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Plant Leaf Disease Detection Using Convolutional Neural Network

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***Abstract*—Early and accurate identification of plant leaf diseases is essential for improving crop productivity and reducing agricultural losses. In many farming environments, especially in small-scale and rural agriculture, disease diagnosis still depends on manual observation and expert consultation, which may not always be available at the right time. To address this challenge, this work presents an intelligent AI-based plant leaf disease detection and crop care recommendation system that supports farmers in both disease identification and post-detection management.**

The proposed model primarily focuses on analyzing uploaded plant leaf images and predicting the most probable disease using a deep learning-based classification approach built on MobileNetV2 transfer learning. The system is capable of identifying diseases across multiple crop species and provides the predicted disease name along with a confidence percentage score, enabling users to understand the reliability of the output.

A key contribution of this work is that the system goes beyond conventional disease classification by generating detailed crop advisory information for the detected disease. Along with the prediction result, the model provides a short disease description, key visible symptoms, major causes, commonly affected plants, treatment and cure suggestions, and a step-by-step treatment guide that farmers can directly follow in the field. In addition, the system recommends suitable agricultural products, future disease prevention strategies, and seasonal plant care practices to support long-term crop health management.

The application is implemented using a Flask-based backend API integrated with a Tkinter desktop frontend, allowing easy image upload and fast result visualization on standard CPU-based systems. The modular structure enables simple updates for disease metadata, care instructions, and future model retraining.

The proposed solution demonstrates how deep learning can be effectively combined with practical agricultural knowledge to create a user-friendly decision support tool for smart farming. By transforming disease prediction into actionable crop care guidance, the system can help farmers take timely preventive measures, improve plant health, and reduce yield loss.

Keywords—Plant leaf disease detection, deep learning, MobileNetV2, transfer learning, smart agriculture, crop disease diagnosis, treatment recommendation, seasonal plant care, agricultural decision support.

I. INTRODUCTION

Agriculture is one of the most important sectors supporting food production and economic development, especially in countries where a large population depends on farming for their livelihood. The health of crops directly influences both yield quality and quantity, making early disease detection a critical part of successful farming. Among the different plant parts, leaves often show the earliest visible symptoms of disease, such as discoloration, spots, wilting, or fungal growth. If these symptoms are not identified and treated at the right time, the disease can spread rapidly and cause significant crop loss.

In traditional farming practices, disease identification is usually carried out through manual observation or by consulting agricultural experts. Although effective, this approach requires time, continuous monitoring, and domain knowledge that may not always be available, particularly for small-scale farmers and rural agricultural communities. Delays in diagnosis often lead to improper treatment, excessive pesticide usage, and reduced productivity.

Recent advancements in artificial intelligence and deep learning have created new opportunities for automating plant disease diagnosis using image-based analysis. Convolutional neural network models, especially lightweight transfer learning architectures, have shown strong performance in recognizing complex visual disease patterns from leaf images. However, many existing systems focus only on predicting the disease label and do not provide practical guidance on how to manage or prevent the disease after detection.

To overcome this limitation, the proposed work presents an AI-based plant leaf disease detection and crop care recommendation system that combines accurate disease classification with actionable agricultural support. The system is built using MobileNetV2 transfer learning, which enables efficient and fast disease recognition on standard CPU-based devices. After analyzing the uploaded leaf image, the model predicts the disease name and displays a confidence percentage score to indicate the reliability of the result.

A major strength of the proposed system is its ability to go beyond simple disease prediction [9]. In addition to the detected disease name, the system provides a detailed disease description, key symptoms, possible causes, affected plants, treatment and cure suggestions, a step-by-step treatment guide, recommended agricultural products, future disease prevention strategies, and seasonal care instructions for better plant health management. This transforms the model from a simple classifier into a practical decision-support tool for farmers.

The overall system is implemented using a Flask backend API and a Tkinter desktop interface, making it easy to upload leaf images and view results in a user-friendly manner. The proposed solution aims to support smart agriculture by enabling timely disease diagnosis, informed treatment decisions, and long-term crop protection practices.

