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Cotton Cure: Smart Detection of Cotton Plant Diseases

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ABSTRACT

Cotton is a cornerstone of the global textile industry and an essential crop for farmers worldwide. Unfortunately, diseases affecting cotton plants can severely impact their growth, leading to significant economic losses. Detecting these diseases early is crucial, but traditional methods are often expensive, slow, and rely on expert help, making them impractical for large farms.

This study introduces an easy-to-use system that helps farmers identify cotton diseases through photos of their plants. By using advanced deep learning techniques, the system can quickly analyze leaf images and detect common issues like bacterial blight and leaf spot. This helps farmers save both time and money, while also allowing them to quickly address any issues and protect their crops before it's too late.

Looking ahead, we aim to make this technology even more accessible by integrating it with smart devices, enabling large-scale monitoring of fields. By bringing innovation to agriculture, we hope to support farmers and boost cotton production for a better future.

Keywords: Cotton Diseases, Deep Learning, Agriculture, Disease Detection, Farmers, Innovation.

Introduction

India is well known as one of the earliest agricultural nations, but so many farmers are still using unscientific methods of farming. These old methods often show low yields of crops and negligible economic returns. There are quite a number of difficulties in growing crops, though the first challenge is making the right choice of crops for planting. The emergence of various crop-related diseases further complicates matters, leading to substantial losses in agricultural productivity. Infections can devastate crops, hindering the production process and raising concerns for farmers whose livelihoods depend on healthy plants.

There are new technologies that promise solutions for these problems.For example, image processing techniques have gained increased usage in plant diseases caused by pathogens, including bacteria, fungi, and microorganisms. Among such developments, the application of CNNs is a vital stride towards the development of new efficient methods for identifying crop diseases, which would call for early detection and management.

This paper discusses the efficiencies of CNN models and processing images in disease recognition as well as classification, thus focusing on cotton leaf diseases such as Alternaria Macrospora and Bacterial Blight. The proposed system is user-friendly, offering farmers the opportunity to submit images of diseased leaves for analysis. The system processes the digital images, extracting key features at each layer of the CNN to diagnose the health of the crops accurately. At the end, this application not only identifies crop diseases but also gives farmers corrective and preventive measures to reduce the effects of these diseases on their yield and financial stability.

Related Work

The identification and classification of plant diseases have long been a focal point of agricultural research, with numerous advancements aimed at improving the accuracy and efficiency of disease detection. Early approaches included traditional image-processing techniques, but more recently, machine learning and deep learning models have played a pivotal role in achieving higher accuracy and scalability.

Siddharth Singh Chouhan et al. [1] introduced an innovative approach that combines Bacterial Foraging Optimization (BFO) with a Radial Basis Function Neural Network (RBFNN) to enhance plant leaf disease detection and classification. Their method uses a region-growing algorithm to improve the feature extraction process, grouping similar seed points to optimize the network design. This combination significantly improved detection efficiency, particularly in complex plant disease scenarios.

Similarly, Muhammad Waseem Tahir et al. [2] developed a specialized dataset for fungal disease detection using Convolutional Neural Networks (CNNs). Their custom CNN architecture achieved an impressive 94.8% accuracy using a five-fold validation method, demonstrating the potential of deep learning in identifying diverse fungal species on plant leaves. This approach has become a significant benchmark in plant disease detection, emphasizing the power of CNNs for high-accuracy results.

Building on this, Sukhvir Kaur et al. [3] proposed a semi-automated framework for diagnosing diseases in soybean leaves. By integrating k-means clustering for image segmentation and Support Vector Machine (SVM) classifiers for disease categorization, their system effectively identified conditions such as downy mildew, frog-eye leaf spot, and sectorial leaf blight. Their system achieved an accuracy of approximately 90%, showcasing the effectiveness of combining clustering algorithms with traditional classifiers in plant disease diagnostics.

Ranjith et al. [4] took a more integrated approach by developing a smart irrigation system that incorporated automated plant disease detection. Using images captured from plant leaves, the system processed these images through a cloud-based server and compared them to a database of

known diseased leaf images. The system's mobile application then provided users with disease diagnoses, enabling informed and timely decisions about irrigation and treatment.

