International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 14, Issue 2, 2026

Crop Disease Detection Using Machine Learning

Mr J S D Venkata Rao[1],Dokuparthi Pujitha[2],Mohammad Karimunnisa[3],Konduru Vinay Kumar[4],Kasthala Joys Mary[5]
[1]Assistant Professor, Computer Science Engineering Department, Potti Sriramulu Chalavadi Mallikarjuna Rao College Of Engineering, One Town ,Vijayawada,India.
[2,3,4,5] Students; Computer Science Engineering Department,Potti Sriramulu Chalavadi Mallikarjuna Rao College Of Engineering, One Town ,Vijayawada, India
Mail Id: jsdvenkat@pscmr.ac.in [1], dokuparthipujitha19@gmail.com [2], mdkarimulla1973@gmail.com[3] , Konduruvinaykumar143@gmail.com [4], kasthalajoys@gmail.com [5]

Abstract: *Crop diseases are one of the major causes of reduced agricultural productivity and economic loss to farmers. Early identification of plant diseases is essential to improve crop yield and ensure sustainable farming practices. Traditional disease detection methods mainly depend on manual observation by farmers or experts, which are time-consuming and often inaccurate. To overcome these limitations, this paper proposes an AI-powered multilingual crop disease detection and smart advisory system using Convolutional Neural Networks (CNN).*

The proposed system analyzes leaf images of various crops such as rice, tomato, potato, and cotton to identify healthy and diseased conditions with high accuracy. A web-based interface is developed using Flask/Streamlit to allow users to upload crop leaf images and receive instant predictions. In addition to disease classification, the system provides multilingual recommendations including symptoms, treatments, fertilizers, pesticides, and preventive measures in English, Telugu, and Hindi for better accessibility among farmers.

Experimental evaluation shows that the CNN model achieves efficient performance in disease recognition while maintaining user-friendly operation. The proposed system supports precision agriculture by combining artificial intelligence with practical farming guidance, thereby reducing crop losses and improving productivity.

Index terms - *Crop Disease Detection, Convolutional Neural Network (CNN), Machine Learning, Deep Learning, Smart Agriculture, Leaf Image Classification, Multilingual Advisory System, Precision Farming, Plant Disease Identification, Web-Based Application.*

1. INTRODUCTION

Agriculture is the backbone of many developing countries and plays a vital role in food production, employment generation, and economic growth. In countries like India, a major portion of the population depends on farming for their livelihood. However, crop productivity is significantly affected by various plant diseases caused by fungi, bacteria, viruses, and pests. These diseases reduce both the quality and quantity of agricultural produce, leading to severe financial losses for farmers. Therefore, early and accurate detection of crop diseases is essential for effective crop management and higher yield.

Traditional crop disease identification methods mainly rely on manual observation by farmers or consultation with agricultural experts. These approaches are time-consuming, costly, and often inaccurate, especially in rural areas where expert support may not be easily available. Moreover, many diseases show similar visual symptoms, making correct diagnosis difficult. With the rapid growth of Artificial Intelligence and Deep Learning, automated image-based disease detection systems have become a practical solution for modern agriculture.

This paper presents an AI-powered multilingual crop disease detection and smart advisory system using Convolutional Neural Networks (CNN). The proposed system analyzes leaf images of crops such as rice, tomato, potato, and cotton to identify healthy and diseased conditions. A web-based platform is developed to allow users to upload leaf images and receive instant predictions. In addition, the system provides multilingual recommendations including treatment methods, fertilizer usage, pesticide suggestions, and preventive measures in English, Telugu, and Hindi, making the solution more accessible to farmers.

The integration of machine learning with multilingual advisory support makes the proposed system a valuable contribution to precision agriculture. It helps farmers take timely decisions, minimize crop losses, and improve overall productivity through smart and user-friendly technology.

2. LITERATURE SURVEY

a) Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification

In the area of image classification, the most recent generation of convolutional neural networks (CNNs) has produced remarkable outcomes. This research focuses on a novel method of using deep convolutional networks to construct a plant disease identification model based on leaf image categorization. A rapid and simple system installation in reality is made possible by the innovative training approach and methodology. In addition to being able to differentiate plant leaves from their surroundings, the created model can identify 13 distinct kinds of plant illnesses from healthy leaves. To the best of our knowledge, this approach to identifying plant diseases has never been suggested before. Throughout the study, every crucial step needed to put this disease identification model into practice is thoroughly explained, beginning with the collection of photos to build a database that is evaluated by agricultural specialists. The deep CNN training was carried out using Caffe, a deep learning framework created by Berkley Vision and Learning Center. The proposed model's experimental findings showed an average accuracy of 96.3% for independent class tests, ranging from 91% to 98%.