II. LITERATURE REVIEW

Plant leaf disease detection has become an important research area in recent years due to the increasing adoption of artificial intelligence in agriculture. Several researchers have proposed machine learning and deep learning techniques to identify crop diseases from leaf images, with the objective of reducing manual effort and improving the speed and accuracy of diagnosis [9][10][11].

Earlier studies mainly relied on traditional image processing methods, where features such as colour, texture, and shape were manually extracted from leaf images. These features were then classified using algorithms such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Decision Trees. Although these methods achieved moderate accuracy under controlled conditions, their performance was highly dependent on image quality, lighting conditions, and background noise. Hence, they were less suitable for real-time agricultural environments [11].

Deep learning-based systems later showed significant improvements in plant disease recognition. In the study “AI-Based Real-Time Disease Diagnosis Using Deep Learning Driven CNNs in Plants,” researchers developed a real-time disease diagnosis system capable of identifying diseases such as tomato blight, leaf spot, potato rust, maize mildew, and mosaic virus infections. The system also supported healthy leaf detection, disease severity estimation, and crop identification. Technologies such as Python, JavaScript, TensorFlow, Machine Learning, and image preprocessing techniques were used to build the model. This work demonstrated the effectiveness of CNN-based systems for instant plant health monitoring[9].

Another important contribution is the work titled “Plant Disease Detection and Classification by Deep Learning.” This study used the PlantVillage dataset and applied deep learning models for detecting diseases across multiple crops including apple, corn, grape, peach, bell pepper, potato, tomato, cherry, soybean, and rice. Diseases such as apple scab, black rot, leaf blight, bacterial spot, powdery mildew, early blight, late blight, and brown spot were successfully classified. The system was implemented using Python, TensorFlow, Keras, OpenCV, and Scikit-learn, while Flask, HTML, CSS, and JavaScript were used for web deployment. Heatmaps and visualization tools were also integrated to improve prediction interpretability. This research proved that deep learning can achieve high classification accuracy across diverse crop species[10].

In another study, “Plant Disease Detection Using Machine Learning,” researchers focused on disease identification using classical machine learning techniques. The system considered crops such as papaya, apple, corn, grape, peach, bell pepper, potato, and tomato. Diseases such as leaf spot, powdery mildew, rust, bacterial spot, yellowing/chlorosis, fungal infection, anthracnose, and papaya ring spot virus were analyzed. The model was implemented using Python, OpenCV, and Scikit-learn, while image colour conversion from RGB to HSV was used for feature extraction. Graphical outputs were used to represent healthy and unhealthy leaves. Although useful, this system had limitations in detecting only selected crops and required handcrafted feature engineering[11].

With the advancement of deep learning, Convolutional Neural Networks (CNNs) such as AlexNet, VGG16, ResNet, Inception, and MobileNet became the preferred approaches because of their ability to automatically learn disease-specific features from images. These models outperformed traditional methods by eliminating manual feature extraction and achieving higher accuracy[2][3][4].

More recently, lightweight transfer learning models such as MobileNetV2 and EfficientNet have gained popularity because they reduce computational cost while maintaining strong performance. These models are suitable for mobile devices and low-resource agricultural environments[2][4][8].

However, one common limitation in many previous systems is that they stop at disease prediction only. Most studies focus mainly on classification accuracy and do not provide practical farmer support such as disease explanation, treatment suggestions, prevention methods, fertilizer guidance, or seasonal crop care recommendations[9][10][11].

The proposed work builds upon these advancements by using MobileNetV2 transfer learning for accurate and lightweight disease classification while extending the system into a complete crop advisory platform. Unlike earlier methods, the proposed model not only predicts the disease and confidence score but also provides symptoms, possible causes, affected plants, treatment recommendations, preventive measures, future disease management strategies, and seasonal care suggestions. Therefore, the proposed solution is more practical and aligned with real agricultural needs.