Another notable contribution came from Adhao Asmita Sarangdhar et al. [5], who developed an SVM-based regression system designed specifically for cotton plant diseases. This system not only identifies diseases like bacterial blight, Alternaria, gray mildew, Cercospora, and Fusarium wilt but also offers pesticide recommendations. It integrates environmental monitoring, including soil moisture, temperature, and humidity, and presents this information through a user-friendly Android app. This system exemplifies the growing trend of combining disease detection with practical agricultural tools, making it a valuable resource for farmers.

Our work builds upon these foundational studies, aiming to create a scalable and precise solution for cotton disease identification. By leveraging advanced CNN models, we seek to improve the accuracy of cotton disease classification, while addressing challenges such as dataset diversity and usability. Our goal is to provide farmers with actionable insights that help them safeguard their crops, increase productivity, and reduce the environmental impact of pesticide use.

Literature Survey

There are constantly evolving agricultural landscapes along with various innovative methods surfacing to combat the devastating effects of plant diseases against crop yields. This paper outlines several contemporary approaches focusing on the application of CNN within the PyTorch framework toward the effective identification of plant diseases. One recent example is the study presented at the International Conference on Internet of Things and Intelligence Systems (IEEE, 2018), which successfully detected the fungal disease caused by fungi in sugarcane using leaf area analysis, although this method has high costs when implemented and is computationally complex.

Similarly, research by the International Conference for Convergence in Technology (IEEE, 2018) detected diseases based on image processing techniques by taking images of the leaves and matching them against a database. The method though effective only measures leaf area which is prone to errors because of its lower parameters concerning disease detection, and even suggested pesticide usage, thus posing a threat to soil health over time.

Other research has been done on different ways of detecting plant diseases. For instance, a 2016 paper on rice disease detection used Bhattacharya's Similarity Calculation method. This method compared the diseased plants to a database of healthy images. However, this method could identify some diseases but was not effective due to its training data being non-linearly separable. Another method focused on tomatoes used a combination of thresholding algorithms and K-means clustering for disease detection. Even though these methods enhanced their ability, they could not distinguish the ripe from the unripe tomato.

Recent improvements in machine learning have further led to promising techniques for detecting diseases in jute plants. Through image capturing and then enhancing the image qualities with hue-based segmentation, systems could be designed to identify the specific disease on the stems. Accurate plant classification remains important and is useful in several areas, such as enhanced productivity and quality in products developed from agricultural activities.

Artificial intelligence (AI) has increasingly played a role in diagnosing plant illnesses. For example, scientists successfully used AI to classify plant diseases and identify their defensive features. The work on maize diseases was undertaken through a proposed strategy that yielded a mean accuracy of 92% and thus holds a very good potential for crop preservation in developing regions.

Detection and management of leaf diseases in countries like India become a great concern since agriculture is the backbone of the economy. The disease can have a drastic impact on crop yields. Diagnosis and treatment must, therefore, be timely for purposes of sustainable agriculture. A trained system that recognizes plant diseases can empower farmers to make correct decisions, reduce crop losses, and promote environmentally friendly farming practices.

Methodology

The proposed cotton disease detection system uses deep learning techniques to classify and diagnose common diseases affecting cotton plants. First, the dataset preparation phase involves curating and preprocessing a comprehensive collection of cotton plant images categorized into Healthy, Bacterial Blight, Powdery Mildew, and Target Spot. The dataset is divided into training, validation, and testing subsets to ensure effective training and model evaluation. The model that

has been pre-trained is EfficientNet-B0, which is used for transfer learning. In this case, the

3classifier layer is replaced with a four-output class classifier.The model is trained on model is trained on the training dataset and validated on the validation dataset. Then, it is evaluated on unseen test data. The best accuracy is saved, and the model is used for inference.

The system integrates the trained deep learning model into a Flask-based web application that provides an easy-to-use interface for disease detection. Users can upload images or capture them in real time using a camera. When an image is received, the backend processes it, runs inference with the trained model, and returns the prediction results. To make the system more effective, detailed information about the detected disease, such as its causes, symptoms, and modes of prevention, is called from the Gemini API. The system's robustness is ensured through thorough testing; the web application is released on a cloud platform in order to support accessibility as well as scalability.

