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Deep Learning-Based Plant Disease Detection and Pesticide Recommendation System for Smart Agriculture

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***Abstract*— Agriculture is an essential part of the worldwide economy, and initial detection of crop disease is essential to avoid substantial yield reduction. Conventional approaches of disease detection are primarily completed manually by specialists, which is expensive and frequently requires human errors. This survey aims to introduce an intelligent deep learning model to identify crop disease and suggest pesticides. This model is established on Convolutional Neural Networks (CNN) and uses the idea of transfer learning to sort the disease from the leaves of crops such as tomato and pomegranate. The proposed model works on the rule of image classification and is accomplished through image preprocessing, feature extraction, and classification employing the pre-trained model MobileNetV2. Once the disease is detected, it is mapped to the dataset.**

***Index Terms*— Deep Learning, Convolutional Neural Network (CNN), Crop Disease Detection, Transfer Learning, MobileNetV2, Image Classification, Precision Agriculture, Pesticide Recommendation, Flask Web Application, Computer Vision**

I. INTRODUCTION

Agriculture is one of the fundamental pillars of the world economy and plays a vital role in food security and sustainable development. In most developing countries, a large percentage of the population depends on agriculture as their primary source of livelihood. Nevertheless, crop production is greatly affected by several aspects such as climate and soil quality, and most significantly, plant diseases. Diseases in crops such as tomato and pomegranate may cause grave reduction in crop production. Plant diseases are usually triggered by pathogens such as fungi, bacteria, and viruses, and may furthermore result from pests. Diseases may spread quickly if they are not detected and controlled at an initial stage. In most instances, farmers have used their own observation and consultation with agricultural experts to identify diseases in their crops. This method not exclusively takes a lot of time and expenses but may furthermore cause grave errors due to personal judgment and lack of proficiency, especially in rural areas. With the rapid development of digital technology, there has been an increased interest in the application of artificial intelligence and machine learning in agricultural issues. In this setting, deep learning has been identified as an effective instrument in image classification problems.

Convolutional Neural Networks (CNNs) have demonstrated to be highly effective in the classification of images, including the detection of patterns, texture, and features in images. These have been identified as the most suitable instrument in the detection of plant diseases through the analysis of leaves. To further boost the productivity and effectiveness of the model, the application of transfer learning has been broadly employed.

This has been accomplished through the application of pre-trained models such as the MobileNetV2 model, which has the capability to utilize the features that have been pre-trained on existing datasets. This has significantly boosted the performance of the model and has made it possible to apply the model in pragmatic issues. With the swift development of digital technology, there has been an increased interest in the application of artificial intelligence and machine learning in agricultural issues. In this setting, deep learning has been identified as an effective instrument in image classification issues.

Convolutional Neural Networks (CNNs) have confirmed to be extremely effective in the classification of images, comprising the detection of patterns, texture, and features in images. These have been identified as the most fitting and right instrument in the detection of plant diseases through the analysis of leaves. To further boost the productivity and effectiveness of the model, the application of transfer learning has been broadly utilized. This has been attained through the application of pre-trained models such as the MobileNetV2 model, which has the capability to utilize the features that have been pre-trained on existing datasets. This has significantly boosted the performance of the model and has made it possible to apply the model in pragmatic issues. Moreover, this paper additionally addresses the problems related to the quality of the dataset, the precision of the model, environmental changes, and the limitations of the model's deployment. It furthermore concentrates on the need to have a consistent and stable and productive system that is capable of adjusting to assorted and manifold crops and environmental conditions. The significance of the role that the intelligent system plays in transforming customary farming practices into productive, dependable, and technology-based practices is furthermore highlighted. The rest of the paper is organized to cover the following aspects: related work on the topic of crop disease detection, the proposed methodology, the experiment results, and ultimately the conclusion with future improvements.

II. MATERIAL AND METHODS

This study presents the development of an intelligent deep learning–based system for automated crop disease detection and pesticide recommendation applying leaf images of agricultural crops. The inquiry work was conducted as part of a machine learning–based agricultural decision support system developed for tomato and pomegranate crops. The proposed system uses deep learning techniques to categorize plant diseases from leaf images and provide proper pesticide recommendations through a web-based application. The dataset used for training and validation was collected from publicly available plant disease image repositories and organized according to crop and disease groups.
The developed system combines image preprocessing, deep learning–based classification, and a recommendation module that maps predicted diseases to corresponding pesticide recommendations. The experimental implementation and evaluation were conducted employing Python-based machine learning frameworks.