Thus, the literature clearly shows the evolution from traditional feature-based methods to intelligent deep learning systems, while also highlighting the need for integrated farmer-support solutions, which the proposed model aims to address.

III. PROPOSED SYSTEM

The proposed system is designed as an AI-based plant leaf disease detection and crop care recommendation platform that helps farmers identify crop diseases at an early stage and take suitable corrective actions [9]. The system not only predicts the disease from a leaf image but also provides detailed treatment guidance and future crop management support, making it a practical solution for smart agriculture.

The workflow begins when the user uploads an image of a plant leaf through the desktop interface. The uploaded image is first passed through an image preprocessing stage, where it is resized to the required 224 × 224 pixel resolution, normalized, and converted into a format suitable for deep learning inference. This preprocessing step ensures that the model receives consistent input regardless of the original image size or quality.

For disease prediction, the system uses a MobileNetV2-based transfer learning model, chosen for its lightweight structure and efficient performance on CPU-based devices. The pretrained backbone extracts important visual features such as color variations, texture changes, lesion patterns, fungal spots, and leaf deformation characteristics. These extracted features are then passed to the custom classification layer, which predicts the most probable disease category.

After classification, the system displays the predicted disease name along with a confidence percentage score, helping the user understand the reliability of the prediction result. Instead of limiting the output to only the disease label, the proposed system extends the functionality into a complete crop advisory module.

Based on the predicted disease, the system automatically retrieves and displays:

a brief disease description
major visible symptoms
common causes of occurrence
plants commonly affected
treatment and cure recommendations
step-by-step treatment procedure
recommended agricultural products
future disease prevention measures
seasonal plant care suggestions

This additional layer of agricultural guidance transforms the model into a decision-support system, enabling farmers to take immediate and informed action after detection.

The backend logic is implemented using a Flask REST API, which handles image preprocessing, model inference, confidence generation, and metadata retrieval. The frontend is developed using Tkinter, allowing simple image upload and result visualization in a user-friendly desktop environment. The modular architecture makes it easy to update disease descriptions, treatment data, and seasonal care recommendations without retraining the core model.

A key advantage of the proposed system is its ability to run efficiently on standard systems without requiring GPU support. This makes the solution cost-effective and accessible for practical use in rural and low-resource agricultural environments.

Overall, the proposed system bridges the gap between AI-based disease prediction and real-world crop care decision-making, providing farmers with both accurate diagnosis and actionable agricultural support.

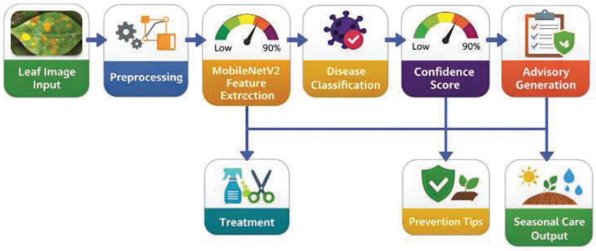


Fig.1: Flowchart of Proposed Plant Leaf Disease Detection System

IV. DATASET DESCRIPTION

The proposed plant leaf disease detection model is trained and validated using the widely recognized PlantVillage dataset, which is one of the most commonly used benchmark datasets for plant disease classification research. The dataset was originally introduced to support automated crop disease diagnosis using image-based deep learning techniques and has been extensively adopted in agricultural AI studies.

The dataset contains a large collection of high-quality leaf images representing both healthy and diseased plant conditions. It includes approximately 54,000+ labeled images, covering 14 different crop species and 38 distinct disease and healthy classes. These classes represent multiple disease categories such as fungal infections, bacterial diseases, viral infections, and healthy leaf conditions.

The crop species included in the dataset are:

- Apple
- Blueberry
- Cherry
- Corn
- Grape
- Orange
- Peach
- Pepper
- Potato
- Raspberry
- Soybean
- Squash
- Strawberry
- Tomato

Each image in the dataset is carefully labeled using the crop name and disease class format, such as:

Tomato___Early_blight

Apple___Black_rot

Corn___Common_rust

This structured labeling format makes the dataset highly suitable for multi-class deep learning classification tasks.