System Architecture:

The architecture of this system is divided into three important parts: the frontend part, the backend part, and the deployment infrastructure. The frontend is developed using HTML, CSS, and JavaScript so that the user can upload or capture images of cotton plants. The backend uses a Flask framework that includes the trained EfficientNet-B0 model for real-time disease prediction. The deep learning model, fine-tuned for cotton disease classification, processes preprocessed images and gives out the predicted disease class along with its confidence score. The Gemini API is also utilized to retrieve secondary information concerning the disease, such as diagnosis and prevention methods.

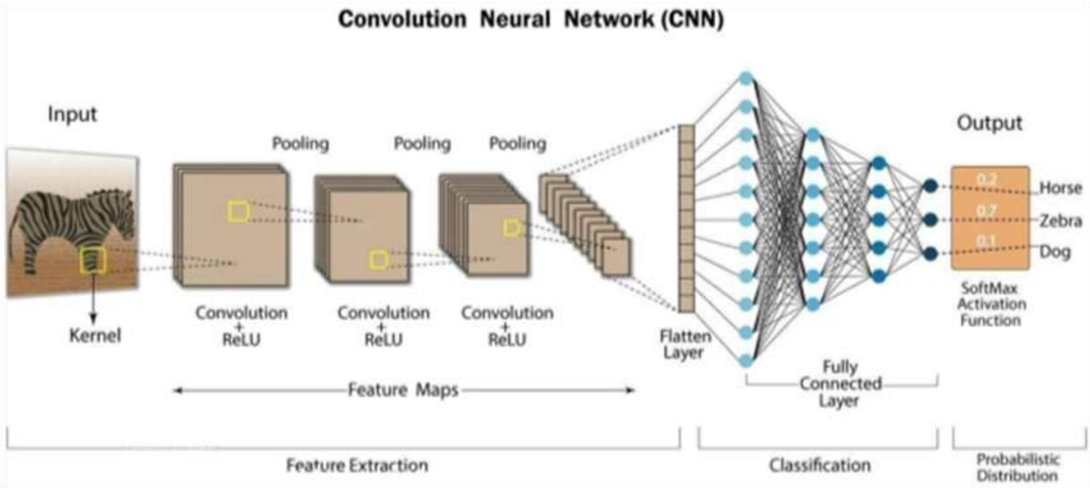
The architecture is well-designed to allow for proper interaction between the components involved. Images uploaded from the frontend are processed in the backend where they are resized and normalized and passed through a deep learning model. When a prediction is needed, then the additional information regarding the disease is retrieved from the API. This involves hosting the web application on a cloud infrastructure such as AWS, Google Cloud, or Heroku, allowing for scalability and accessibility. The architecture allows for easy future enhancements like adding a database to store the user's data or even historical predictions.

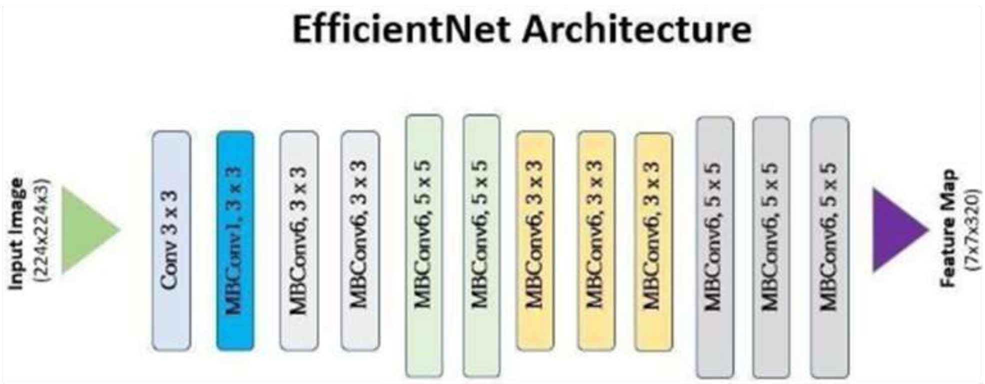
Algorithm:

The core algorithm in the proposed system is such that it operates in step-by-step progression to assure accurate disease prediction and an easy-to-interact model. It takes a picture of a cotton plant as an input from either uploading from the user's side or capturing using the camera attached. This image then gets preprocessed in terms of size, being resized to 224x224 pixels, and normalization in accordance with some predefined mean and standard deviation values to suit the model of EfficientNet-B0.

