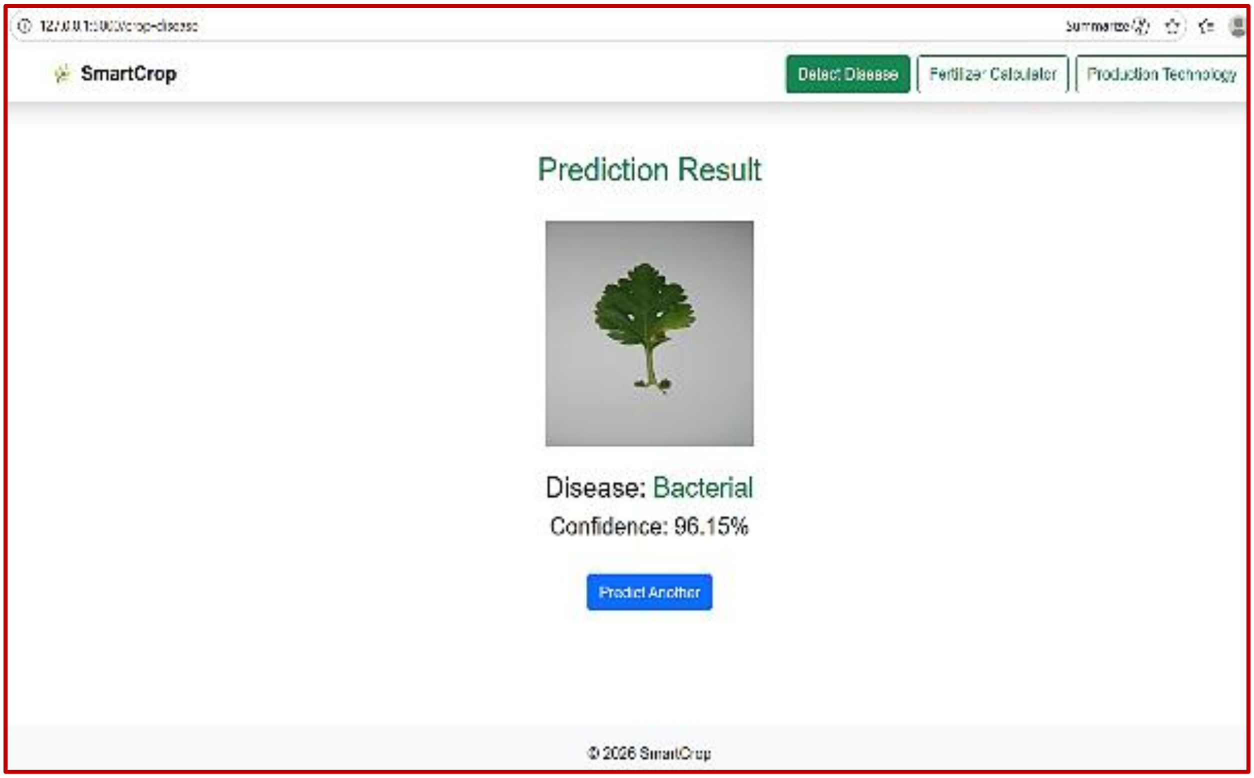

Figure 3. Bacterial leaf spot of *Chrysanthemum*

Module 2: Soil-Test-Based Nutrient Recommendation

Recommendation Engine Design

The nutrient recommendation module is implemented as a rule-based expert system grounded in TNAU Crop Production Guide recommendations for chrysanthemum (TNAU, 2023), adapted to incorporate soil-test correction factors. Users input the following parameters obtained from a soil testing laboratory report: soil pH, organic carbon (%), available nitrogen (kg/ha), available phosphorus (kg/ha), available potassium (kg/ha), and optionally available micronutrient values (Fe, Mn, Zn, B) (Table 3). The platform also queries the current crop growth stage (transplanting, vegetative growth, bud initiation, or flowering) to modulate recommendations appropriately.