For this work, the color image version of the dataset is primarily used, as it preserves important disease-specific visual patterns such as lesion color, spot texture, yellowing, edge burn, and fungal growth regions. The original PlantVillage repository also provides grayscale and segmented versions, but the RGB format was selected because colour information plays a significant role in identifying leaf diseases more accurately.

Before training, the dataset images are preprocessed by resizing them to 224 × 224 pixels, normalizing pixel values, and organizing them into training and validation sets. A subset of the dataset is used in the experimental setup to ensure faster training and efficient CPU-based deployment while maintaining class diversity.

A major advantage of the PlantVillage dataset is its balanced disease representation and clean background conditions, which help the model learn disease-specific features effectively during the initial training stage. The dataset provides strong support for transfer learning models such as MobileNetV2, making it suitable for lightweight and fast agricultural disease diagnosis systems.

Overall, the selected dataset provides a reliable and well-structured foundation for developing the proposed AI-based disease detection and crop advisory model.

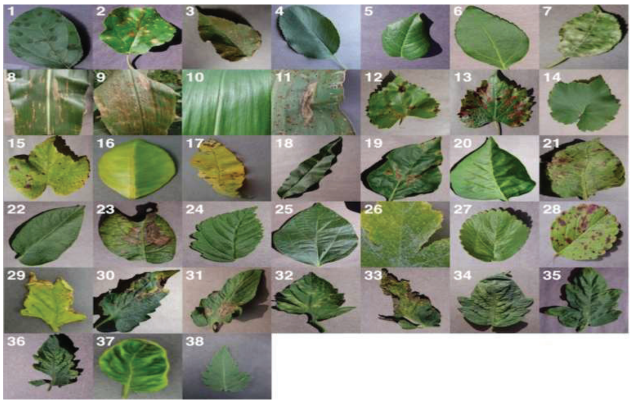


Fig 2: Trained plant leaf diseases

V. METHODOLOGY

The methodology of the proposed work focuses on building an intelligent plant leaf disease detection and crop advisory system using deep learning and transfer learning techniques. The complete workflow is designed to transform a raw leaf image into a meaningful disease diagnosis along with practical treatment guidance for farmers.

The overall methodology consists of multiple stages, including dataset preparation, image preprocessing, model training, disease prediction, confidence estimation, and advisory generation.

5.1 Data Collection

The first stage of the methodology involves collecting labeled plant leaf images from the PlantVillage dataset, which contains images of both healthy and diseased leaves across multiple crop species. The dataset includes 38 disease and healthy classes from 14 different plants.
These images serve as the primary training source for teaching the model to recognize disease-specific visual patterns.

5.2 Image Preprocessing

Before training and prediction, all leaf images are passed through a preprocessing pipeline to ensure consistency in input quality.
The preprocessing steps include:
resizing each image to 224 × 224 pixels
converting images into RGB format
normalizing pixel values
optional data augmentation for better generalization
converting the image into model-compatible tensor format

This stage helps the model focus on meaningful disease features rather than differences caused by image size or lighting.

5.3 Model Development Using Transfer Learning

The core disease detection engine is built using MobileNetV2, a lightweight convolutional neural network architecture.
Instead of training the network from scratch, transfer learning is used by initializing the model with pretrained ImageNet weights. This allows the system to reuse previously learned visual feature extraction capabilities such as:
edges
textures
spot patterns
lesion structures
color changes
A custom classification layer is then added to adapt the network for 38 plant disease categories.
This approach improves:
training speed
classification performance
CPU efficiency
deployment feasibility

5.4 Model Training

The prepared dataset is divided into training and validation sets.
During training, the MobileNetV2 backbone extracts deep visual features from the input leaf images, while the custom dense layer learns to map these features into the correct disease class.
The model learns important disease indicators such as:
yellow spots
fungal growth regions
brown lesions
edge drying
mosaic patterns
leaf curling
The training process continues until the model achieves stable validation performance.

