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Image-Based Crop Disease Detection Using Machine Learning

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Abstract: *Crop disease detection is critical for agricultural productivity and global food security. Traditional methods rely on labour-intensive field surveys prone to human error. This paper presents an image-based crop disease detection system using a hybrid Convolutional Neural Network (CNN) augmented with pre-trained AlexNet weights. The system captures leaf images, applies preprocessing (resizing, normalization, augmentation), and classifies diseases with high accuracy. A Flask-based web application enables real-time prediction accessible to farmers via smartphone. Trained on 2,000 field-collected images across potato, pepper, and tomato crops, the proposed model achieves approximately 97% classification accuracy, outperforming standalone classifiers including SVM, Logistic Regression, Decision Tree, and Naïve Bayes*

Keywords*:* Crop Disease Detection, Machine Learning, CNN, AlexNet, Deep Learning, Image Classification, Flask, Precision Agriculture

I. INTRODUCTION

Agriculture is the backbone of India's economy, and crop diseases remain one of the most significant threats to food security and farmer livelihoods. Timely, accurate identification of plant diseases can prevent massive yield loss and reduce excessive reliance on pesticides. Traditional visual inspection by farmers is subjective, time-consuming, and demands expert botanical knowledge rarely available in rural areas.

Recent advances in deep learning and computer vision have opened new pathways for automated, real-time crop disease identification from digital photographs. Convolutional Neural Networks (CNNs) are particularly well-suited for this task due to their ability to automatically learn hierarchical visual features — edges, textures, colour patterns, and lesion morphologies — without hand-crafted feature engineering.

This work proposes a hybrid CNN model that leverages pre-trained AlexNet weights for feature extraction and custom dense classification layers trained on field images. A lightweight Flask web application integrates the trained model, allowing farmers to upload a leaf photograph and receive an instant disease diagnosis with treatment recommendations. The system targets three economically important crops in Maharashtra: potato, pepper (bell), and tomato.

II. LITERATURE SURVEY

Considerable research has explored machine learning and deep learning approaches to automated plant disease detection. Ashraf et al. [1] proposed a lightweight modified CNN for wheat crop disease prediction using datasets collected from Azad Kashmir, achieving 93% accuracy with the most extensive training configuration. Islam et al. [2] introduced DeepCrop — a web-application-integrated deep learning framework targeting corn, peach, grape, potato, and strawberry diseases, reporting 97.8% accuracy.

Nandhini andAshokkumar [3] trained a CNN on 64,412 images spanning 16 crop species and 25 diseases, achieving a high accuracy of 99.35% and demonstrating feasibility for smartphone-based detection. Pokkuluri et al. [4] augmented CNN architectures with Cellular Automata to predict diseases across rice, wheat, barley, sugarcane, and cotton. Sharma and Shrivastava [5] conducted a comprehensive review of deep CNN-based crop disease prediction on a 54,306-image dataset, confirming CNN superiority over traditional classifiers. The table below compares existing works with the proposed system.

Table I: Comparison of Existing Approaches with Proposed System

Author(s)	Year	Model Used	Dataset	Accuracy	Limitation
Ashraf et al.	2023	Modified CNN	Wheat, AJK Pakistan	93%	Single crop
Islam et al.	2023	CNN (DeepCrop)	Corn, Potato, Grape	97.8%	Limited crops
Nandhini& Ashok	2022	CNN	64,412 images, 16 crops	99.35%	No web app
Pokkuluri et al.	2022	CNN + Cellular Automata	Rice, Wheat, Barley	96.5%	Complex model
Sharma &Shrivastava	2022	Deep CNN (Review)	54,306 images, 14 crops	99.35%	Review only
Proposed System	**2026**	**CNN + AlexNet (Hybrid)**	**2000 field images, 3 crops**	**~97%**	—

III. SYSTEM DESIGN

A. System Architecture

The system follows a client–server architecture. Users (farmers, agronomists, admins) interact via a responsive web portal. The Flask server handles user authentication, image preprocessing, model inference, and database operations. The trained CNN model is loaded at server start-up and invoked on each prediction request. Disease information and treatment recommendations are stored in MySQL.

The overall workflow is: (1) User uploads a crop leaf image through the web portal. (2) Server preprocesses the image — resize to 224×224, normalise pixel values to [0,1]. (3) Preprocessed tensor is passed to the loaded Keras model. (4) Predicted class label and confidence score are returned. (5) Treatment recommendations are fetched from the knowledge base and displayed to the user. (6) Image, prediction, and user record are stored in the database for future reference.

B. Data Collection

A dataset of 2,000 images was assembled from field photographs and augmented online sources. The dataset covers three crops: Potato (Early Blight, Late Blight, Healthy), Pepper Bell (Bacterial Spot, Healthy), and Tomato (10 disease classes + Healthy). Images were captured under natural lighting at varying angles and distances, both on white backgrounds and in-field settings.