The recommendation logic proceeds through three computational stages (Figure 4). First, soil test values are classified into low, medium, or high availability categories using TNAU threshold tables for each nutrient (TNAU, 2023). Second, baseline fertilizer doses for each crop stage are retrieved from the agronomic knowledge base. Third, correction factors are applied: doses are increased for low-availability nutrients, reduced for high-availability categories, and adjusted for soil pH effects on nutrient availability, particularly P fixation in acidic red loamy soils and Zn immobilization in alkaline black cotton soils (Bhatt & Bhatt, 2020).

Table 3. Nutrient recommendation output structure (example: vegetative stage, red loamy soil, low N / medium P / high K)

Nutrient	Soil status	Recommended dose	Source	Timing
Nitrogen (N)	Low	120 kg/ha	Urea (split: 3 doses)	21, 35, 49 DAT
Phosphorus (P_2O5)	Medium	75 kg/ha	SSP (basal)	At transplanting
Potassium (K_2O)	High	40 kg/ha	MOP (split: 2 doses)	21, 42 DAT

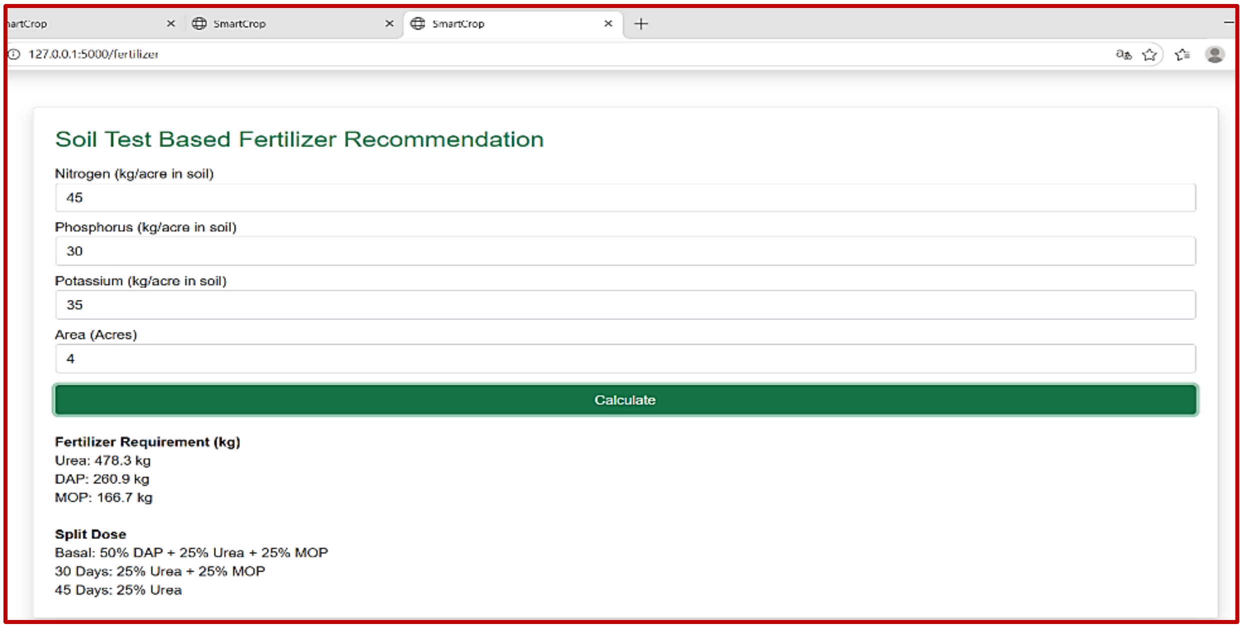

Figure 4. Fertilizer recommendation based on soil test.