b) Using Deep Learning for Image-Based Plant Disease Detection Crop diseases pose a serious danger to food security, but in many parts of the world, the infrastructure needed to quickly identify them is still lacking. Smartphone-assisted illness detection has been made possible by recent advancements in computer vision made possible by deep learning and growing smartphone adoption worldwide. We train a deep convolutional neural network to recognize 14 crop species and 26 illnesses (or lack thereof) using a public dataset of 54,306 photos of healthy and sick plant leaves taken under controlled settings. The viability of this strategy is demonstrated by the trained model's 99.35% accuracy on a held-out test set. Overall, there is a clear route for smartphone-assisted crop disease detection on a gigantic global scale thanks to the method of training deep learning models on ever larger and publicly accessible picture datasets.

c) Deep learning models for plant disease detection and diagnosis

In this work, convolutional neural network models were created utilizing deep learning techniques to detect and diagnose plant diseases using straightforward leaf photos of both healthy and sick plants. An open library of 87,848 photos, comprising 25 different plants in a set of 58 different classes of [plant, illness] pairs, including healthy plants, was used to train the models. After training a number of model architectures, the top one achieved a 99.53% success rate in detecting the correct [plant, illness] pair (or healthy plant). The model's very high success rate makes it an extremely helpful early warning or advise tool, and it's a strategy that might be further developed to enable an integrated plant disease diagnosis system to function under actual cultivation settings.

d) Classification of cotton leaf spot diseases using image processing edge detection techniques

The advanced computer technology presented in this proposed work is designed to assist farmers in making better decisions about many elements of crop development. Increased output greatly depends on accurate crop disease assessment and diagnosis in the field. The most significant fungal disease affecting cotton is called foliar, and it affects all growing regions of India. In this study, we classify the illnesses using the HPCCDD Proposed Algorithm and express new technical solutions employing mobile photos of cotton leaf spot symptoms. In order to accomplish intelligent farming, such as early disease detection in the groves and targeted fungicide administration, the classifier is being trained. This suggested work is based on Image RGB feature ranging approaches, where the collected pictures are first processed for improvement in order to detect the illnesses (using Ranging values). The target areas (disease spots) are then obtained by segmenting color images. The edges are then identified using homogenization techniques like Sobel and Canny filters; these extracted edge characteristics are then employed in classification to identify the illness areas. Lastly, farmers receive pest recommendations to protect their crops and minimize yield loss.

e) Digital image processing techniques for detecting, quantifying and classifying plant diseases

An overview of methodologies for identifying, measuring, and categorizing plant diseases using digital photographs in the visible spectrum is provided in this work. Only techniques that investigate obvious signs in leaves and stems were taken into consideration, despite the fact that disease symptoms might appear in any section of the plant. This was done for two major reasons: first, to keep the paper's length to a minimum, and second, since procedures pertaining to roots, seeds, and fruits have certain features that call for a particular study. Based on their purpose, the chosen ideas are categorized into three classes: categorization, severity quantification, and detection. Each of those classifications is further classified based on the algorithm's primary technical solution. Researchers working on both vegetable pathology and pattern recognition might find this publication helpful since it offers a thorough and understandable summary of this significant area of study.

3. METHODOLOGY

i) Proposed Work:

The proposed work focuses on developing an AI-powered multilingual crop disease detection and smart advisory system using Convolutional Neural Networks (CNN). The system is designed to automatically identify diseases from uploaded crop leaf images and provide instant predictions with high accuracy. It supports multiple crops such as rice, tomato, potato, and cotton by using trained deep learning models for disease classification.

The workflow begins with image acquisition, where the user uploads a crop leaf image through a web-based interface. The uploaded image is preprocessed using resizing, normalization, and enhancement techniques before being passed to the CNN model. The trained model extracts important visual features such as spots, discoloration, texture changes, and leaf damage patterns to classify the crop as healthy or diseased.

After prediction, the system generates a smart advisory report containing disease name, symptoms, recommended fertilizers, pesticide suggestions, treatment methods, and preventive measures. To improve usability among farmers, the advisory content is provided in multiple languages such as English, Telugu, and Hindi. This feature ensures easy understanding and practical usage in rural agricultural environments.