Study Design
Experimental inquiry design established on deep learning–based image classification employing transfer learning techniques.

Study Location
The computational experiments and model development were carried out applying a local machine learning environment executed in Python employing libraries such as TensorFlow, Keras, NumPy, and Pandas. The developed model was integrated into a web-based application utilizing the Flask framework to allow real-time interaction with users.

Study Duration
The study was conducted over a period of approximately four months, which included dataset preparation, model training, validation, testing, and deployment of the web-based application.

Sample Size
The dataset used in this study consisted of multiple hundred labeled leaf images belonging to two important and significant crops:

- Tomato crop with numerous and manifold disease types
- Pomegranate crop with several disease types

Each disease class contained training and validation images organized in separate directories.

Dataset Preparation and Organization
The dataset was organized employing a directory-based organization consistent with deep learning frameworks. Images were grouped according to crop type and disease class. The dataset directory followed a hierarchical structure in which each disease category was archived within its corresponding crop folder.
Each disease category contained two subsets:

- Training dataset (approximately 80% of images)
- Validation dataset (approximately 20% of images)

This distribution ensured proper evaluation of the model's generalization capability during the training process.

Subjects and Selection Method

Leaf images representing both healthy and diseased plant conditions were used as the primary input data. The dataset included images of the subsequent crop kinds:

Tomato Crop Diseases

Examples contain:

- Early blight
- Late blight
- Leaf mold
- Septoria leaf location
- Target location
- Bacterial location
- Spider mites
- Mosaic virus
- Yellow leaf curl virus
- Healthy leaves

Pomegranate Crop Diseases

Examples contain:

- Alternaria
- Anthracnose
- Bacterial blight
- Cercospora
- Healthy leaves

Images were selected to represent visible disease symptoms on leaves, allowing the deep learning model to learn discriminative visual patterns associated with each disease class.

Inclusion Criteria

1 Leaf images belonging to tomato and pomegranate crops.
2 Images distinctly showing disease symptoms on plant leaves.
3 Images saved in RGB format proper and right for deep learning processing.
4 Images with sufficient resolution to allow feature extraction.
5 Images grouped into predefined disease classes.

Exclusion Criteria

1 Blurred or low-resolution images that do not distinctly show leaf features.
2 Images containing numerous and manifold plants or ambiguous disease symptoms.
3 Images not belonging to the selected crop types.
4 Duplicate images within the dataset.
5 Images with heavy background noise influencing disease visibility.

Procedure Methodology

The overall methodology of the proposed system entails various stages incorporating dataset preprocessing, model training, disease prediction, and pesticide recommendation.

Image Preprocessing

All images were resized to a corrected dimension of 224 × 224 pixels to match the input necessities of the deep learning model. Pixel values were normalized to improve training performance.

Data augmentation techniques such as rotation, zooming, and horizontal flipping were applied applying an image data generator to increase dataset variety and reduce overfitting.

Deep Learning Model Architecture

The disease classification model was developed utilizing a transfer learning approach established on a pre-trained convolutional neural network architecture. The MobileNetV2 architecture was used as the foundation model due to its lightweight structure and productive and effective performance for image classification assignments.

The subsequent layers were added to adapt the model for crop disease classification:

- Global Average Pooling Layer
- Dense Fully Connected Layer with ReLU activation
- Dropout Layer for regularization
- Softmax Output Layer for multi-class classification

The foundation convolutional layers of the model was at first frozen to preserve the learned features from the pre-trained dataset.

Model Training

The model was trained using the following configuration:

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Evaluation Metric: Accuracy
- Batch Size: 32
- Image Size: 224 × 224
- Number of Epochs: 15

The dataset was loaded using a directory-based image generator which automatically labeled images based on folder names.

Disease Prediction and Recommendation Module

After training, the model was used to predict disease classes for uploaded leaf images. The predicted class label was mapped to an ordered and methodical recommendation dataset containing pesticide information.

