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Crop Disease Detection Using Convolutional Neural Network for Smart Agriculture

K Ramalakshmi[1], Kumar N[2], Gowtham H[3], Arun Teja S[4], Pavan M[5]

[1]AU - Center of Excellence in Computer Vision, Alliance University, Bangalore – 562106
[2,3,4,5]Dept of CSE, Alliance University

Abstract
Crop diseases are affecting the productivity of the agricultural industry with severe economic and food security implications worldwide. Detection of crop diseases at an early stage has become crucial to control the disease and maintain sustainable agriculture practices. Traditional techniques of disease detection include manual inspection and visual assessment, which are not only time-consuming but also result in inaccurate outcomes. Recent developments in deep learning techniques, such as Convolutional Neural Networks (CNN), have shown promising results in the classification of images and detection of diseases. CNN has been found to efficiently identify and classify diseases by recognizing discriminative features of the leaves. In this research, we propose a deep learning model for the detection of crop diseases, particularly for tomatoes, potatoes, corn, apples, strawberries, and cherries. Experiment results and outcomes show that the CNN model has highly accurate results and is an efficient tool for the automated detection of diseases in crops.

INTRODUCTION
The agricultural sector is the backbone of the world's economy. This is because agriculture is the main source of food for human consumption. Besides, agriculture is the main source of raw materials for different sectors of the economy. Unfortunately, the agricultural sector is constantly under threats of different ecological factors, pests, and diseases. According to the Food and Agriculture Organization of the United Nations, plant diseases have been costing the global economy about $220 billion each year. This is due to the loss of about 20-40% of total crops produced globally.

In developing countries, the first method for the identification of diseases is by direct observation through visual inspection carried out by the farmers. This is a highly subjective process which relies on the experience of the individual. At times, the presentation of different diseases may be similar. This may result in a mismatch. Not only does the plant not receive the treatment it needs for cure, but the environment is also harmed as a result.

Computer Vision (CV) and Deep Learning (DL) provide a new paradigm that may solve the issue. The paradigm of Convolutional Neural Networks (CNNs) has revolutionized the field of image recognition by removing the necessity of any manual feature development. Unlike other machine learning paradigms such as SVMs or K-Nearest-Neighbors (KNN), CNNs can be trained by backpropagation from raw pixel information.

A. Problem Statement
The present practice of relying upon human expertise to detect crop diseases cannot be sustained due to the lack of agricultural experts in rural areas and the high error rates of manual observations. An

urgent need exists to develop a highly accurate and automated crop disease detection system, which can operate under various environmental conditions and detect various classes of crop diseases.

B. Objectives of the Study

The main goals of the present research project are:

1. To propose a deep architecture for a Convolutional Neural Network that is optimized for leaf-based disease classification.
2. To design an effective image preprocessing pipeline for different lighting conditions, backgrounds, and noise.
3. To perform multi-crop analysis on different fruits: Tomato, Potato, Corn, Apple, Strawberry, Cherry.
4. To assess the performance of the model by utilizing appropriate metrics such as accuracy, precision, and loss curves.
5. To offer a scalable framework that may be used with mobile or IoT-based agricultural monitoring tools.

C. Contribution of Research

This research contributes to the field of smart agriculture by providing:

A comprehensive comparison of 50 existing methodologies, highlighting current technical gaps.

- A detailed analysis of the limitations in the real world, such as background noise.
- A framework for accessibility-driven design so that these technologies are accessible for non-technical farmers.

LITERATURE REVIEW

In the last decade, there has been exponential growth in the application of Artificial Intelligence in agriculture. Initially, research was conducted on traditional image processing techniques such as thresholding and edge detection. However, it was found that these techniques were not effective in dealing with the texture and orientation of natural fields.

Ngugi et al. (2024) emphasized that though machine learning helped in this regard, the advent of Deep Learning with CNNs has been a paradigm shift in accuracy. Jafar et al. (2024) focused on Solanaceae crops like tomato and potato and found that CNNs were able to identify between early blight and late blight with greater than 90% precision, which often confuses the human eye.

Ashurov et al. (2025) recently introduced the use of depthwise separable convolutions, which reduce the parameters of the network, making the models faster for mobile use without compromising much on the accuracy of the models. In another study, Sujatha et al. (2025) reported a high accuracy of 95% using CNN and advanced augmentation techniques.

However, despite these achievements, several researchers (e.g., Shafik et al., 2024) have highlighted that "the model trained on clean datasets like PlantVillage does not perform well when it is tested

METHODOLOGY AND SYSTEM DESIGN

The proposed system follows a modular architecture designed to handle the full pipeline from raw image capture to disease diagnosis.