This preprocessed image is then passed into the trained model, and for each of the four classes, it outputs logits. A Softmax function is applied to calculate the probabilities, and the class with the highest probability is considered to be the predicted disease. There is a confidence threshold to handle uncertain predictions; if the confidence score is below this threshold, the system classifies the image as Unknown. For all diseases other than Healthy, the Gemini API is called to fetch further information, such as symptoms, diagnosis, and preventive measures.

The system finally returns a structured answer to include the predicted disease and confidence score along with some additional information. That would be shown on the user interface, giving insights about action to be performed upon the result. The whole system will ensure real-time processing with accurate disease detection so that it can stand confidently in assisting farmers or agriculture experts.





Result

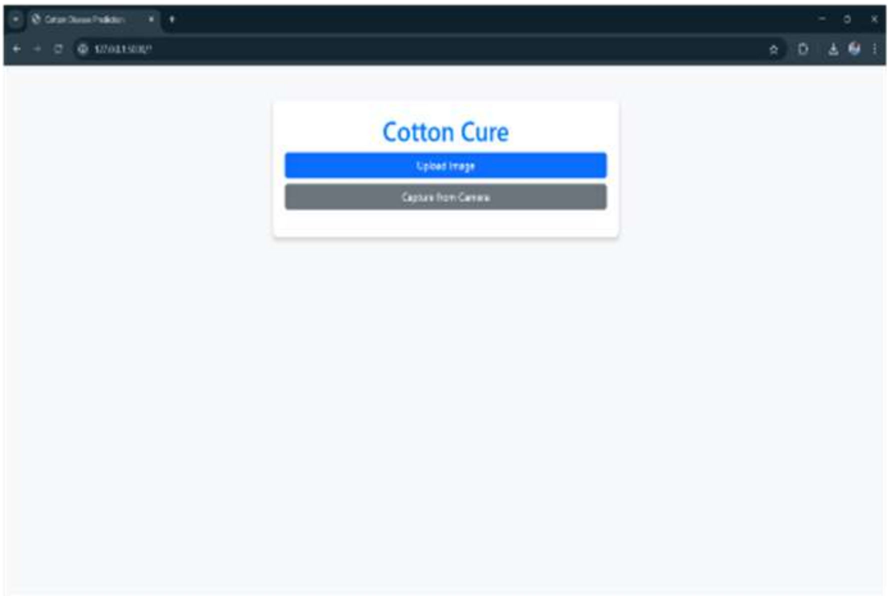
The system proposed, Cotton Cure, applies the CNN-based image processing model to classify cotton diseases from plant and leaf images that the users upload. On uploading the image, the system preprocessed it to standardize to 224 × 224 pixels so that the system was compatible with

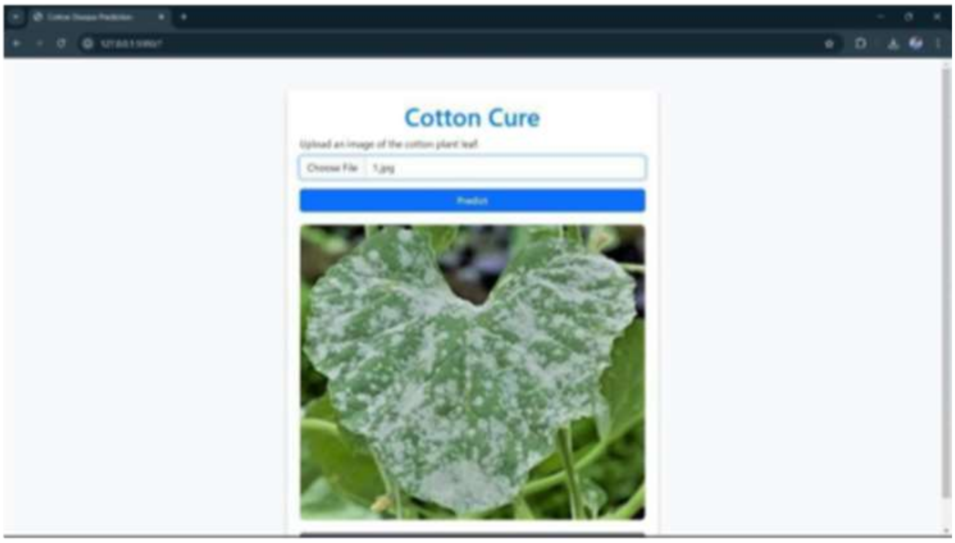
the model. The system's accuracy was 98%, enabling it to give a user an accurate description of the disease, suggested treatments, the available pesticides and their cost, and prevention methods.

