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Smart Crop Doctor: An AI Driven Chilli Plant Disease Detection

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Abstract: Agriculture is one of the most important sectors that supports food production and the economy. Chilli cultivation is highly affected by several diseases that reduce crop quality, productivity, and farmers' income. In many rural areas, farmers still depend on manual inspection and agricultural experts to identify plant diseases. This process is often time-consuming, expensive, and not easily accessible to all farmers.

To address this issue, the proposed system "Smart Crop Doctor" introduces an intelligent and user-friendly solution for automatic chilli plant disease detection. The system uses Artificial Intelligence and Deep Learning techniques to analyze chilli leaf images and identify diseases accurately. A transfer learning model called MobileNetV2 is used to classify healthy and infected leaves with improved prediction performance.

In addition to disease detection, the system also provides treatment suggestions, prevention methods, expert consultation support, and crop management guidance. The application is developed as a web-based platform so that farmers can access it easily using computers or mobile devices. The system also stores crop history and diagnosis records for future monitoring and analysis.

Experimental observations show that the proposed framework provides reliable disease prediction, fast response time, and practical support for farmers. The system helps in early disease identification, reduces crop losses, improves productivity, and promotes modern smart farming practices.

Keywords: Smart Agriculture, Plant Disease Detection, Deep Learning, MobileNetV2, Chilli Leaf Classification, Precision Farming, AI Advisory System

I. INTRODUCTION

Agriculture plays a very important role in supporting economic development and ensuring food security. Among various agricultural crops, chilli is one of the most widely cultivated crops because of its nutritional value, commercial importance, and high market demand. However, chilli plants are highly vulnerable to several diseases caused by fungi, bacteria, viruses, and pests. These diseases can severely affect plant growth, reduce crop quality, and decrease agricultural productivity if not detected at an early stage.

Traditionally, farmers identify diseases by observing symptoms on leaves and consulting agricultural experts. Although this method is useful, it requires experience and expert knowledge. In many rural and remote areas, farmers may not have quick access to agricultural specialists. As a result, disease diagnosis may be delayed, leading to incorrect treatment methods, increased farming costs, and heavy crop losses.

With the advancement of Artificial Intelligence, Machine Learning, and Computer Vision technologies, automated plant disease detection systems have become possible. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown excellent performance in image classification tasks. These models can automatically learn important visual features from plant images and provide accurate disease predictions.

The proposed Smart Crop Doctor system is developed to provide an intelligent agricultural decision-support platform for chilli farmers. The system combines AI-based disease detection, treatment recommendations, chatbot support, expert consultation, and crop history management within a single platform. The main objective of the system is to help farmers identify diseases quickly, receive proper treatment guidance, and improve agricultural productivity through smart technology.

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II. RELATED WORK

Several researchers have proposed different methods for plant disease detection using image processing, machine learning, and deep learning techniques. Earlier studies mainly focused on traditional image processing methods such as color segmentation, texture analysis, and shape-based feature extraction to identify plant diseases. Although these approaches provided acceptable results in controlled environments, their performance was often affected by lighting variations, background noise, and environmental conditions.

With the advancement of Artificial Intelligence, many researchers introduced Machine Learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forest classifiers for plant disease classification. These methods improved prediction accuracy compared to traditional techniques, but they still required manual feature extraction and expert knowledge for better performance.

Recent developments in Deep Learning and Convolutional Neural Networks (CNNs) significantly improved automated disease detection systems. CNN-based models automatically learn important visual features from plant images and provide higher classification accuracy. Transfer learning models such as MobileNetV2, ResNet, and VGG16 have been widely used because they reduce training time and computational complexity while maintaining reliable prediction performance.

Some agricultural applications also integrated cloud-based storage, chatbot assistance, and mobile accessibility to improve usability for farmers. However, most existing systems mainly focus on disease prediction and provide limited support for treatment guidance and expert consultation. Many systems also lack crop history management and personalized farmer assistance.

The proposed Smart Crop Doctor system overcomes these limitations by integrating deep learning-based disease classification, AI-driven advisory support, expert consultation, and crop record management into a single web-based platform. This integrated approach makes the system more practical, user-friendly, and suitable for real-time agricultural applications.

Pictures plus words help people learn better, Mayer showed in his work labeled five. When lessons mix sound, reading, and visuals, minds stay focused longer, remember deeper. TimelineX builds on this idea by weaving speech, written lines, moving clips, still frames - all shaped by artificial intelligence - into stories from the past. Learning history becomes clearer through these layered pieces working together.

Gamification, according to Deterding and his team [6], means adding bits of game design into places that aren't games - just so people stay more involved and driven. Noticing wins through rewards or watching progress climb on a bar can actually lift how students feel about learning. TimelineX took cues from such ideas, weaving in daily check-ins shaped like challenges alongside playful tasks mixed with feedback loops. Instead of just ticking boxes, users move through layers of activity that build habits slowly, almost without noticing. Little markers of effort add up, turning repetition into something that feels less like work over time.

