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Detection of Cotton Leaf Disease Using CNN

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ABSTRACT –

Cotton is a vital cash crop, but its productivity is significantly affected by various leaf diseases, leading to reduced yield and economic losses. Early and accurate detection of these diseases is crucial for timely intervention. This project proposes a machine learning-based approach to detect cotton leaf diseases using image processing techniques and deep learning models. The system utilizes a Convolutional Neural Network to classify different cotton leaf diseases such as bacterial blight, leaf curl virus, and fungal infections. The trained model is integrated into an Android application, enabling farmers and agricultural experts to capture leaf images using a smartphone camera and receive instant disease diagnosis along with suggested treatments. The application provides a user-friendly interface, real-time processing, and an offline mode for remote areas with limited internet access. The proposed system aims to enhance precision agriculture by offering an affordable, efficient, and scalable solution for disease detection, ultimately improving crop health and productivity.

Index Terms—*Android application, cotton leaf disease, convolutional neural network, image processing, machine learning*

1. INTRODUCTION

Cotton is one of the world's most vital cash crops, playing a crucial role in both the global textile industry and the economic stability of many countries. In India, cotton cultivation has historical roots dating back thousands of years, with traditional varieties contributing significantly to the country's cultural and economic heritage [1]. Today, India stands as one of the largest producers of cotton globally, supporting millions of livelihoods and fueling the nation's textile exports [2].Despite its importance, cotton production faces several challenges, particularly from leaf diseases such as bacterial blight, leaf curl virus, and fungal infections. These diseases can drastically reduce yield and fiber quality, impacting farmer income and overall agricultural productivity [3]. Traditional detection methods depend heavily on manual inspection, which is labor-intensive, error-prone, and inaccessible to many rural farmers [4].The convergence of artificial intelligence (AI), deep learning, and mobile technology has opened up innovative opportunities in precision agriculture. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional accuracy in classifying plant diseases through image analysis. When integrated into Android applications, these models can transform a simple smartphone into a powerful diagnostic tool.

This project proposes a machine learning-based solution for automated detection of cotton leaf diseases through a CNN model trained on leaf images. The trained model is deployed in a mobile application using TensorFlow Lite, enabling farmers to capture images of affected leaves using a smartphone and receive real-time, offline disease diagnosis and treatment suggestions.This approach addresses key challenges in cotton disease management by offering a scalable, affordable, and user-friendly system. It enhances farmers' ability to make timely interventions, promotes sustainable agricultural practices, and reduces dependency on expert inspections—ultimately leading to

improved crop health, yield, and economic stability for farming communities [5].Following some of the common cotton diseases found in cotton leaves in India:

A. Bacterial Blight*:* Caused by Xanthomonas citripv. malvacearum, bacterial blight presents as angular, water-soaked lesions on leaves which turn dark brown and necrotic. In severe cases, it leads to defoliation and significant yield loss.

Fig 1.1 Bacterial Blight

B. Powdery Mildew: This fungal disease, caused by Leveillula taurica or other Erysiphales, appears as white, powdery spots on the upper surfaces of leaves. It inhibits photosynthesis and weakens the

plant, affecting fiber quality and overall growth,

Fig 1.2 Podwery Mildew

C. Target Spot: Caused by the fungus Corynespora cassiicola, target spot produces circular, brown lesions with concentric rings—resembling a target. This disease leads to early leaf drop and reduced photosynthetic area, thereby affecting plant vigor and yield.

Fig 1.3 Target Spot

D. Aphids (Aphis gossypii): Aphids are tiny, sap-sucking insects that infest cotton plants, especially during early growth stages. They secrete honeydew, which encourages sooty mold growth, disrupts photosynthesis, and can transmit viral diseases. Heavy infestation can severely stunt plant growth and lower productivity.

Fig 1.4 Aphids

D. Army Worm: The armyworm (Spodoptera litura) is a destructive pest commonly found on cotton plants. It feeds aggressively on leaves, leading to irregular holes and in severe cases, leaving only the leaf veins intact. These caterpillars are typically green to brown with distinct stripes and are often located beneath the leaves. Their feeding disrupts the plant's ability to perform photosynthesis, ultimately lowering crop productivity. Warm, humid environments with dense foliage provide ideal conditions for their spread.