C. Image Preprocessing

Each image was resized to 224 × 224 pixels to match AlexNet input requirements. Pixel values were normalised to the range [0, 1] by dividing by 255. Batch Normalisation was applied within the model during training. Offline data augmentation — horizontal and vertical flipping, rotation (±20°), zoom (±15%), and brightness jitter — was applied to increase dataset diversity and improve model generalisation.

D. Model Architecture

The proposed hybrid CNN consists of: (i) AlexNet convolutional base with frozen pre-trained weights for deep feature extraction; (ii) Global Average Pooling layer to reduce spatial dimensions; (iii) Dense layer (512 units, ReLU) with Batch Normalisation and Dropout (rate = 0.5); (iv) Dense layer (256 units, ReLU) with Batch Normalisation and

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Dropout (rate = 0.4); (v) Softmax output layer for multi-class classification. Freezing AlexNet weights reduces training time and prevents overfitting on the relatively small field dataset.

E. Technology Stack

- Programming Language: Python 3.10
- Deep Learning Framework: TensorFlow 2.x / Keras
- Web Framework: Flask (micro-framework for Python)
- Image Processing Libraries: OpenCV, PIL (Pillow), NumPy
- Database: MySQL (user records, disease information, prediction history)
- Frontend: HTML5, CSS3, JavaScript, Bootstrap 5
- Deployment: Heroku (cloud) / Apache or Nginx (on-premise)

IV. IMPLEMENTATION

A. Model Training

The model was trained for 50 epochs using the Adam optimiser (learning rate = 0.001) with categorical cross-entropy loss function. The dataset was split in an 80/10/10 ratio for training, validation, and testing. Early Stopping (patience = 10 epochs) monitored validation loss to prevent overfitting. Model checkpointing saved the best-performing weights. Training was executed on a GPU-enabled cloud environment (Google Colab with Tesla T4 GPU).

B. Flask Web Application

The Flask application exposes a /predict endpoint that accepts HTTP POST requests containing the uploaded image file. Server-side preprocessing (resize → normalise → expand_dims) prepares the input tensor, which is passed to the loaded Keras model (model.h5). The predicted class index is mapped to a disease name, and the confidence score is computed from the Softmax output. Treatment recommendations are retrieved from the MySQL knowledge base and rendered in the response HTML page.

C. Deployment & Infrastructure

The application was containerised using a HerokuProcfile for cloud deployment. Static model weights are bundled within the application directory. Cloud hosting on Heroku ensures global accessibility without requiring GPU hardware on the farmer's device. The system is also compatible with local deployment using Apache/Nginx for institutional use. HTTPS and role-based access control are implemented for security.

V. RESULTS AND DISCUSSION

The proposed hybrid CNN + AlexNet model achieved approximately 97% accuracy on the held-out test set. The table below compares the performance of all classifiers evaluated on the same dataset under identical train/test split conditions.

Table II: Classifier Accuracy Comparison

Algorithm	Test Accuracy (%)
Naïve Bayes	82.4
Decision Tree	88.7
Logistic Regression	91.2
Support Vector Machine	93.5
CNN + AlexNet (Proposed)	**~97.0**

The results confirm that deep learning with transfer learning significantly outperforms traditional machine learning classifiers for image-based disease identification. The hybrid CNN + AlexNet model benefits from rich pre-trained feature representations that generalise well to plant leaf imagery. Dropout and Batch Normalisation effectively controlled overfitting despite the limited dataset size. Real-time prediction on the deployed web portal averaged 1.2 seconds per image on the Heroku free tier, confirming suitability for practical field use.

VI. FUTURE SCOPE

- Integration with IoT soil and weather sensors for multi-modal, context-aware disease prediction.
- Drone and satellite imagery pipeline for large-scale farm monitoring without manual image capture.
- Expansion of the dataset to 50+ crop species and 100+ disease categories.
- Edge computing deployment (Raspberry Pi / mobile TFLite) for offline rural usage.
- Predictive analytics to forecast disease outbreaks based on historical data and climate patterns.
- Personalised advisory system tailored to farm size, location, season, and soil conditions.
- Integration with government e-governance portals and agri-market platforms.

VII. CONCLUSION

This paper presented an image-based crop disease detection system using a hybrid CNN architecture augmented with pre-trained AlexNet weights. The system detects diseases in potato, pepper, and tomato crops from leaf photographs with approximately 97% accuracy. The integration of a Flask web application makes the model accessible to farmers via any internet-connected device, bridging the gap between advanced deep learning research and practical agricultural needs.

Among all classifiers evaluated — Naïve Bayes, Decision Tree, Logistic Regression, SVM, and the proposed CNN + AlexNet hybrid — the proposed model achieved the highest accuracy, validating the effectiveness of transfer learning for crop disease classification on limited field datasets. The system provides actionable treatment recommendations and stores diagnosis history, offering a scalable, cost-effective, and farmer-friendly solution for precision agriculture in India and beyond.

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