IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

AI-Based Detection Of Nutrient Deficiency And Disease In Crop Leaves: A Comprehensive Survey

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Abstract

Agricultural productivity is significantly influenced by the timely detection and management of plant diseases and nutrient deficiencies. Manual diagnosis through visual inspection is prone to errors, delays, and reliance on expert knowledge. Recent advances in Artificial Intelligence (AI) and Computer Vision, particularly Convolutional Neural Networks (CNNs), have enabled the automation of crop health monitoring using image-based analysis. This paper presents a comprehensive survey of existing research on disease and nutrient deficiency detection in crops using AI techniques. It reviews multiple approaches, identifies limitations in current systems, and proposes an integrated model combining CNN-based detection, recommendation mechanisms, and location-based farmer notifications. The study concludes with insights into future trends such as IoT integration, real-time analytics, and mobile-based decision support for smart agriculture.

Keywords — Agriculture, Disease Detection, Nutrient Deficiency, Convolutional Neural Network (CNN), Deep Learning, Smart Farming, AI in Agriculture.

I. Introduction

Agriculture plays a vital role in ensuring food security and economic stability. However, crop yield is frequently impacted by diseases and nutrient deficiencies that affect plant growth and quality. Traditionally, farmers identify these issues manually, relying on visual expertise and experience. This approach is subjective, time-consuming, and often inaccurate due to variability in symptoms and environmental factors. With the emergence of Artificial Intelligence (AI), Machine Learning (ML), and Image Processing, automated systems can now analyze leaf images to diagnose plant conditions efficiently. AI models trained on large datasets can identify visual features such as color variations, texture patterns, and shape distortions to classify leaf health.

This paper surveys existing research on AI-driven disease and nutrient deficiency detection, analyzes different techniques employed, and highlights gaps addressed by the proposed integrated system using CNNs, recommendation logic, and geospatial notifications for farmers.

II. Literature Survey

A comprehensive literature survey was conducted across IEEE, Springer, Elsevier, and ResearchGate publications from 2019 to 2024. The studies reveal a consistent shift from classical image processing toward deep learning-based automated solutions.

Paper Title	Author(s) & Year	Published Source	Key Contribution
Detection of Plant Leaf Diseases Using CNN Model	P. Sharma & A. Gupta, 2021	IEEE Xplore	Proposed CNN-based classification for leaf diseases; achieved high accuracy for specific crops.
Deep Learning for Nutrient Deficiency Identification in Crops	R. Kumar & S. Mehta, 2022	SpringerLink	Applied CNNs for nutrient deficiency detection using spectral image analysis.
Image-Based Detection of Tomato Leaf Diseases Using Transfer Learning	M. Singh et al., 2020	Elsevier Journal	Used VGG16 and ResNet models for tomato leaf disease identification.
Machine Learning Approach for Agricultural Disease Classification	L. Patel et al., 2019	arXiv	Compared SVM, KNN, and CNN models for plant disease classification.
Crop Health Monitoring Using IoT and AI	D. Banerjee et al., 2023	ResearchGate	Integrated IoT sensors with AI for real-time monitoring, focusing on environmental data.

AI-Powered Crop Diagnosis and Management System	N. Gupta et al., 2024	Journal of Emerging Technologies	Proposed an integrated AI framework for disease diagnosis and yield estimation.