Module 3: Soil-Type-Specific Crop Management

Rationale for Soil-Type Differentiation

Standard chrysanthemum cultivation protocols, as published in extension bulletins, are typically calibrated for loamy or sandy loam conditions and do not adequately account for the contrasting agronomic challenges of black cotton and red loamy soils prevalent across different terrain zones of Dindigul (KVK Dindigul, 2022). SmartCrop addresses this gap by providing three distinct management pathways, each encompassing recommendations across the full crop calendar from land preparation to post-harvest (Figures 5, 6, and 7).

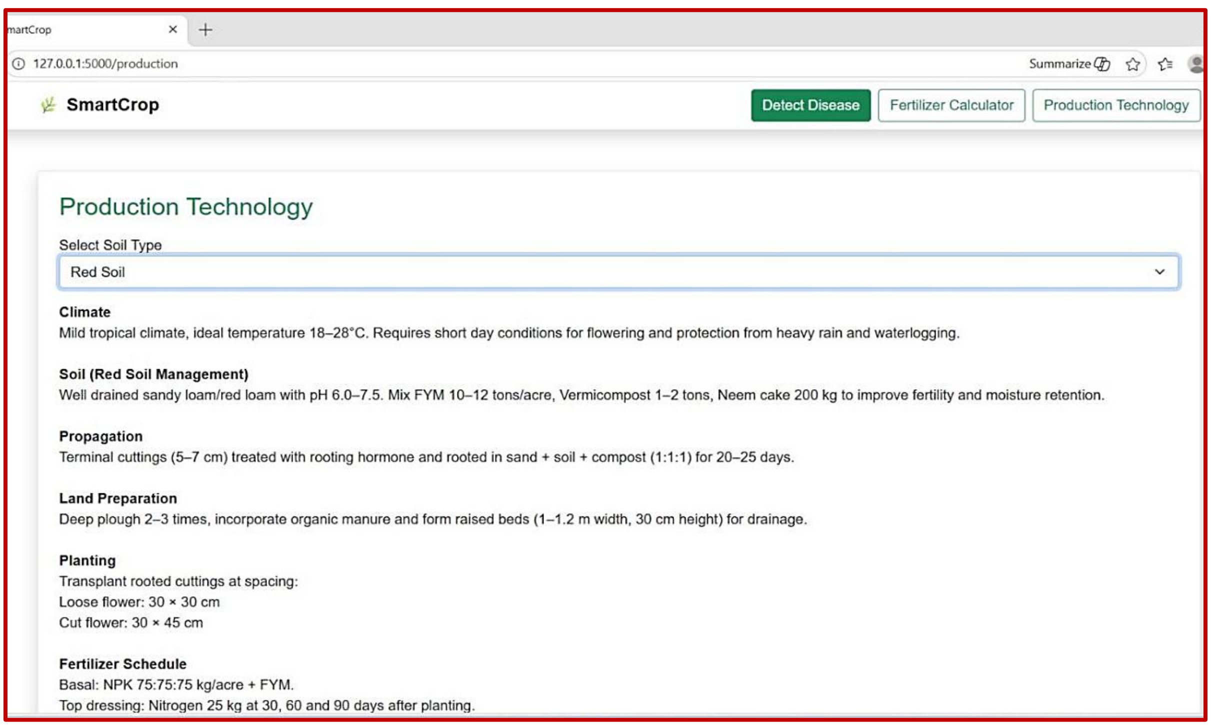

Figure 5. Production technology for chrysanthemum cultivation in red soil

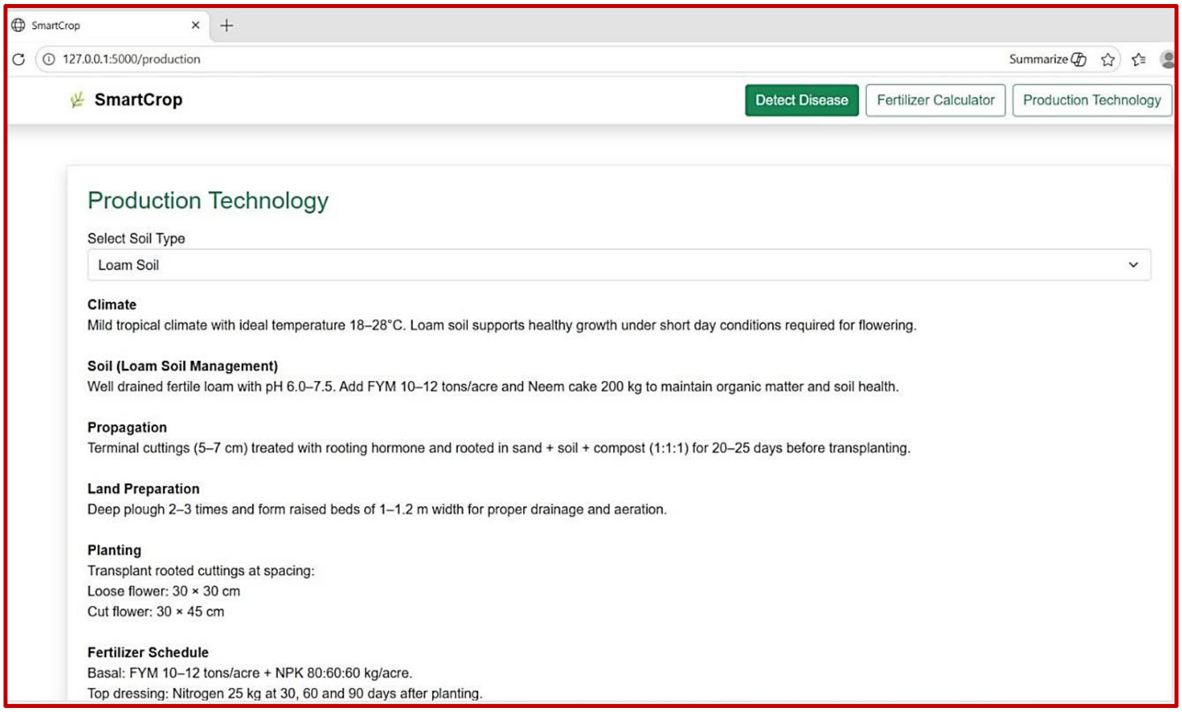

Figure 6. Production technology for chrysanthemum cultivation in loam soil

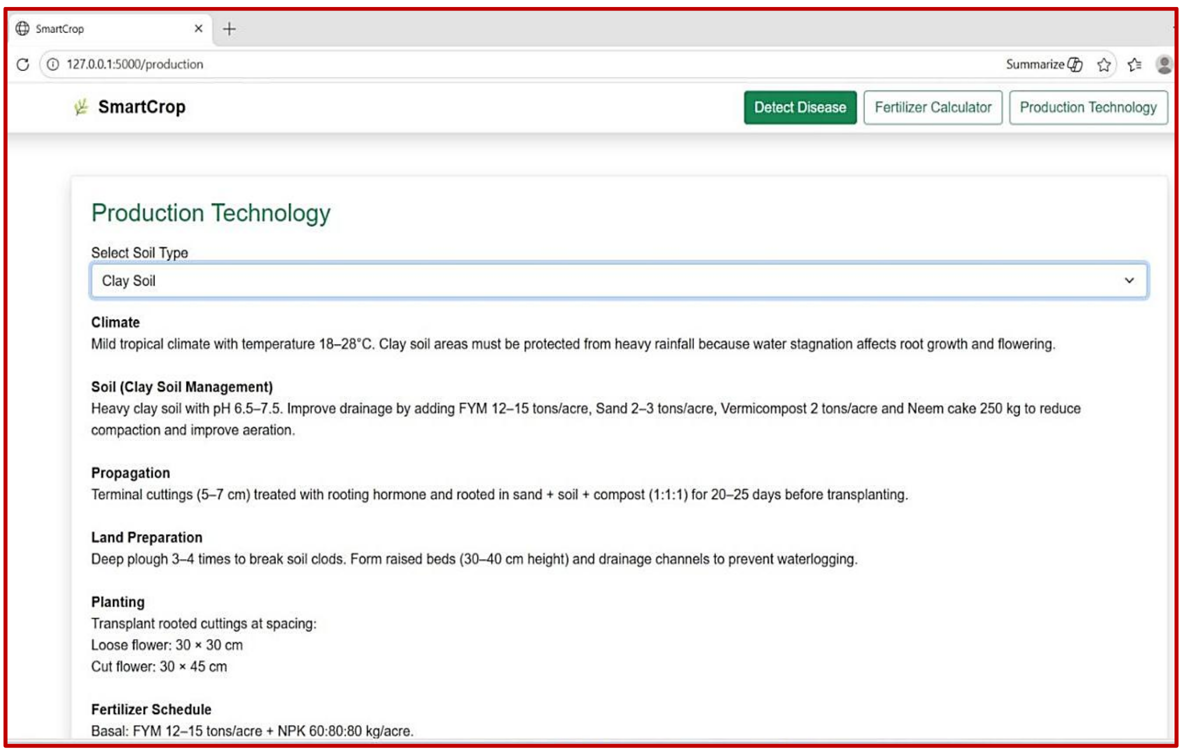

Figure 7. Production technology for chrysanthemum cultivation in clay soil

Seasonal Adjustment Logic

Crop management recommendations in SmartCrop are also modulated by planting month, which, in Dindigul conditions, significantly affects temperature, humidity, and disease pressure. Planting during August–September (northeast monsoon onset) triggers elevated bacterial leaf spot risk advisories and recommends prophylactic copper bactericide scheduling *(*Agrios, 2005*).