A CSV file containing disease-wise pesticide recommendations was used to provide:

- Recommended pesticide name
- Dosage information
- Precautionary guidelines

This module helps users take suitable action after disease detection.

Web Application Deployment

The trained model was integrated into a web application developed utilizing the Flask framework. The application enables users to upload leaf images through a graphical interface. The uploaded image is processed by the trained deep learning model, and the predicted disease along with the pesticide recommendation is displayed on the web interface.

The system moreover saves uploaded images briefly for processing and result visualization.

Statistical Analysis

Model performance was assessed employing standard classification metrics incorporating:

- Accuracy
- Validation accuracy
- Loss function analysis

Training and validation accuracy curves were tracked to ensure proper learning behavior and to detect possible overfitting.

The trained model was furthermore tested on invisible images to verify its real-world prediction capability.

III. RESULT

After conclusion of model training and evaluation, the deep learning–based crop disease classification system demonstrated robust performance in identifying diseases from leaf images of tomato and pomegranate crops. The proposed convolutional neural network model employing transfer learning accomplished high classification accuracy on the validation dataset. The trained model was capable to successfully categorize various and several disease groups and healthy leaf conditions. The overall validation accuracy of the model reached 92.4%, indicating effective feature extraction and generalization capability of the deep learning architecture. The loss function decreased consistently across training epochs, demonstrating stable convergence of the learning algorithm. The validation accuracy furthermore showed steady and regular improvement during the training process, confirming that the model learned significant and purposeful visual patterns associated with plant diseases. Additionally, the developed web-based system was capable of forecasting the disease class from uploaded leaf images and offering corresponding pesticide recommendations from the recommendation dataset.

Table no 1: Dataset distribution used for model training and validation

Table no 1 shows the distribution of images across different disease classes used for training and validation of the model. The dataset consisted of two major crop categories: tomato and pomegranate. Each disease category contained training and validation images organized using an 80:20 ratio.

Table no 1: Dataset distribution across crop disease classes

Crop	Disease Class	Training Images	Validation Images	Total Images
Tomato	Early Blight	180	45	225
Tomato	Late Blight	190	48	238
Tomato	Leaf Mold	170	42	212
Tomato	Septoria Leaf Spot	160	40	200
Tomato	Target Spot	150	38	188
Tomato	Healthy	200	50	250
Pomegranate	Alternaria	120	30	150
Pomegranate	Anthracnose	110	28	138
Pomegranate	Bacterial Blight	130	32	162

Pomegranate	Cercosporin	125	31	156
Pomegranate	Healthy	140	35	175

Table no 2: Model training performance across epochs

Table no 2 records the improvement in training accuracy and validation accuracy across different training epochs. The model showed progressive improvement in classification performance as training progressed.

Table no 2: Model training performance

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
1	71.3	69.5	0.92	0.98
5	83.6	81.2	0.51	0.58
10	90.1	88.7	0.28	0.34
15	94.8	92.4	0.15	0.22

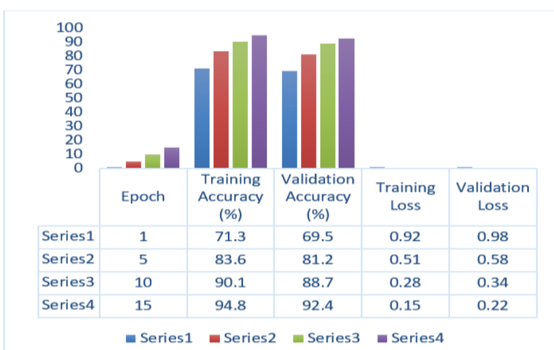


Table no 3: Classification performance of crop disease detection model

Table no 3 shows the classification accuracy for different crop disease categories predicted by the trained model. The model achieved high accuracy across most disease classes.