A. Data Acquisition and Preparation

The efficacy of any CNN-based model is intrinsically related to the diversity of the training data provided. A multi-species dataset has been curated, including both healthy and diseased samples, for the purpose of this study.

- Tomato: Early Blight, Late Blight, Leaf Mold,
- Potato: Early blight, Late

B. The Preprocessing Pipeline

Raw images are rarely suitable for direct input into a neural network. Our pipeline involves:
Image Resizing: All images are resized to 128x128 pixels. This size is chosen to balance structural information and computational cost.

1. Normalization: Pixel values range from 0 to 255, and we normalize them between the range [0,1].
2. Noise Reduction: Gaussian blurring is used to reduce the presence of noise, which may interfere with the edge detection layers.
3. Data Augmentation: To avoid overfitting, we also apply random rotations between 0◦ and 30◦, horizontal/vertical flips, and zooming. This is because a farmer may take a picture from any angle while in the field.

C. CNN Architecture Detail

The network is designed to learn features in a hierarchical way.

- Feature Extraction Layers: There are three blocks containing ConvolutionReLU-Pooling layers. The initial layers recognize basic shapes (edges, dots), while deeper layers recognize complex textures (lesion patterns).
- Dropout Layers: These are added after the fully connected layers at a rate of 0.5. This is done to prevent co-adaptation of the neurons.
- Classification Head: Dense layer with Softmax activation to determine the probability distribution over all the classes of diseases.

IMPLEMENTATION DETAILS

The system has been implemented with the Python ecosystem.

- Libraries: TensorFlow 2.x and Keras for model definition, OpenCV for image manipulation, and Matplotlib for visualization.
- Hardware: The training was done on a computer that has an NVIDIA RTX GPU for speeding up the convolution operations.
- Hyperparameters: In this work, we used the Adam optimizer with a learning rate of 0.001 and a batch size of 32.

A. Challenges in Training

One of the major issues was the problem of class imbalance. In reality, some diseases are more prevalent than others. This causes the model to become biased towards the majority class. We solved this by using class weights in the loss function to penalize errors for rare diseases.

DEPLOYMENT AND ACCESSIBILITY

For a research project to have a real-world impact, it must be accessible to the end-user: the farmer.

A. Farmer-Centric Design

We suggest the concept of "Farmer-Centric" in which the technical intricacy of the CNN is abstracted by the simple interface of the mobile device. Key features:

- Ofline Capability: A lightweight version of the model, using TensorFlow Lite, can be run locally on the phone without the need for a stable internet connection in the remote fields.

- Multi-lingual Support: The results of the diagnosis are given in the local language of the region.
- Actionable Advice: Instead of just "Tomato Late Blight," the system would offer "Apply [Fungicide Name] and prune infected leaves."

B. Explainable AI (XAI)

In order to establish trust, we employ Grad-CAM (Gradient- weight
Class Activation Mapping). This shows what the CNN "looked" at to come up with its prediction. If the CNN is highlighting the real lesion on the leaf, the farmer can trust the result.

Performance Analysis

A. Training and Validation Metrics

The model was trained for 50 epochs. The accuracy increased rapidly in the first 10 epochs and leveled off after that.

- Training Accuracy: 95
- Validation Accuracy:
- Precision:
- Recall:

B. Confusion Matrix Analysis

Further analysis of the code showed that the model got confused between "Late Blight" and "Early Blight" due to the similarity of the visual patterns. However, the accuracy of the model for "Healthy" and "Diseased" was almost 99%, so the farmer would at least be alerted of something being wrong.

Comparative Analysis of Research Papers

The following tables provide a massive-scale comparison of 50 major research contributions in this field, highlighting their methodologies and limitations.

Discussion on Strategic Advancements

The future of agricultural AI lies in the transition from simple classification to intelligent reasoning. Integration with Internetof Things (IoT) sensors can provide environmental context. For example, if humidity is high and the CNN detects a suspicious spot, the system can assign a higher probability to "Late Blight" because environmental conditions favor fungal growth. Furthermore, the use of Vision Transformers (ViT) represents the next frontier, potentially offering better global feature extraction than traditional local-sliding convolutional filters.

Conclusion

This research has shown that Convolutional Neural Networks are a reliable tool for the automated detection of crop diseases, with an accuracy of over 93% in validation results. By developing a scalable preprocessing pipeline and a deep neural network architecture, we have been able to develop a system that can effectively classify diseases for six different types of crops. In addition to this, this research has also highlighted the technical gap that currently exists in literature, particularly with regards to developing a model that can perform effectively in noisy environments. Going forward, the development of this technology will depend on the integration of this model with explainable AI and mobile technologies to ensure that it reaches the farmers who need it most. This research has opened the doors to a future where agriculture can be conducted in a more intelligent and sustainable manner.

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