III. METHODOLOGY

The Smart Crop Doctor system follows a simple and systematic process for detecting chilli plant diseases and providing farmer support. The methodology begins when the farmer uploads a chilli leaf image through the web application. The uploaded image is first checked and processed to improve image quality before disease prediction.

During preprocessing, operations such as resizing, normalization, and image enhancement are performed to make the image suitable for the deep learning model. Data augmentation techniques are also used during training to improve model performance under different environmental conditions.

After preprocessing, the image is passed to the MobileNetV2 deep learning model. The model extracts important features from the chilli leaf image and predicts whether the leaf is healthy or affected by a disease. The system can identify different diseases such as leaf spot, anthracnose, leaf curl virus, whitefly infection, damping off, and veinal mottle virus. Once the disease is detected, the advisory module generates treatment recommendations, prevention methods, and crop management suggestions. An AI chatbot is also included to answer farmers' queries in simple language. If additional support is required, farmers can use the expert consultation feature to connect with agricultural specialists.

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Finally, all prediction results and crop records are stored in the MongoDB database for future monitoring and analysis. This methodology helps provide fast, accurate, and real-time disease detection and support for farmers.

1. System Architecture

The Smart Crop Doctor framework integrates multiple modules such as disease detection, advisory support, expert consultation, and crop management within a single web-based environment. The system architecture is designed to ensure smooth communication between the frontend interface, backend services, deep learning model, and database management system.

The process begins when the farmer uploads a chilli leaf image through the frontend interface. The backend processes the image and forwards it to the MobileNetV2 classification model. The model extracts deep features from the image and predicts the disease category. Based on the prediction result, the advisory engine generates treatment recommendations and preventive suggestions.

The expert consultation module allows users to interact with agricultural experts for additional support and personalized recommendations. All diagnosis records, user interactions, and treatment details are stored in the MongoDB database for future monitoring and analysis.

The system architecture diagram on page 3 clearly illustrates the interaction between the farmer, frontend, backend, CNN model, advisory engine, expert support module, and database system.

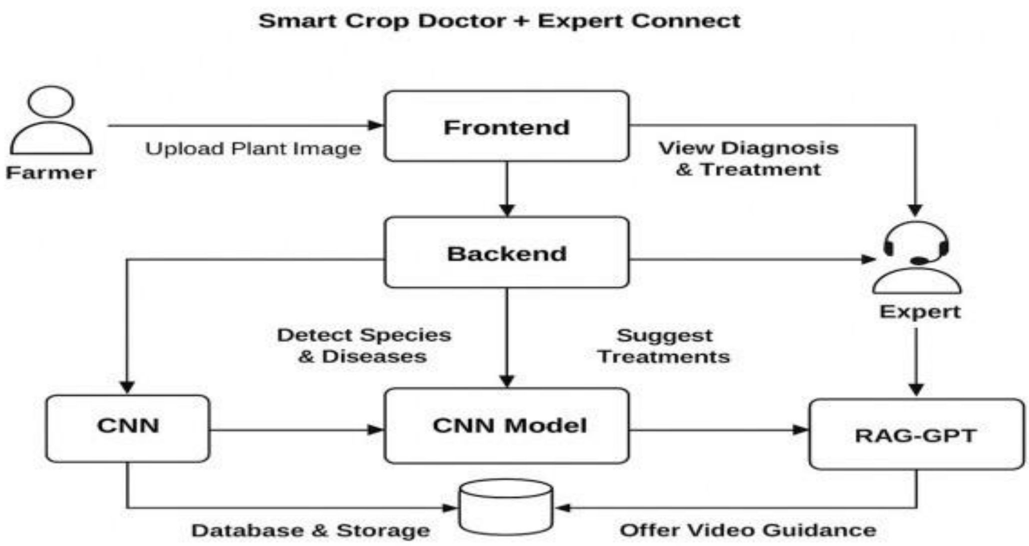

Fig. 1. Proposed System Architecture of smart crop doctor

2. System Workflow

The Smart Crop Doctor system works through a sequence of steps to detect chilli plant diseases and provide proper guidance to farmers. The workflow starts when the user uploads a chilli leaf image through the web application. The uploaded image is then sent to the preprocessing module where resizing, normalization, and image validation are performed to improve image quality and prepare it for prediction.

After preprocessing, the image is passed to the MobileNetV2 deep learning model. The model analyzes the leaf image, extracts important visual features, and predicts the disease category. The system then identifies whether the leaf is healthy or affected by diseases such as leaf spot, anthracnose, leaf curl virus, whitefly infection, damping off, or veinal mottle virus.

Once the disease is identified, the advisory module generates treatment recommendations, prevention methods, and crop management suggestions. The AI chatbot helps farmers by answering crop-related questions in simple language. If the disease condition is severe or complex, the expert consultation module allows farmers to connect with agricultural specialists for additional support.