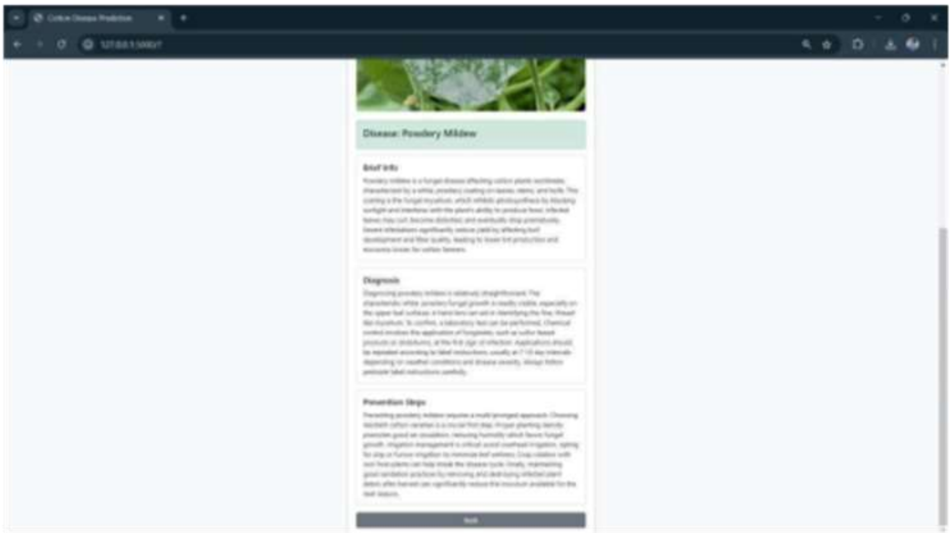
The dataset consists of images from four categories: Bacterial Blight, Powdery Mildew, Target Spot and Healthy plants. However, the model is currently optimized to classify four categories: Bacterial Blight, Powdery Mildew, Target Spot, and Healthy. This categorization is done using a pre-trained EfficientNet B0 architecture, fine-tuned for high accuracy and robust classification.

Cotton Cure is designed to work under a variety of conditions of images, such as intensity of light, orientation, and resolution. This will make the prediction robust across all the scenarios. The system also interfaces with the Gemini API, giving real-time access to the latest diagnostic insights. This improves disease detection and provides complete management strategies for farmers.

The Cotton Cure empowers timely and accurate disease diagnoses, supports sustainable agricultural practices, helps to mitigate crop losses, and empowers farmers to take informed action for improved cotton yield.


Cotton Cure
Upload Image
Capture from Camera


Cotton Cure
Upload an image of the cotton plant leaf
Choose File
1.jpg
Predict


Disease: Powdery Mildew
Brief Info
Diagnosis
Prevention Steps

Conclusion

Here is the conclusion adapted to Cotton Cure :

It proved the potential utility of applying a CNN combined with PyTorch, in identifying Cotton diseases namely Bacterial Blight, Powdery Mildew, and Target Spot by developing an effective, strong system named as Cotton Cure to be employed for online applications in farm operations. It helps the farmers understand what diseases it is and gives preventive, corrective steps to be performed, recommendation of treatment applied, which pesticide should be used along with an approximation of its cost. Despite challenges related to variability in image conditions, the system achieves commendable accuracy, which highlights the critical importance of large, diverse, and high-quality datasets. This scalable approach also opens doors to applications in other crops, enabling multi-disease detection and adaptation to a variety of agricultural contexts.