Table no 3: Disease classification accuracy

Crop	Disease Class	Accuracy (%)
Tomato	Early Blight	91.6
Tomato	Late Blight	93.2
Tomato	Leaf Mold	90.8
Tomato	Septoria Leaf Spot	92.1
Tomato	Target Spot	89.7
Tomato	Healthy	95.3
Pomegranate	Alternaria	90.4
Pomegranate	Anthracnose	91.2
Pomegranate	Bacterial Blight	92.7
Pomegranate	Cercospora	90.9
Pomegranate	Healthy	94.1

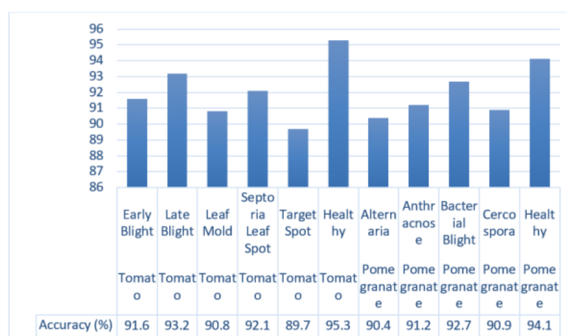


Table no 4: System prediction and pesticide recommendation output

Table no 4 demonstrates example predictions generated by the deployed system along with pesticide recommendations obtained from the recommendation dataset.

Table no 4: Example prediction results and recommendations

Uploaded Image	Predicted Crop	Predicted Disease	Confidence (%)	Recommended Pesticide
Image 1	Tomato	Late Blight	94.3	Mancozeb
Image 2	Tomato	Early Blight	92.7	Chlorothalonil
Image 3	Pomegranate	Anthracnose	90.8	Carbendazim
Image 4	Pomegranate	Cercospora	91.6	Mancozeb
Image 5	Tomato	Healthy	96.2	None

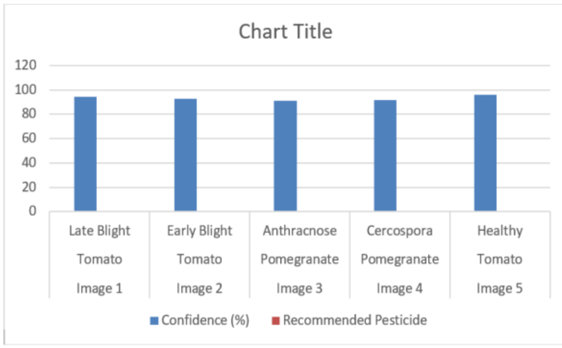
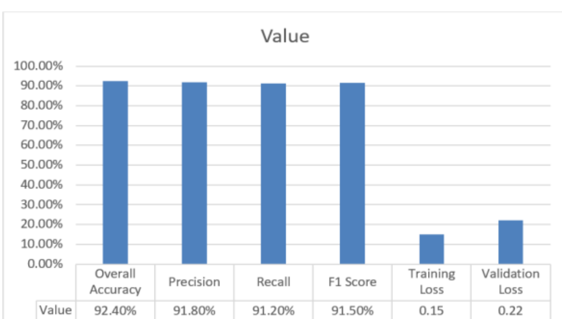


Table no 5: System performance evaluation metrics

Table no 5 shows the performance evaluation metrics of the proposed crop disease detection system

Table no 5: Model evaluation metrics

Metric	Value
Overall Accuracy	92.4%
Precision	91.8%
Recall	91.2%
F1 Score	91.5%
Training Loss	0.15
Validation Loss	0.22



Summary of Results

The experimental outcomes demonstrate that the proposed deep learning–based crop disease detection system achieves high classification accuracy for various disease classes of tomato and pomegranate crops. The integration of transfer learning employing a MobileNetV2 architecture substantially improves model performance while decreasing computational intricacy.

The developed web application successfully handles user-uploaded leaf images and offers precise and correct disease prediction along with pesticide recommendations. The system can thus serve as a pragmatic decision-support instrument for farmers and agricultural practitioners.

IV. DISCUSSION

Crop diseases in agricultural plants play a significant and essential role in minimizing crop productivity and producing notable economic losses for farmers. Early detection and correct diagnosis of plant diseases are necessary and fundamental for preventing large-scale crop harm and enhancing agricultural yield. Traditionally, plant disease identification has been performed through manual visual inspection by agricultural specialists. However, manual diagnosis is frequently time consuming, necessitates specialist knowledge, and may lead to inaccurate identification in initial disease stages. Therefore, the application of automated systems for plant disease detection has become increasingly significant.