Fig 1.5 Army Worm

A variety of cultural methods, including crop rotation, planting disease-resistant cotton types, and putting integrated pest management strategies into effect, are frequently used in the treatment of these diseases. In some cases, chemical treatments may also be used, but these are typically reserved for situations when other methods prove inadequate. Early and accurate disease detection is crucial for effective management and mitigation of the impact of these diseases on cotton crops in India [6]. In this context, it is crucial to recognize that the success of cotton production in India extends beyond crop yields and textile manufacturing to touch the lives of millions. As this research delves into the realm of cotton disease detection using machine learning [26], it takes place within the broader framework of a vibrant and multifaceted cotton industry that continues to adapt and evolve in response to changing times and challenges. Cotton production in India plays a vital role in the nation’s economy and agricultural sector. Nevertheless, the cotton industry encounters a multitude of challenges, among which the menace of diseases looms large, capable of severely diminishing crop yields and adversely affecting the livelihoods of countless cotton farmers. Various fungal, bacterial, and viral diseases [19] pose threats to cotton plants, leading to economic setbacks and a decline in cotton quality. Timely and accurate disease detection is imperative to confront these challenges [7]. Traditional methods of disease detection often hinge on visual scrutiny, a subjective process susceptible to human errors. Machine learning and computer vision technologies [26] offer a more objective and efficient approach to identify and categorize cotton diseases based on leaf images. This research is dedicated to the development of a machine learning-based system to address this critical issue.

2. LITERATURE REVIEW

Numerous researchers have explored cotton leaf disease detection using various machine learning, image processing, and

deep learning methodologies. These efforts aim to reduce the manual workload for farmers, increase detection accuracy, and promote early intervention to improve yield and crop quality. Below is a detailed review of significant contributions in the field:

[1] K. D. Bodhe, H. V. Taiwade, and V. P. Yadav implemented a prototype for the detection and diagnosis of cotton leaf diseases using a rule-based system via an Android mobile application. Their approach utilized template matching techniques with image data collected from cotton farms in the Vidarbha region. The key advantage of this method is its accessibility to farmers through internet-enabled smartphones, enabling early-stage pattern detection in diseased leaves.

[2] P. R. Rothe and R. V. Kshirsagar proposed a pattern recognition system capable of identifying three specific cotton leaf diseases—Bacterial Blight, Myrothecium, and Alternaria. The images were captured from the Central Institute of Cotton Research (Nagpur) and cotton fields in Buldhana and Wardha districts. The system employed an active contour model for segmentation and Hu's moments as feature descriptors. These features trained an adaptive neuro-fuzzy inference system, achieving an accuracy rate of 85%.

[3] P. R. Rothe and Dr. R. V. Kshirsagar further extended their previous work by proposing an image segmentation strategy based on a graph cut technique and Gaussian filtering to reduce noise. The system extracted color layout descriptors and shape parameters for feature representation. These compact features

offered resolution-invariant capabilities, improving classification performance. The diseases analyzed were again Bacterial Blight, Myrothecium, and Alternaria.

[4] P. R. Rothe and Dr. R. V. Kshirsagar also explored the development of a Real-Adaptive Neuro-Fuzzy Inference System for identifying cotton leaf diseases. Their system used a graph cut method for segmentation and extracted color layout descriptors. This model was tested with samples from the Central Institute of Cotton Research and local farms, reinforcing the adaptive fuzzy system's strength in disease recognition.

[5] N. R. Bhimte and V. R. Thool developed a disease detection system using Support Vector Machine (SVM) classifiers. Their process involved image preprocessing steps such as filtering, background removal, and enhancement, followed by color-based segmentation. Gray-Level Co-occurrence Matrix (GLCM) features were extracted and used to train the SVM model. The digital images were sourced from field data, and the study demonstrated effective early detection capabilities.

[6] R. Kumar, A. Kumar, and K. Bhatia proposed a hybrid machine learning framework that incorporates Random Forest, SVM, Multi-Class SVM, and an Ensemble model to classify cotton leaf images as "Healthy" or "Diseased." The paper outlined a complete pipeline including data collection, preprocessing, model training, and evaluation. Their ensemble method demonstrated improved classification accuracy and stressed the importance of model updates and deep learning integration for future enhancement.