The integration of the Gemini API further enhances the practical utility of the system by allowing real-time access to the latest diagnostic insights. Future enhancements, such as integrating IoT for real-time image capture and improving dataset diversity and attributes, could significantly amplify its impact. Moreover, a collaborative platform for farmers to share experiences and discuss disease trends can further showcase the transformative potential of technology in modern agriculture.

This work not only contributes to reducing crop losses but also aligns with broader efforts to leverage artificial intelligence for sustainable agriculture. By empowering farmers to adopt data-driven, resilient agricultural practices, Cotton Cure is a promising tool for enhancing

productivity and profitability. The convergence of deep learning, IoT, and collaborative platforms underscores a future where technology empowers farmers to overcome challenges and foster sustainable growth in agriculture.

References.

1 Navina Pandhare, Vrunali Panchal, Shivam S.Mishra, Mrs. Darshna Tambe, April 2022, “COTTON PLANT DISEASE DETECTION USING DEEP LEARNING” IRJMTS.

2 Agriplex India Technical Team Agro, management- of-majorcotton-diseases. AgriplexIndia Technical Team Agro, June 30, 2022”.

3 Ms. Priya Ujawe, Dr. Smita Nirkhi, “Review on Different Types of Tomato Crop Disease and Detection Using Deep Learning Technique”, 2022, International Journal of Engineering and Creative Science.

4 Sriramakavacham Ramacharan, 2021, “A Three-Stage Method for Diseases Detection of Cotton Leaf using Deep Learning CNN Algorithm”, Research Gate.

5 Muhammad Suleman Memon, Pardeep Kumar, and Rizwan Iqbal, 2022, “Meta Deep Learn Leaf Disease Identification Model for Cotton Crop”, MDPI

6 Al-bayati, J. S. H., & Üstündağ, B. B. (2020) “Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural Networks”, International Journal of Computational Intelligence Systems. Computational Intelligence Systems.

7 Nikhil Shah, Sarika Jain, “Detection of disease in Cotton leaf using Artificial Neural Network”, 2019 IEEE

8 A. Jenifa, R. Ramalakshmi, V. Ramachandran, “Classification of cotton leaf Disease using Multi-support Vector Machine”, 2019 IEEE.

9 J. Ma, K. Du, F. Zheng, L. Zhang, Z. Gong, and Z. Sun, ‘‘A recognition method for cucumber diseases using leaf symptom images based on deep convolution neural network,” Computer Electron. Agriculture. Vol 154, pp. 18-24, Nov.2018.

10 S. Chouhan, A. Kaul, U. Singh, S. Jain,” Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards Plant Pathology”, 2017.

11 M. W. Tahir, N. A. Zaidi, A. A. Rao, R. Blank, M. J. Vellekoop and W. Lang"A Fungus Spores Dataset and a Convolutional Neural Networks based Approach for Fungus Detection",IEEE TRANSACTION ON NANOBIOSCIENCE, MAY 2018.

12 S. Kaur , S. Pandey, S. Goel"Semi-automatic leaf disease detection and classification system for soybean culture",The Institution of Engineering and Technology 2018.

13 Ranjith, S. Anas, I. Badhusha, Zaheema OT, Faseela K, M. Shelly"Cloud Based Automated Irrigation And Plant Leaf Disease Detection System Using An Android Application",International Conference on Electronics, Communication and Aerospace Technology ICECA 2017.

14 A. A. Sarangdhar, Prof. Dr. V. R. Pawar "Machine Learning Regression Technique for Cotton Leaf Disease Detection and Controlling using IoT",International Conference on Electronics, Communication and Aerospace Technology ICECA 2017.

15 Tejonidhi M.R, Nanjesh B.R, Jagadeesh Gujanuru Math, Ashwin GeetD'sa "Plant Disease Analysis Using Histogram Matching Based on Bhattacharya's Distance Calculation" International Conference on Electrical, Electronics and Optimization Techniques (ICEEOT)-20164 Vector Machine”, 2019 IEEE