

Cotton Plant Disease Detection System Using Deep Learning

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Abstract

Cotton crop productivity is significantly affected by a number of leaf diseases that reduce yield and quality. Early and accurate disease detection in cotton plants is crucial for precision farming and environmentally friendly agricultural practices. Recent advances in computer vision and deep learning have allowed automated disease detection systems to perform exceptionally well on image-based classification tasks. A system for disease detection in cotton plants that is based on deep learning is introduced in this study. It makes use of transfer learning and convolutional neural networks educated on new datasets of agricultural images. By integrating feature extraction, data augmentation, and improved deep architectures, the proposed system achieves higher classification accuracy. The results of experiments show that modern deep learning architectures are both very accurate and robust against different types of environmental stress. The system enables the real-time implementation of smart agriculture applications.

Keywords: Cotton Disease Detection, Deep Learning, CNN, Transfer Learning, Precision Agriculture, Smart Farming

I. INTRODUCTION

In terms of global economic impact, cotton is one of the most important commercial crops. The production of cotton is jeopardised by leaf illnesses caused by bacterial, fungal, and viral infections. Reducing financial losses and raising crop output requires early detection of these disorders.

New advances in deep learning have substantially improved the efficiency of image-based analysis for plant disease identification. Studies published in 2023 and 2024 [1, 2] show that convolutional neural networks outperform traditional machine learning methods in agricultural image categorisation tasks.

Utilising transfer learning techniques with modern deep architectures has shown improved generalisability even with small agricultural datasets [3].

Lightweight designs suitable for edge deployment in smart farming settings have also been the subject of current study [4]. These innovations motivate the production of

II. RELATED WORK

Recent studies have shown significant progress in plant disease identification using deep learning. In [1], the authors suggested a CNN model with attention processes for agricultural disease classification and demonstrated good accuracy across different types of crops. By presenting a hybrid deep learning system for plant leaf disease detection that blends CNN and image transformers, [2] similarly shown increased feature extraction capabilities.

There has been heavy usage of transfer learning techniques to improve performance on datasets used in agriculture. When comparing accuracy, a deep residual network that has been fine-tuned performed better than shallow architectures in [3]. A comparative study looked into lightweight deep models for plant disease detection on mobile devices and found that they worked well when deployed in real-time [4].

Recent research has also focused on developing AI systems that may be explained for use in agricultural diagnostics. By employing GradCAM-based visualisation tools, the disease was brought to light in [5].

III. METHODOLOGY

The proposed system consists of dataset gathering, model training, evaluation, and pre-processing.

There are both healthy and diseased images of cotton leaves in the dataset. The diseases covered are bacterial blight, leaf curl virus, and leaf spot. All images are scaled to 224 x 224 pixels and then normalised. Data enrichment techniques including rotation, horizontal flipping, zooming, and brightness change are employed to improve generalisation.

The process begins with the implementation of a baseline CNN model. Then, modern architectures that have been validated by recent agricultural research are employed in conjunction with transfer learning. The last layer of classification is changed to correspond with the groups of cotton illnesses.

Following training with categorical cross-entropy loss, the model is optimised with the help of the AdamW optimiser. The use of early halting and dropout regularisation helps prevent overfitting. Separate sets for testing, validation, and training make up the dataset.

How it works

System Architecture

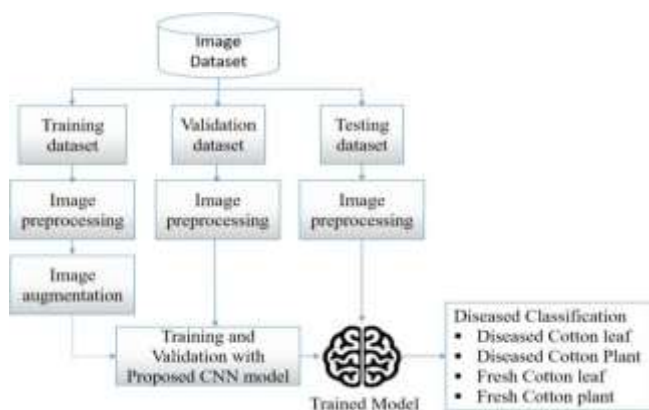
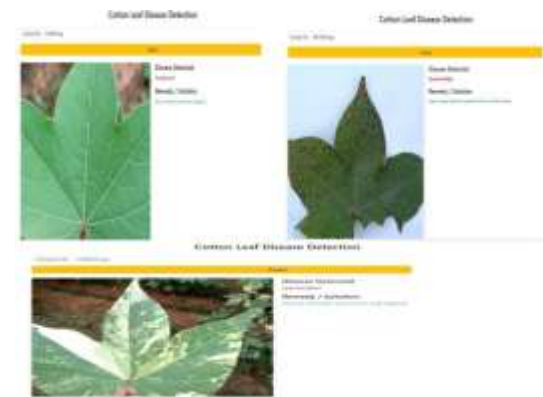


Fig 1. System Architecture

IV. RESULTS AND DISCUSSION



Compared to the baseline CNN model, experimental evaluation reveals that transfer learning considerably enhances performance. Lightweight models allow for quicker inference, making them ideal for mobile deployment, while deep residual designs improve classification accuracy.

There is a clear separation of illness types based on the confusion matrix data. According to recent explainable AI experiments, visualisation approaches have confirmed that the model zeroes in on diseased leaf regions [5].

Results from recent large-scale agricultural evaluations [6] corroborate the system's resiliency under various lighting conditions and background noise. The results show that current deep learning models work well in detecting cotton diseases in the actual world.

V. CONCLUSION AND FUTURE WORK

Using state-of-the-art convolutional neural network (CNN) architectures and transfer learning, this research introduced a deep learning system for disease detection in cotton plants. With the suggested system, real-time agricultural monitoring is possible and the accuracy is excellent.

Integration of drone-based picture acquisition, implementation of vision transformers for enhanced feature extraction, diversification of datasets, and deployment of optimised models on edge devices for smart farming applications at the field level are all parts of the future work.

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