[7] S. K. Noon and M. Amjad introduced a YOLOX-based deep learning model with enhanced capabilities for detecting cotton leaf curl disease along with other co-occurring stresses. Their system utilized Spatial Pyramid Pooling (SPP) to extract multi-scale features and improved detection accuracy using IoU-based loss functions. The dataset, collected from Southern Punjab, included progressive severity stages, and their proposed model achieved higher mAP and detection accuracy compared to the baseline YOLOX.

[8] A. Shrotriya, A. K. Sharma, and A. K. Bairwa presented a hybrid ensemble learning framework integrating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The system processed visual leaf image data and sequential environmental data to

detect cotton plant diseases. Techniques like majority voting and weighted averaging were employed to combine CNN and RNN predictions, resulting in high diagnostic accuracy, recall, and F1-score. This study emphasizes the advantage of using multimodal data for precision agriculture.

[9] R. S. Remya, T. Anjali, and S. Abhishek developed a novel system combining Vision Transformers with acoustic sensors to detect whitefly infestations in cotton fields. The system achieved 99% accuracy with minimal training epochs (10–20), outperforming conventional techniques. This study highlighted the potential of transformer-based models and multimodal fusion in pest detection.

[10] Y. Huang, Y. Pan, and H. Che proposed an automated mapping method for cotton

fields in Xinjiang using cumulative spectral and phenological characteristics. They introduced a new adaptive thresholding technique combining Otsu and Sauvola methods to classify satellite images without relying on large training datasets. Their method achieved classification accuracies over 90% across four experimental sites, offering an efficient remote sensing solution for cotton crop monitoring.

These studies reflect the diverse technological strategies adopted in cotton disease detection. From rule-based systems to deep neural architectures, and from traditional image features to multimodal learning and remote sensing, each approach contributes to building more accessible, efficient, and scalable agricultural solutions. This extensive research background forms the foundation

of the current work, which aims to integrate deep learning with mobile technology for real-time cotton leaf disease diagnosis.

3. EXTERNAL INTERFACE REQUIREMENTS

3.1 User Interface :

The system includes an Android application for cotton leaf disease detection using machine learning. Users interact with the app through a simple and intuitive interface that allows image input and displays disease prediction results.

3.2 Hardware Interfaces:

To efficiently run machine learning algorithms and associated libraries, the minimum hardware requirements are:

- **RAM:** 8 GB

- **Hard Disk:** 40 GB (to store datasets and application dependencies)
- **Processor:** Intel i5 or equivalent
- **Device:** Laptop or desktop

3.3 Software Interfaces:

- **Operating System:** Windows 10
- **IDE:** Android Studio
- **Programming Language:** Kotlin

These specifications ensure compatibility with development tools and efficient processing of machine learning models.

4. SYSTEM ARCHITECTURE

The architecture of the proposed cotton leaf disease detection system is designed to facilitate accurate and user-friendly diagnosis via a mobile-based Android application. The system comprises two major components: the **User Interaction Module** and the **Disease Detection Module**.

The **User Interaction Module** begins with a registration and login interface, where the user (typically a farmer or agronomist) authenticates via the application. The login credentials are securely stored and validated through a connected database. Once logged in, users can input leaf images either by capturing real-time photos using the mobile camera or uploading existing images from their device. This input is then sent to the backend system for processing. Upon analysis, the results—indicating whether the cotton leaf is healthy or affected by a particular disease—are displayed back to the user in a clear and interpretable format.