The proposed system combines disease detection with real-time decision support, making it more effective than traditional classification-only systems. It reduces dependency on agricultural experts, saves time, minimizes crop loss, and promotes precision farming through intelligent and accessible technology.

ii) System Architecture:

The system architecture of the proposed crop disease detection model follows a layered client-server framework integrated with deep learning modules. The first layer is the user interface, developed using Flask/Streamlit, where farmers or users upload crop leaf images through a web browser. This interface is designed to be simple, responsive, and user-friendly for easy access in real-time agricultural environments. The second layer is the preprocessing and application server layer. Once the image is uploaded, the server performs image preprocessing operations such as resizing, normalization, and quality enhancement. The processed image is then forwarded to the trained CNN-based classification engine. The deep learning model extracts visual features such as color variations, spots, texture changes, and lesions to identify the crop type and corresponding disease class accurately.

The final layer is the output and advisory layer. After prediction, the system displays the disease name, confidence result, and multilingual recommendations including symptoms, fertilizers, pesticides, treatments, and preventive measures in English, Telugu, and Hindi. This complete architecture enables automated disease diagnosis along with farmer-centric decision support, making the system efficient, scalable, and suitable for smart agriculture applications.

iii) Modules:

1. User Interface Module

This module provides an interactive web-based platform where users can upload crop leaf images and view prediction results. It is developed using Flask/Streamlit with a simple design for farmer-friendly usage.

2. Image Acquisition Module

This module accepts leaf images in formats such as JPG, PNG, and JPEG from mobile phones or computers. It ensures proper image selection and smooth upload into the system for further processing.

3. Image Preprocessing Module

The uploaded image is resized, normalized, and enhanced to improve quality before classification. This step removes noise and converts the image into a suitable format for the CNN model.

4. Crop Classification Module

This module first identifies the crop category such as Rice, Tomato, Potato, or Cotton using a trained crop classifier model. It helps route the image to the appropriate disease prediction model.

5. Disease Detection Module

The CNN-based disease detection model analyzes leaf patterns such as spots, discoloration, and texture changes to predict whether the crop is healthy or affected by a specific disease. It provides accurate real-time classification results.

6. Smart Advisory Module

After prediction, this module generates detailed recommendations including disease symptoms, treatment methods, fertilizers, pesticides, and prevention steps to support farmers in decision-making.

7. Multilingual Support Module

This module converts the advisory output into multiple languages such as English, Telugu, and Hindi. It improves accessibility and understanding for farmers from different regions.

8. Result Display Module

This module shows the final disease prediction, confidence score, and advisory information clearly on the web interface. It ensures quick interpretation and easy usability.

iv) Algorithms:

1. Convolutional Neural Network (CNN)

Convolutional Neural Network is the main deep learning algorithm used in the proposed system for crop disease detection. It processes leaf images through multiple convolution and hidden layers to automatically learn important visual features such as spots, lesions, color changes, and texture variations. CNN provides high accuracy in image classification tasks and is highly suitable for identifying plant diseases from leaf images in real time.

2. Image Preprocessing Algorithm

The image preprocessing algorithm is used before sending images to the CNN model. It performs operations such as resizing the uploaded image into a fixed dimension, normalizing pixel values, and enhancing image clarity. This step removes unwanted noise, improves image consistency, and ensures that all images are in a standard format for accurate disease prediction.

3. Softmax Classification Algorithm

Softmax is used in the output layer of the CNN model for multiclass disease prediction. It converts the final output values into probability scores for each disease category. The disease class with the highest probability score is selected as the final result. This algorithm is very useful when the system has to classify multiple diseases among several crop categories.

4. Max Pooling Algorithm

Max pooling is used between convolution layers to reduce the size of feature maps while preserving the most important information. It selects the maximum value from each region of the image and removes less useful details. This reduces computation time, controls overfitting, and improves the efficiency of the CNN model during training and prediction.

5. Rectified Linear Unit (ReLU) Activation Algorithm

ReLU is an activation function used inside CNN hidden layers to introduce non-linearity into the model. It converts negative values into zero and keeps positive values unchanged. This helps the network learn complex disease patterns faster, avoids vanishing gradient problems, and improves training speed and performance.

6. Multiclass Prediction Algorithm

The multiclass prediction algorithm is used to classify uploaded leaf images into multiple crop and disease categories such as rice blast, tomato leaf mold, potato blight, and cotton leaf curl disease. It compares extracted image features with trained classes and predicts the most matching disease label. This makes the system flexible and useful for detecting several diseases using a single platform.

4. EXPERIMENTAL RESULTS

The proposed AI-powered crop disease detection system was tested using a labeled dataset containing multiple crop leaf images from rice, tomato, potato, and cotton categories. The dataset included both healthy and diseased leaf samples under different classes. During experimentation, the images were preprocessed using resizing and normalization techniques before being fed into the Convolutional Neural Network (CNN) model for training and testing. The model demonstrated strong learning capability in identifying disease patterns such as spots, discoloration, lesions, and texture abnormalities from leaf images.