Finally, all prediction results and consultation records are stored securely in the MongoDB database for future

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monitoring and analysis. The system then displays the diagnosis result and advisory response to the user through the web interface. This workflow helps farmers receive fast, accurate, and real-time agricultural support.

3. Database Design

The Smart Crop Doctor system uses MongoDB to store and manage all the important information related to users, disease predictions, treatment details, and crop records. The database is designed in a simple and efficient way so that the system can quickly save and retrieve information whenever required.

The database contains different sections for managing various activities of the system. The user section stores farmer details such as name, email, password, and contact information. This helps the system manage user registration and login activities securely.

Another important part of the database stores disease prediction records. Whenever a farmer uploads a chilli leaf image, the system saves details such as the uploaded image, predicted disease name, prediction result, date, and time. This helps farmers keep track of previous disease reports and monitor crop health over time.

The database also stores treatment recommendations and prevention methods for different diseases. After the disease is identified, the system retrieves suitable treatment suggestions from the database and displays them to the user. This helps farmers take quick action to protect their crops.

An expert consultation section is included to store farmer queries and responses from agricultural specialists. This allows farmers to receive additional guidance for severe or complex disease conditions.

The crop history section maintains complete records of previous diagnoses, treatments, and monitoring details. These records can help farmers analyze crop conditions and make better farming decisions in the future.

MongoDB was selected because it is flexible, easy to manage, and capable of handling large amounts of agricultural data efficiently. The database works smoothly with the Flask backend and the MobileNetV2 deep learning model, helping the Smart Crop Doctor system provide fast and reliable support to farmers.

4. Tools and Technologies

The Smart Crop Doctor system was developed using simple and modern technologies that help in disease detection, data storage, and web application development. These tools work together to provide fast and accurate support for farmers.
Python was used as the main programming language because it is easy to use and widely used for Artificial Intelligence and Deep Learning projects.

TensorFlow and Keras were used to build and train the deep learning model for chilli leaf disease detection. These technologies help the system identify diseases from leaf images accurately.

MobileNetV2 was used as the main deep learning model. It is a lightweight and fast model that provides good prediction accuracy and supports real-time disease detection.

Flask was used for backend development. It helps connect the frontend, deep learning model, and database so that the system works smoothly.

MongoDB was used as the database to store user details, disease prediction records, treatment information, and crop history. It helps manage data efficiently.

HTML, CSS, and JavaScript were used to design the frontend interface of the web application. These technologies make the system simple, interactive, and easy for farmers to use.

OpenCV was used for image preprocessing tasks such as resizing and improving image quality before prediction.
The project was developed using tools like Visual Studio Code and Jupyter Notebook, which helped in coding, testing, and training the model.

All these tools and technologies helped in building a fast, reliable, and user-friendly Smart Crop Doctor system for automated chilli plant disease detection and farmer support.

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IV. RESULTS AND DISCUSSION

The Smart Crop Doctor system was tested using different chilli leaf images containing both healthy and diseased samples. The MobileNetV2 deep learning model successfully identified various chilli plant diseases with reliable prediction performance. The system was able to classify diseases accurately under different environmental conditions such as lighting changes, leaf orientation, and background variations.

The use of transfer learning and data augmentation improved the overall performance of the model. The system showed stable prediction behavior and better feature extraction capability during testing. The trained model was able to clearly distinguish healthy leaves from infected leaves with good consistency.

The web-based application also provided real-time disease prediction and treatment guidance. Farmers could upload chilli leaf images and quickly receive disease diagnosis results along with prevention methods and treatment suggestions. The expert consultation feature further improved the usefulness of the system by allowing farmers to get additional support from agricultural specialists.

The lightweight MobileNetV2 architecture helped the system provide faster prediction speed with lower computational complexity. This makes the framework suitable for practical agricultural applications and smart farming environments. Overall, the experimental results show that the Smart Crop Doctor system is efficient, reliable, and useful for early disease detection, reducing crop losses, and improving agricultural productivity.

V. CONCLUSIONS AND FUTURE WORK

The Smart Crop Doctor system was developed to help farmers detect chilli plant diseases quickly and accurately using Artificial Intelligence and Deep Learning techniques. The system uses the MobileNetV2 model to identify diseases from chilli leaf images and provide treatment suggestions. It also includes expert consultation and crop history management features to support farmers in making better agricultural decisions.

The web-based platform is simple, user-friendly, and capable of providing real-time disease prediction. Experimental results showed that the system can successfully identify healthy and diseased leaves with reliable performance. Early disease detection can help farmers reduce crop losses, improve productivity, and save time and money.

In the future, the system can be improved by adding support for multiple crops and more plant diseases. A mobile application can also be developed to make the system easier for farmers to use in agricultural fields. Voice support in regional languages may help farmers who are not comfortable using text-based systems.

Future enhancements may also include weather-based disease prediction, cloud storage, and IoT integration for smart farming applications. These improvements can make the Smart Crop Doctor system more efficient, scalable, and useful for modern agriculture.

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