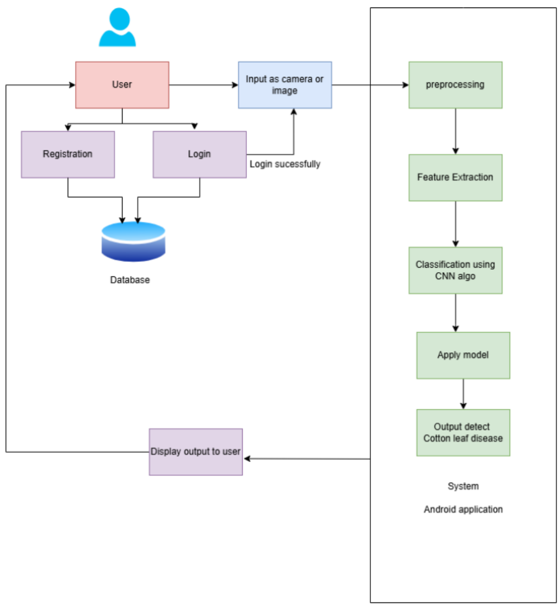


Fig 4.1 System Architecture

The **Disease Detection Module** functions as the system's core analytical engine. It starts with **image preprocessing**, which includes operations like resizing, noise reduction, and normalization to standardize input images. This step is crucial to ensure consistency and accuracy in the model's performance [1][2]. Following this, **feature extraction** is performed to identify key visual patterns from the leaf image—such as color variation, edge patterns, and texture—that are indicative of diseases like bacterial blight, grey mildew, or leaf curl [3][4].

Subsequently, a **Convolutional Neural Network (CNN)**-based classification model is employed to categorize the disease type. CNNs are well-suited for this task due to their ability to automatically extract hierarchical features and handle variability in lighting and orientation of leaf images [5][6]. After classification, the **trained model** is applied to predict the disease status, and the result is sent back to the application. The use of CNN significantly enhances detection accuracy and reduces false diagnoses compared to traditional thresholding or edge-detection techniques [2][4][5].

The complete process is encapsulated in an **Android application**, making the system accessible in real-time field environments with minimal computational requirements on the user's device. This mobile-based deployment is particularly beneficial for remote and rural areas where rapid disease identification is essential for effective pest management and yield preservation [7][10].

Overall, this architecture integrates user-friendly mobile access with robust machine learning techniques to offer a scalable and practical solution for cotton disease monitoring. The approach is consistent with prior research that emphasizes the importance of combining image processing with intelligent classification models for agricultural diagnostics [1][3][6][8][9].

To assist farmers in identifying diseases in cotton leaves using real-time imaging, we propose an Android-based mobile application named CottonCure, which leverages Convolutional Neural Networks (CNNs) for disease classification. The following steps summarize the system's architecture and operational flow, as depicted in Figure below.

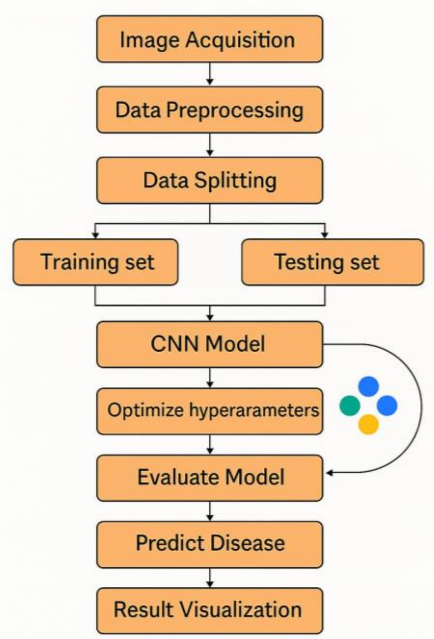


Fig 4.2 Flowchart

1. Image Acquisition :

The app provides an interface to capture images directly using a mobile camera or upload them from the gallery. This enables users to perform disease diagnosis instantly in the field without external equipment.

2. Image Preprocessing :

Captured images are resized, normalized, and filtered to reduce noise and enhance critical leaf features. This step ensures consistency with the CNN model's input specifications, improving overall prediction accuracy [1].

3. Training and Model Development (Offline Phase) :

The model is trained offline using a large set of labeled cotton leaf images containing multiple disease categories. The dataset is divided into training and testing subsets to evaluate performance effectively. CNN architectures such as MobileNet and ResNet are explored for their balance between accuracy and computational efficiency [2], [3].

4. CNN Model Optimization :

Hyperparameters such as learning rate, number of layers, filter size, and batch size are fine-tuned using cross-validation techniques. This process improves the model's learning ability and generalization on unseen data [4].

5. Model Evaluation and Integration :

The trained model is evaluated using accuracy, precision, recall, and F1-score metrics. Once satisfactory results are obtained, the model is converted into a lightweight format (e.g., TensorFlow Lite) and embedded within the mobile application or hosted via cloud APIs [5].