The CNN model achieved high classification accuracy with efficient prediction performance across multiple disease classes. Experimental outputs showed that the system successfully identified diseases such as Rice Blast, Brown Spot, Tomato Mosaic Virus, Potato Late Blight, and Cotton Leaf Curl Disease with reliable confidence scores. The web-based interface generated instant results after image upload, proving the real-time usability of the system.

In addition to disease prediction, the system effectively displayed multilingual advisory information including symptoms, treatment methods, fertilizers, pesticides, and prevention measures in English, Telugu, and Hindi. This feature improved accessibility for farmers and increased the practical value of the model beyond normal classification systems. The results confirm that the proposed framework is accurate, scalable, and highly useful for smart agriculture applications..

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$Pr\,e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list.

The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot Pr\,e\,cision)}{(Recall + Pr\,e\,cision)}$$

Fig 1 upload input

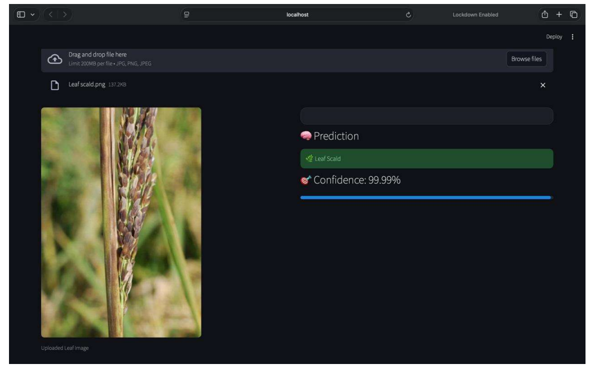

Fig2 select language
Fig 3 predicted results

5. CONCLUSION

This paper presented an AI-powered multilingual crop disease detection and smart advisory system using Convolutional Neural Networks (CNN) for improving agricultural productivity. The proposed system successfully detects diseases from crop leaf images of rice, tomato, potato, and cotton with high accuracy through automated image classification techniques. By replacing traditional manual inspection methods, the system provides faster, reliable, and real-time disease diagnosis for farmers.

The integration of multilingual recommendations such as symptoms, treatment methods, fertilizers, pesticides, and preventive measures in English, Telugu, and Hindi makes the system highly practical and farmer-friendly. This feature helps users from different regions easily understand disease management solutions and take timely action to reduce crop losses.

Experimental analysis confirmed that the CNN model performs efficiently in identifying multiple crop diseases while maintaining user-friendly operation through a web-based platform. Therefore, the proposed system serves as an effective smart agriculture solution that combines artificial intelligence with real-world farming support, contributing to sustainable farming and increased crop yield.

6. FUTURE SCOPE

The proposed crop disease detection system can be further enhanced by expanding the dataset to include more crop varieties, regional plant species, and a larger number of disease classes. Training the model with real-time field images captured under different weather, lighting, and background conditions can improve robustness and prediction accuracy in practical agricultural environments. Future versions

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 14, Issue 2, 2026

may also integrate advanced deep learning models such as Transfer Learning, Vision Transformers, and hybrid architectures for better performance.

The system can also be converted into a mobile application so farmers can capture leaf images directly using smartphones and receive instant results in the field. Integration with Internet of Things sensors, drones, and smart cameras can enable continuous crop monitoring and early disease alerts. Cloud deployment may support large-scale usage across villages, cooperatives, and agricultural agencies.

Another important future direction is the addition of personalized advisory services such as soil-based fertilizer recommendations, weather-aware spraying schedules, pest forecasting, and market linkage suggestions. More regional language support and voice assistance can improve accessibility for farmers with limited literacy. These enhancements can transform the proposed model into a complete intelligent farming assistant for precision agriculture and sustainable crop management.

REFERENCES

[1] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 1–11, 2016.

[2] A. Mohanty, D. Hughes, and M. Salathe, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, pp. 1–10, 2016.

[3] K. P. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.

[4] P. Revathi and M. Hemalatha, "Classification of Cotton Leaf Spot Diseases Using Image Processing Edge Detection Techniques," *International Journal of Engineering Research & Technology*, vol. 1, no. 10, 2012.

[5] J. G. A. Barbedo, "Digital Image Processing Techniques for Detecting, Quantifying and Classifying Plant Diseases," *SpringerPlus*, vol. 2, no. 660, 2013.

[6] TensorFlow Documentation, "TensorFlow: An End-to-End Open Source Machine Learning Platform," Available: https://www.tensorflow.org/

[7] OpenCV Documentation, "Open Source Computer Vision Library," Available: https://opencv.org/

[8] Flask Documentation, "Flask Web Framework," Available: https://flask.palletsprojects.com/