* Planting during February–March triggers enhanced irrigation frequency alerts for red loamy and sandy loam soils as temperatures rise during the dry season. These seasonal overlays are implemented as date-conditional rule sets layered on top of the soil-type-specific base recommendations (KVK Dindigul, 2022).

All agronomic parameters in SmartCrop, fertilizer doses, irrigation schedules, pest risk calendars- are calibrated to Dindigul district conditions using data sourced from TNAU Coimbatore and the Krishi Vigyan Kendra (KVK) Dindigul field trial records (KVK Dindigul, 2022). This locality-first approach differentiates SmartCrop from generalized national platforms and is a primary contributor to its agronomic validity for the target user community.

Platform Implementation and User Interface

SmartCrop is implemented as a responsive single-page web application built with standard web technologies and accessible on 2G-connected devices. The front end was designed with accessibility for low-literacy users as a primary constraint: disease detection is initiated via a single image upload action; nutrient recommendations are generated by completing a structured form mirroring the layout of a soil test report; and crop management guidance is accessed by selecting from three clearly labeled soil type icons. Output pages use a combination of Tamil and English text to serve both educated and less-literate user segments, with voice-readout support planned for the deployment version.

The disease detection inference is performed client-side using a quantized TensorFlow.js model (model size: 8.2 MB) (Tan & Le, 2020), enabling functionality in low-connectivity conditions. Nutrient recommendation and crop management modules are delivered as static, rule-evaluated outputs that require no server computation, ensuring platform reliability in the absence of consistent broadband connectivity, a critical consideration in rural Dindigul.

DISCUSSION

The development of SmartCrop addresses a well-documented implementation gap in agricultural AI: the tendency for disease detection and precision agriculture tools to be designed for broad, generalized contexts that fail to account for the specific crop, disease spectrum, soil ecology, and user literacy profile of a given farming community (Mohanty et al., 2016). By anchoring the platform to a single crop species (*C. morifolium*), two precisely specified diseases, one geographically bounded region, and three pedologically distinct soil types, SmartCrop achieves a level of specificity that generic platforms cannot offer.