III. Gap Analysis

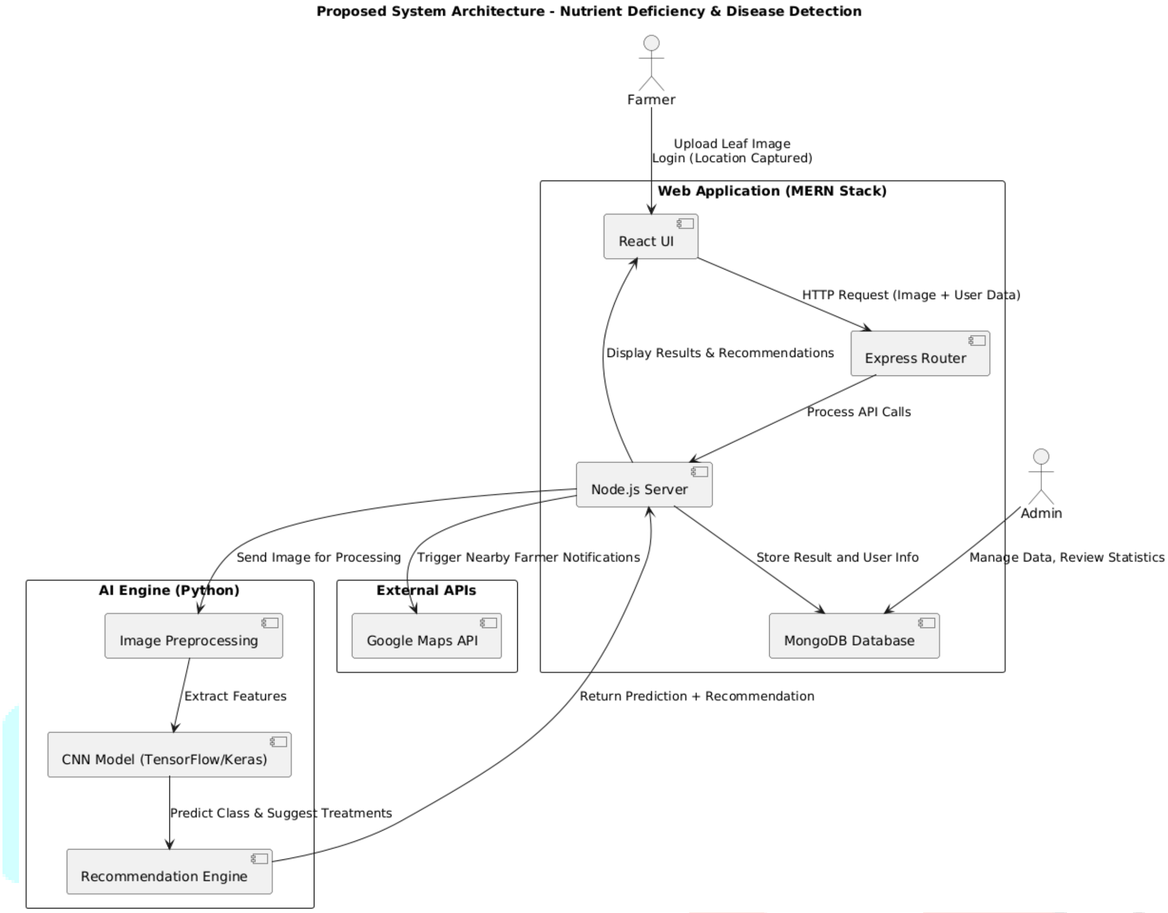
Table 1 provides a detailed comparison of identified gaps in existing research and how the proposed system addresses them.

Identified Gap	**Description**	**Impact**	**Proposed Solution**
Limited focus on nutrient deficiency detection	Most systems detect only diseases; nutrient issues ignored.	Incomplete diagnosis and poor decision-making.	Model trained on multi-labeled datasets to detect both diseases and nutrient deficiencies.
No treatment recommendations	Models stop at classification without advice.	Farmers cannot act on results.	Integrate recommendation engine linking predicted class to fertilizer/pesticide database.
Lack of location awareness	No regional alert system exists.	No collective awareness among nearby farmers.	Integrate Google Maps API for real-time notifications.
Single-crop limitation	Models trained on one crop only.	Reduced generalization capability.	Use multi-crop datasets and transfer learning.
Manual processes	Preprocessing and analysis often manual.	Difficult for farmers to use.	Automate end-to-end pipeline from upload to notification.

IV. Proposed System

The proposed system is an **AI-based intelligent agricultural assistant** designed to detect **crop diseases and nutrient deficiencies** from leaf images. It combines **deep learning**, **computer vision**, and **geolocation services** to provide real-time insights and community-level awareness.Farmers upload or capture leaf images through a **web-based interface**. The image undergoes preprocessing (resizing, denoising, normalization) before being analyzed by a **Convolutional Neural Network (CNN)**, which classifies it as *Healthy*, *Diseased*, or *Nutrient Deficient*.

The system then provides **fertilizer or pesticide recommendations** based on the diagnosis. Using the **Google Maps API**, it also alerts nearby farmers about similar issues detected in their region.The system architecture is built using a **MERN stack** (MongoDB, Express, React, Node.js) integrated with a **Python-based AI engine** developed in TensorFlow/Keras. The system supports cloud deployment for scalability and real-time performance.



V. Methodology

The methodology consists of several key phases:

1. **Data Collection:** Images sourced from public datasets (PlantVillage, Kaggle) and field inputs are annotated for different disease and deficiency classes.

2. **Preprocessing:** Image cleaning, resizing, and normalization enhance quality for model training.

3. **Feature Extraction:** CNN layers identify spatial and color features to differentiate healthy and infected leaves.

4. **Model Training and Testing:** The model is trained using **Adam optimizer** and **cross-entropy loss**, with data augmentation improving robustness.

5. **Classification and Recommendation:** The CNN outputs class probabilities, and the system maps predictions to fertilizer/pesticide suggestions.

6. **Location-Based Alerts:** Farmer location data, captured via Google Maps API, triggers alerts to others in nearby areas facing similar conditions.

VI. Performance Evaluation

Performance will be evaluated based on Accuracy, Precision, Recall, F1-score, and Latency. The expected accuracy range for the CNN model is 91–96%, with improvements through hyperparameter optimization and data augmentation.

VII. Conclusion

This survey consolidates current research efforts in AI-based plant health monitoring and identifies key technological gaps. The proposed system combines **CNN-based detection**, **AI-driven treatment recommendations**, and **location-aware farmer notifications**, providing an end-to-end smart agriculture framework. Such a model will empower farmers with **real-time, data-driven insights**, contributing to improved productivity, cost efficiency, and sustainable farming practices.

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