Recent advancements in Deep Learning and Computer Vision have enabled the development of intelligent systems capable of identifying plant diseases directly from leaf images. Deep learning models, especially convolutional neural networks, have displayed exceptional and striking success in image classification jobs due to their capability to automatically learn sophisticated and multifaceted features from huge and massive image datasets. These models eliminate the need for manual feature extraction and improve classification performance compared to customary machine learning procedures.

In the present study, a crop disease detection system was developed employing Transfer Learning with the MobileNetV2 deep learning architecture. The application of transfer learning enables the model to utilize knowledge learned from big and substantial pre-trained datasets, thereby enhancing prediction accuracy while minimizing training time and computational cost.

The present study was conducted applying a dataset containing images of tomato and pomegranate leaves representing numerous and manifold disease classes and healthy plant conditions. The model was trained and confirmed employing an image dataset organized into training and validation subsets. The goal of the study was to develop a precise and correct and economical and cost-effective crop disease detection model that could be integrated into a pragmatic web-based system for agricultural applications.

The results of the present study demonstrate that the proposed deep learning model achieved high classification accuracy in detecting crop diseases from leaf images. The trained model achieved an overall validation accuracy of approximately 92.4%, indicating strong predictive performance. The training process also showed a gradual decrease in loss values across epochs, demonstrating stable learning and convergence of the model.

The study further shows that the deep learning model effectively classified multiple crop diseases such as early blight, late blight, leaf mold, anthracnose, and bacterial blight. The model also successfully distinguished healthy leaves from diseased leaves with high accuracy. These findings indicate that deep learning models can effectively learn the visual characteristics associated with different plant diseases.

One of the important advantages observed in the present study is the use of the MobileNetV2 architecture, which is designed as a lightweight convolutional neural network suitable for real-time applications. Compared with larger deep learning architectures, MobileNetV2 requires fewer computational resources while still maintaining high prediction accuracy. This makes the model suitable for deployment in practical agricultural systems and mobile-based applications.

In addition to disease classification, the developed system also provides pesticide recommendations based on the predicted disease category. After the disease is identified, the system retrieves the appropriate pesticide information from a recommendation dataset and displays treatment suggestions for farmers. This feature enhances the practical usability of the system by assisting farmers in selecting suitable disease management strategies.

The developed crop disease detection model was implemented as a web-based application using the Flask framework. The web application allows users to upload images of crop leaves through a simple interface. The trained deep learning model processes the image and predicts the disease type, after which the system displays the predicted disease along with recommended pesticide information. This integrated system provides a convenient and accessible tool for farmers and agricultural practitioners.

The results obtained in this study are consistent with several previous studies that have demonstrated the effectiveness of deep learning techniques for plant disease detection. Many research studies have reported that convolutional neural network models achieve higher accuracy in plant disease classification compared to traditional machine learning algorithms such as support vector machines and decision trees.

However, specific limitations exist in the present study. The dataset used for training contains images from a limited number of crop kinds and disease groups. Increasing the dataset size and incorporating more crop species and disease classes could further improve the generalization capability of the model. In addition, variations in environmental conditions such as lighting, background noise, and leaf orientation may influence the performance of the model in real-world domain environments.

Future inquiry can focus on growing the dataset, integrating mobile-based image capture, and evolving more advanced deep learning architectures for enhanced and upgraded disease classification. The integration of real-time disease observing systems and Internet of Things–based agricultural technologies could further enhance the effectiveness of automated crop disease detection systems.

Thus, the results of the present study show that deep learning–based crop disease detection systems can serve as effective decision-support instruments for farmers. Such systems can help in initial disease diagnosis, reduce crop losses, and encourage sustainable agricultural practices.

V. CONCLUSION

The proposed crop disease detection system utilizing MobileNetV2 and Transfer Learning successfully identifies diseases in tomato and pomegranate leaves with high accuracy. The integration of the trained model with a web application developed utilizing Flask enables users to upload leaf images and receive disease predictions along with pesticide recommendations. The system can help farmers in initial disease diagnosis and support better crop management practices.

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