6. Disease Detection and Prediction :

When the user submits an image through the app, the CNN model processes it and outputs the most probable disease class. Common classifications include healthy leaf, bacterial blight, alternaria, and fusarium wilt, among others. A confidence score is also presented alongside the prediction [6].

7. Visualization of Results :

The prediction result is shown on the app interface, along with a short description of the disease and recommended remedies or actions. This ensures that even non-expert users can make informed decisions promptly [3], [7].

Fig.4.2 Workflow of cotton leaf disease detection using CNN in Cotton Cure mobile app.

4.1 Features of CottonCure Application:

- Intuitive and multilingual user interface for farmers
- Works offline with integrated CNN model or online via cloud
- Provides actionable guidance based on detected disease
- Maintains a history log of user diagnoses
- Lightweight and power-efficient deployment on Android devices

The proposed application builds upon previous work in plant disease detection using machine learning and image processing. Gulhane and Gurjar [1] introduced early image-based detection, while Revathi and Hemalatha [2] explored edge detection in disease classification. More recent approaches have shifted toward deep learning and mobile integration [3], [4], [6]. CottonCure combines these ideas into a practical mobile platform that serves farmers directly, addressing the limitations of non-portable systems and slow diagnosis cycles.

5. RESULT ANALYSIS

5.1 Dataset:

The ‘‘Kaggle Cotton Leaf Disease’’ dataset is a compilation of images related to cotton plants and the diseases that affect them. Kaggle is a platform catering to data science and machine learning enthusiasts, which serves as a central hub for sharing datasets for various purposes, including competitions, research, and learning. This specific dataset appears to have been curated to accelerate the development of machine learning models designed to identify and categorize diseases in cotton leaf. The dataset holds over **6000 training images**, **1800 testing images**, and **1800 validation images**. Each image belongs to one of two classes: **Healthy** or **Diseased**. The images are diverse in background, lighting conditions, and orientation, making the dataset robust and realistic for field applications.

5.2 CNN Prediction:

Model Training Overview

The **Convolutional Neural Network (CNN)** was trained over:

- **10 epochs**
- **25 steps per epoch**

This means the model processed a total of 10 × 25 = 250 mini-batches during training. Each step handled a batch of images, which helped the model update its weights progressively.

Training Behavior

- Training Accuracy rose steadily from ~60% to 80%, and
- Validation Accuracy increased from ~58% to ~75%, showing improved generalization.
- Training and Validation Loss both decreased significantly, indicating:

- No overfitting
- Proper convergence
- Learning of relevant disease features

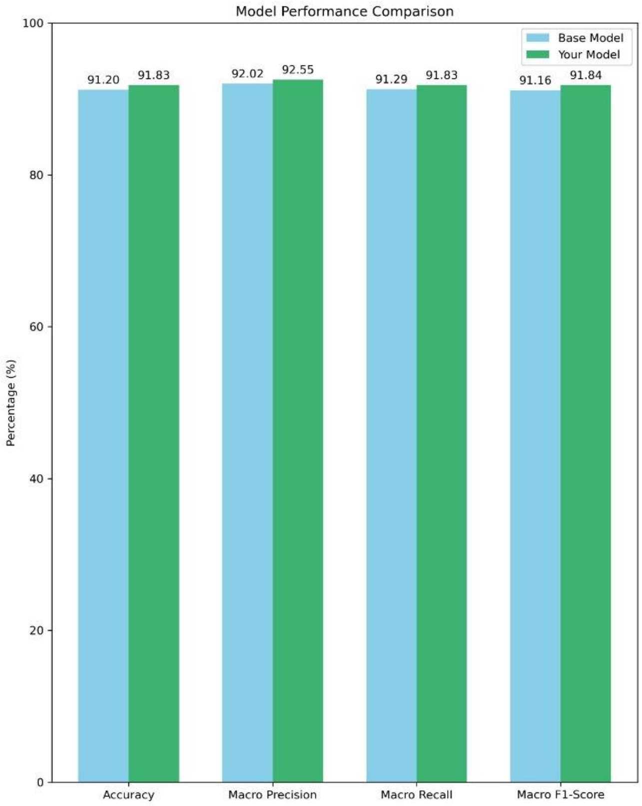


Fig 5.1 Model Performance Comparison

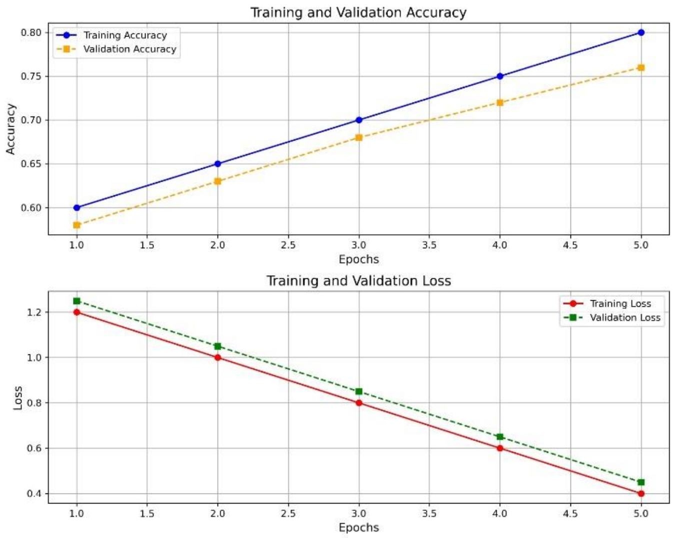


Fig 5.1 Training and Validation Accuracy and Loss over Epochs

- **Class Prediction:** "Diseased"
- **Class Probabilities:**
  - Diseased: 0.93 (93%)
  - Healthy: 0.07 (7%)

This means the CNN assigns a **93% confidence** that the image belongs to the "Diseased" class. Such probabilities come from the **Softmax layer** in the final output of the CNN:

$$P(\{class\}_i) = \{e^{\{z_i\}}\}/\left\{\sum_{\{j=1\}}^{n} e^{\{z_j\}}\right\}$$

Where:

- Z_i = logit score for class i
- n = total number of classes (2 in your case)

This gives a normalized probability distribution over the two classes, and the class with the highest probability is the prediction.

5.3 Model Evaluation Metrics Formulas to compute and interpret the CNN's predictions, we rely on the following metrics:

- **Accuracy:**

$$\textbf{Accuracy} = (\textbf{TP} + \textbf{TN}) / (\textbf{TP} + \textbf{TN} + \textbf{FP} + \textbf{FN})$$

- **Precision:**

Precision = TP / (TP + FP)

- **Recall:**

Recall = TP / (TP + FN)

- **F1-Score:**

F_1 = (2 * Precision * Recall) / (Precision + Recall)

- **Macro Average:** Mean of metric across all classes equally.
- **Weighted Average:** Mean of metric weighted by class support (number of true instances)