5.5 Disease Prediction

Once training is completed, the model is deployed for real-time prediction.
When the user uploads a leaf image:
the image is preprocessed
MobileNetV2 extracts visual features
the classifier predicts the disease class
the system returns the top disease label

The final output includes:

predicted disease name
confidence percentage
top possible matching classes

This helps users understand the model’s certainty.

5.6 Confidence Score Generation

To improve usability, the raw prediction probability is converted into a human-friendly confidence percentage score.
This confidence score helps farmers understand how strongly the model supports the predicted disease class.
A confidence display layer is used so that prediction reliability is clearly visible in the result screen.

5.7 Disease Advisory Generation

A major extension of the methodology is the crop advisory module.
After detecting the disease, the system retrieves additional disease-related metadata from stored files and structured JSON content.
The advisory output includes:
disease description
key symptoms
major causes
affected plants
treatment and cure
step-by-step treatment workflow
recommended agricultural products
future prevention methods
seasonal crop care
This stage converts the system into a complete agricultural decision-support solution.

5.8 System Deployment

The final system is deployed using:
Flask backend API for prediction
Tkinter frontend for desktop interaction
The user uploads a leaf image through the GUI, and the backend processes the image and returns the result in real time.
This deployment strategy ensures:
simple usability
CPU-based operation
fast inference
easy metadata updates

VI. SYSTEM ARCHITECTURE

The proposed system architecture is designed as a multi-layer AI-based plant disease detection and crop advisory framework that integrates image processing, deep learning prediction, metadata-driven recommendations, and a user-friendly desktop interface.

The architecture begins with the user interaction layer, where the farmer or end user uploads a plant leaf image through the Tkinter-based desktop application. This layer is intentionally designed to be simple and accessible so that even users with limited technical knowledge can easily use the system.

Once the image is uploaded, it is forwarded to the preprocessing layer, where the input image undergoes resizing, normalization, and RGB conversion. The image is standardized to 224 × 224 pixels, ensuring compatibility with the MobileNetV2 model input requirements. This layer helps maintain consistency in the quality and format of the incoming data.

The preprocessed image is then passed to the deep learning inference layer, which forms the core of the system. This layer uses the MobileNetV2 transfer learning model to extract meaningful visual features such as lesion textures, fungal spots, discoloration regions, edge burn patterns, and leaf deformation characteristics. These learned features are analyzed by the classification head to determine the most probable disease class.

After classification, the output enters the confidence estimation layer, where the prediction probability is converted into a human-readable confidence percentage. This percentage helps users understand the certainty level of the diagnosis and improves trust in the system's recommendations.

The next major component is the disease advisory knowledge layer, which extends the architecture beyond simple prediction. Based on the identified disease class, the system retrieves relevant disease metadata from structured text and JSON files. This knowledge module provides:

disease description

key symptoms

causes of infection

affected plants

treatment and cure steps

step-by-step field guidance

recommended agricultural products

future prevention strategies

seasonal crop care recommendations

This layer transforms the model into a practical crop decision-support architecture rather than a standalone classifier.

The backend service layer is implemented using a Flask REST API, which coordinates communication between the frontend, preprocessing pipeline, trained MobileNetV2 model, and advisory knowledge base. The API processes prediction requests through the /predict endpoint and returns structured results to the desktop interface.

Finally, the output visualization layer displays the prediction results in a clear and user-friendly format, including disease name, confidence score, symptoms, treatment workflow, prevention tips, and seasonal care guidance.

The modular nature of the architecture allows easy updates to:

disease classes

advisory metadata

treatment products

seasonal recommendations

future retrained models

without affecting the complete system workflow.

Overall, the proposed architecture ensures accurate disease detection, fast CPU-based inference, and actionable crop management support, making it suitable for practical smart farming applications.