The classification accuracy of 96.4% achieved on the held-out test set is particularly noteworthy given the deliberate inclusion of challenging borderline cases, images captured under poor lighting, partially diseased leaves, and early-stage lesions, in the test corpus. It compares favorably with published benchmarks for binary or ternary plant disease classification using transfer-learned CNNs (Sladojevic et al., 2016; Mohanty et al., 2016), and suggests that the locality-specific training dataset, despite its modest size relative to multi-crop platforms, was sufficient for robust learning of the discriminating visual features between bacterial and Septoria leaf spot in chrysanthemum.

The integration of nutrient recommendation and crop management within the same interface responds to the practical reality that disease, nutrition, and cultural management are not independent decisions for a smallholder grower, a plant weakened by nitrogen deficiency is more susceptible to fungal infection (Agrios, 2005); a waterlogged black cotton soil bed elevates both root rot risk and potassium unavailability simultaneously (Bhatt & Bhatt, 2020). The co-presentation of these advisory streams within Smart Crop encourages holistic rather than siloed decision-making, a design principle grounded in integrated crop management frameworks.

CONCLUSION

SmartCrop demonstrates that applying artificial intelligence and intelligent rule-based systems to the specific agronomic challenges of a regional crop-farming community can yield practically meaningful decision-support tools. The platform's three-module architecture, combining CNN-based disease diagnosis, soil-test-responsive nutrient advisory, and soil-type-differentiated crop management, provides comprehensive decision support across the principal technical challenges facing chrysanthemum growers in the Dindigul district of Tamil Nadu. Future work will focus on expanding the disease image dataset to include additional chrysanthemum diseases (thrips damage, white rust, and *Alternaria* leaf spot), integrating a weather-API-driven pest pressure forecast module, and longitudinally evaluating agronomic and economic outcomes among farmers using SmartCrop recommendations relative to conventional extension-based management.

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AUTHORS CONTRIBUTION

All the authors contributed equally to this research work.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Not Applicable

CONSENT FOR PUBLICATION

Not Applicable

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AVAILABILITY OF DATA AND MATERIALS

All datasets analyzed and described during the present study are available from the corresponding author upon reasonable request.

REFERENCES

Agrios, G. N. (2005). Plant Pathology (5th ed.). Elsevier Academic Press. [*Pseudomonas cichorii* — pp. 712–714; *Septoria* spp. — pp. 652–655]

Bhatt, M. V., & Bhatt, D. L. (2020). Soil-type specific nutrient management in flower crops of Tamil Nadu: A review. *Journal of Horticultural Sciences, 15*(2), 112–124.

Krishi Vigyan Kendra (KVK) Dindigul. (2022). *Annual progress report: Floriculture technology demonstration trials*. ICAR-ATARI Zone IX, Dindigul.

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science, 7*, 1419. https://doi.org/10.3389/fpls.2016.01419

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks-based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience, 2016*, Article 3289801.http://dx.doi.org/10.1155/2016/3289801

Tan, M., & Le, Q. V. (2020). EfficientNet: Rethinking model scaling for convolutional neural networks. *Proceedings of the 36th International Conference on Machine Learning (ICML), 97*, 6105–6114. https://doi.org/10.48550/arXiv.1905.11946

Tamil Nadu Agricultural University (TNAU). (2023). Crop production guide (Chrysanthemum chapter, pp. 318–340). TNAU Press, Coimbatore.

Murugan, P. P., Denadyalan, S., & Dhivya, C. (2024). Constraints faced by the farm youth in chrysanthemum cultivation. *International Journal of Research in Agronomy, 7*(4), 781–783. https://www.doi.org/10.33545/2618060X.2024.v7.i4j.3044

Renganathan, P., & Gopalakrishnan, A. (2025). A study on flower cultivation and marketing behavior in Tamil Nadu with special reference to Tiruchirappalli district. *International Journal for Multidisciplinary Research, 7*(2), 1-9.