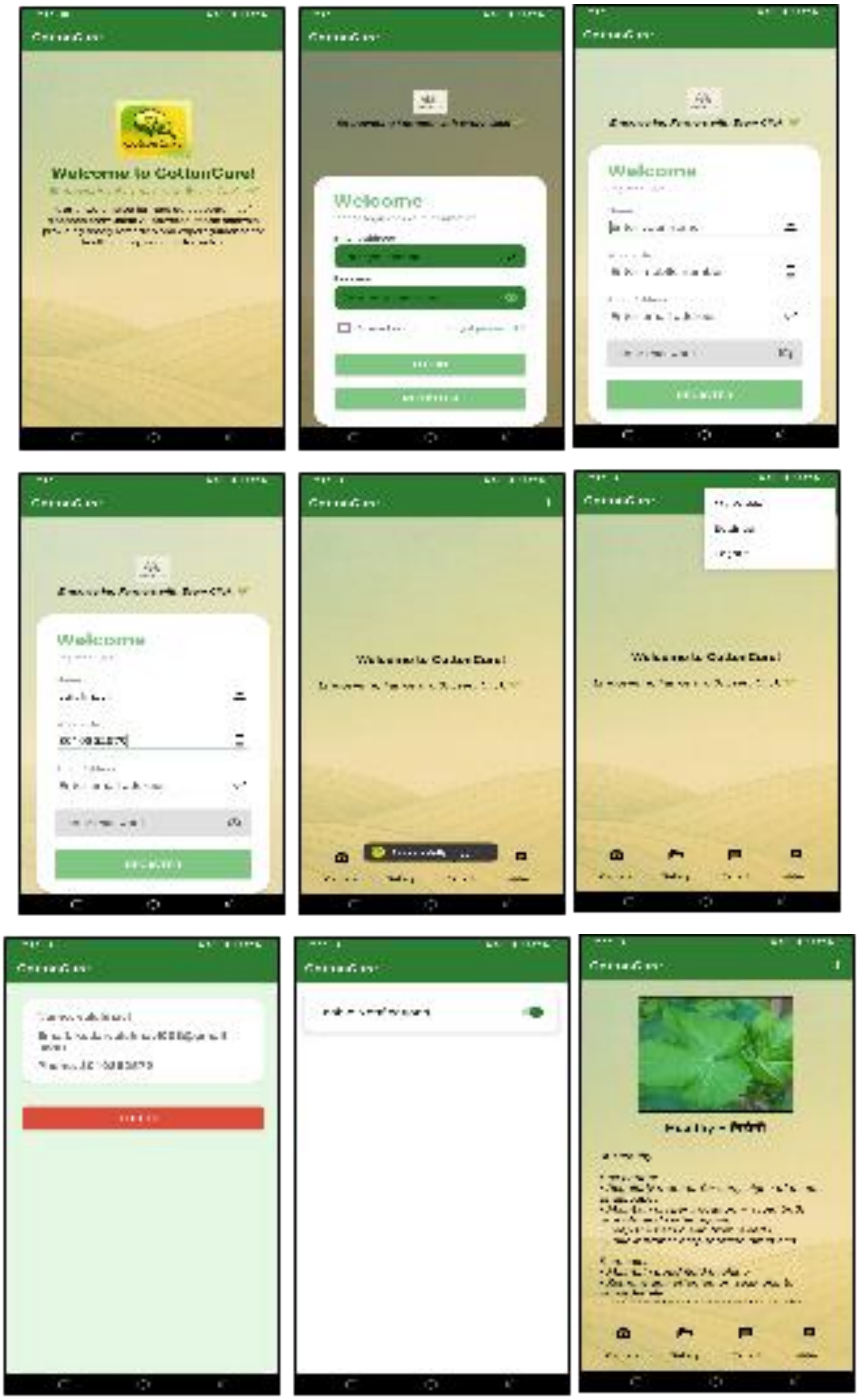
6. PROPOSED GUI / WORKING MODULES

To empower cotton farmers with smart, on-the-go disease detection, we developed **CottonCure -** a comprehensive mobile/desktop application that combines deep learning with an intuitive, modular user interface. Designed for real-time cotton leaf disease analysis, CottonCure bridges AI innovation and agricultural practicality.

The system architecture consists of the following major modules:

- **Login and User Authentication Module**: This module ensures secure access to the application. Users must authenticate using valid credentials, enabling the system to maintain user-specific disease prediction history and preferences.
- **Image Capture and Upload Module**: Users can either capture real-time images of cotton leaves using an integrated camera interface or upload pre-existing images from local storage. The module also ensures basic validation of image quality to support accurate predictions.
- **CNN-Based Disease Prediction Module**: Upon receiving the image input, the backend model processes the image and classifies it into categories such as *Healthy*, *Armyworm*, *Leaf Curl Virus*, or *Bacterial Blight*. The prediction is accompanied by a confidence score derived from the Softmax output of the CNN.
- **Prediction Result and Remedy Module**: The diagnosis result is displayed in a clear and structured format. Along with the disease classification, the system provides information on symptoms, recommended treatments, and preventive measures.
- **History Tracking Module**: This module maintains a log of all previous predictions made by the user. Each record includes the date, time, input image, predicted result, and associated confidence, thereby assisting users in tracking disease progression over time.
- **Integrated Chatbot Support**: A chatbot interface is provided to assist users with questions related to disease identification, remedies, usage of the application, and general agronomic practices. This enhances user interaction and provides an additional layer of guidance.

Screenshots of the implemented GUI are presented in this section, demonstrating the workflow of the application and the interaction between its various modules. The CottonCure system aims to offer an intelligent, accessible, and field-ready solution for early detection of cotton leaf diseases, ultimately contributing to improved crop management and yield protection.