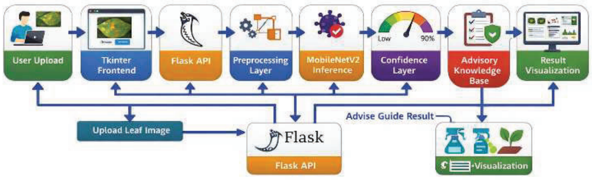
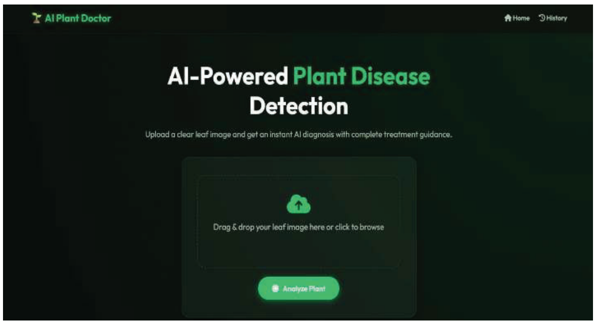


Fig 3: System Architecture of the Proposed Plant Leaf Disease Detection System

VII. RESULTS AND DISCUSSION

The proposed AI-based plant leaf disease detection and crop advisory system was evaluated using the PlantVillage dataset and tested through the developed desktop application to analyze its practical usability in real-world crop diagnosis scenarios. The results demonstrate that the system is capable of providing fast, reliable, and highly informative disease predictions along with actionable treatment guidance.



AI-Powered Plant Disease Detection

Upload a clear leaf image and get an instant AI diagnosis with complete treatment guidance.

Drag & drop your leaf image here or click to browse

Fig 4: Homepage Interface

The MobileNetV2-based transfer learning model showed strong performance in identifying diseases across multiple crop species and disease categories. During testing, the model was able to successfully recognize common disease symptoms such as leaf spots, yellowing, blight patterns, rust lesions, fungal growth regions, and mosaic texture variations. The use of transfer learning helped the model learn these complex disease-specific visual features efficiently, even with a lightweight architecture suitable for CPU-based deployment.

A major positive outcome of the system is its fast inference speed, where prediction results are generated in less than one second on standard CPU systems. This makes the proposed solution practical for use on normal laptops and low-resource devices without requiring GPU acceleration. The quick response time significantly improves usability in real-time agricultural advisory applications.

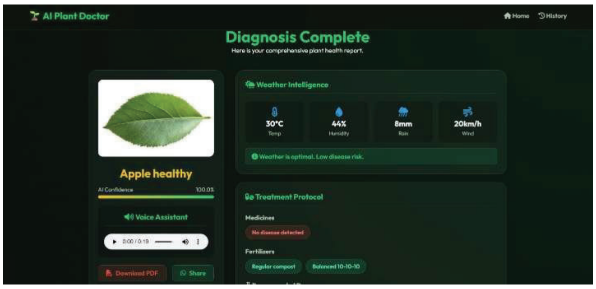


Fig 5: Analysis Page

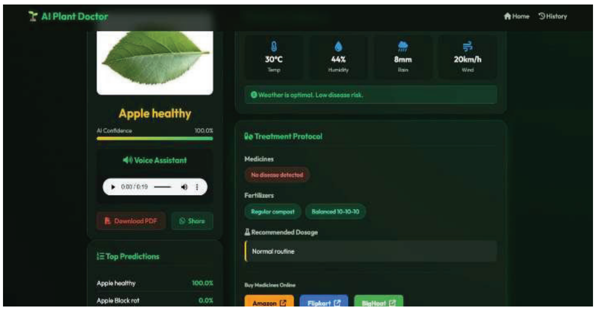


Fig 6: Detailed Result Screen: Treatment and Recommendation Section

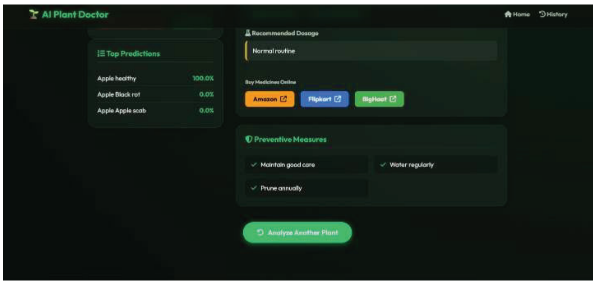


Fig 7: Final Section, Result Page

The output results are not limited to only the predicted disease name. For each uploaded leaf image, the system successfully displays:

disease name

confidence percentage

disease description

key symptoms

causes of infection

affected crops

treatment and cure suggestions

step-by-step treatment workflow

prevention tips

seasonal plant care guidance

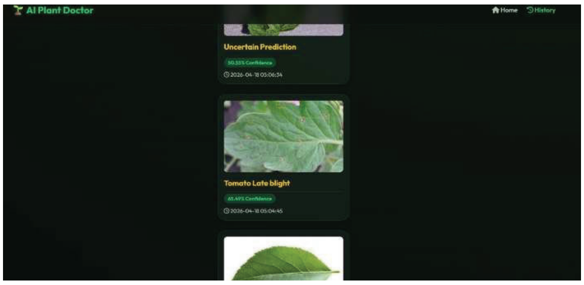


Fig 8: History Page

This rich result generation makes the system much more useful compared to conventional disease classifiers that stop at label prediction.

From a discussion perspective, one of the strongest contributions of the model is the integration of AI-based classification with a knowledge-driven advisory module. This combination bridges the gap between prediction accuracy and practical farmer decision support. Instead of requiring the farmer to search separately for disease remedies, the system directly provides treatment and prevention guidance in the same workflow.

Another important observation is that the confidence score display improves transparency and user trust. By showing how strongly the model supports a prediction, users can better understand the reliability of the diagnosis before applying treatments.

Although the system performs well on the PlantVillage benchmark dataset, one practical limitation is that the dataset mostly contains clean background laboratory-style images. In real agricultural fields, leaf images may include variations such as:

complex backgrounds

uneven lighting

partial leaf visibility

multiple overlapping leaves

camera blur

pest damage noise

These factors may affect prediction performance in uncontrolled environments.

Despite this limitation, the proposed system demonstrates strong potential for real-time smart agriculture applications, especially as a farmer-friendly desktop advisory tool. The integration of prediction, confidence estimation, treatment support, and seasonal care makes it a complete and practically meaningful crop health assistance system.

Overall, the results confirm that the proposed approach successfully transforms deep learning-based disease classification into a real-world agricultural decision-support solution.

VIII. CONCLUSION

This work presents an intelligent and practical AI-based plant leaf disease detection and crop advisory system developed to support early disease diagnosis and effective crop management. The proposed model uses MobileNetV2 transfer learning to identify plant leaf diseases from uploaded images with fast and reliable performance, while remaining lightweight enough to run efficiently on standard CPU-based systems.

A key strength of the proposed work is that it extends beyond conventional disease classification. In addition to predicting the disease name and confidence percentage, the system provides a complete advisory workflow that includes disease description, visible symptoms, possible causes, affected crops, treatment and cure suggestions, step-by-step field guidance, recommended products, future prevention methods, and seasonal plant care recommendations. This makes the solution significantly more useful for real-world farming compared to systems that provide only the disease label.

The integration of a Flask backend API with a Tkinter desktop frontend ensures a smooth user experience for image upload, prediction, and result visualization. The modular system design also allows easy updates to disease knowledge, treatment metadata, and seasonal care information without modifying the core prediction pipeline.

From a practical perspective, the developed system demonstrates how deep learning can be effectively combined with agricultural domain knowledge to create a farmer-friendly decision-support tool. By converting prediction outputs into actionable crop care guidance, the model helps users take timely corrective measures, reduce disease spread, and improve overall plant health.

Overall, the proposed solution successfully bridges the gap between AI-based disease recognition and real-world agricultural decision-making, making it a promising step toward smart farming and sustainable crop management systems.

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