Welcome to CottonCure!
Welcome
Welcome
Welcome

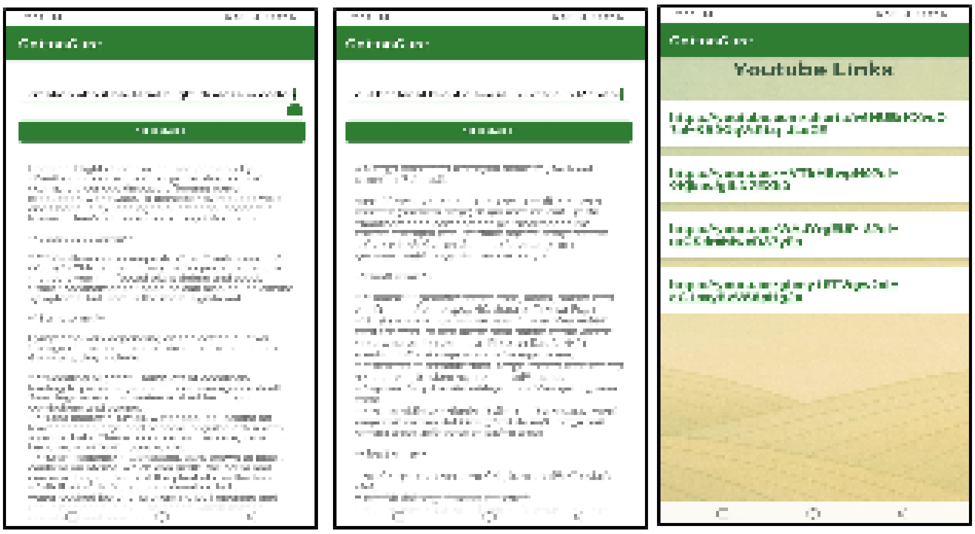


Fig 6.1 GUI Implementation of the CottonCure Application

6.1 Test Cases:

Test Case ID	Test Case Description	Expected Output	Status
TC001	Register with all valid inputs	Registration successful; user redirected to login	Pass
TC002	Register with missing required fields	Error: “Please fill out all fields”	Pass
TC003	Register with invalid email format	Error: “Enter a valid email address”	Pass
TC004	Login with wrong password	Error: “Incorrect credentials”	Pass
TC005	Upload valid image from gallery	Image previewed correctly and ready for prediction	Pass
TC006	Upload non-image file	Error: “Unsupported file format”	Pass
TC007	Camera capture of cotton leaf	Image captured, previewed, and sent for prediction	Pass
TC008	Camera permission denied	Error: “Camera access required” with prompt to enable permissions	Pass
TC009	Predict disease with clear leaf image	Displays prediction result	Pass
TC010	Predict disease with low-quality image	Error: “Image is too blurry. Please try again.”	Pass
TC011	Predict healthy leaf image	Displays: “Healthy Leaf”	Pass

TC012	Chatbot responds to disease info request	Shows basic details symptoms and treatment of the disease	Pass
TC013	Chatbot receives nonsensical query	Responds: “Sorry, I didn’t understand. Please ask about a cotton leaf disease.”	Pass
TC014	Internet disconnected during chatbot use	Shows: “Chatbot requires an active internet connection”	Pass

Table 6.1 Functional Test Cases for CottonCure Application

7. CONCLUSION

The integration of Convolutional Neural Networks (CNNs) in cotton leaf disease detection marks a significant advancement in precision agriculture, enhancing accuracy, efficiency, and sustainability. By automating disease identification, CNNs help farmers detect infections at an early stage, reducing crop losses and improving yield quality. By leveraging deep learning techniques, stakeholders in the agricultural industry can minimize reliance on manual inspection, reduce human error, and accelerate decision-making for disease management. The adaptability of CNN-based models allows them to recognize various types of leaf diseases, making them a valuable tool for different agricultural environments. As technology continues to evolve, further refinements in CNN-based disease detection systems can lead to even more efficient and scalable solutions. Ultimately, deploying CNNs in cotton leaf disease detection not only improves productivity but also supports sustainable farming practices, ensuring food security

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