FineKrop: Crop Disease Detection Using Deep Learning

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1. Abstract - *FineKrop is a deep learning-based system developed for detecting diseases in tomato leaves using computer vision techniques.The system accepts a leaf image through a web-based interface, pre-processes the image, and uses a Convolutional Neural Network (CNN) to classify it into one of four categories: healthy, early blight, late blight, and Tomato Yellow Leaf Curl Virus. A balanced dataset of 4,000 tomato leaf images was prepared from the PlantVillage dataset and divided into training, validation, and testing sets using a 70:15:15 ratio. The CNN model achieved a testing accuracy of 88.17%, with a precision of 88.30%, recall of 88.17%, and F1-score of 87.85%. The results demonstrate that the proposed system can effectively classify the selected tomato leaf categories under the tested dataset conditions. However, further evaluation using field-collected images is required to assess its performance under real agricultural conditions. FineKrop provides a foundation for developing accessible image-based crop disease detection tools for agricultural applications.*

Keywords-Crop Disease Detection, Deep Learning, Computer Vision, Convolutional Neural Network (CNN), Image Processing, Plant Disease Classification, Smart Agriculture.

2. INTRODUCTION

Agriculture plays an important role in food production and the economy, but crop diseases can significantly affect productivity and crop quality. Traditional disease identification often depends on visual inspection by farmers or agricultural experts. This approach can be time-consuming, subjective, and difficult to apply when expert assistance is not immediately available. Early and reliable identification is therefore important for reducing crop losses and supporting timely crop management.

Recent advances in artificial intelligence, particularly deep learning and computer vision, have created opportunities for automated plant disease recognition. Image-based models can learn disease-related visual characteristics directly from training data and classify unseen leaf images. Convolutional neural networks are especially suitable for image classification.

FineKrop is proposed as a deep-learning-based crop disease detection system. A user provides a crop leaf image, the image is preprocessed, and a trained CNN model predicts the disease category. The objective is to make disease identification faster, simpler, and more accessible through a user-friendly application.

2.1 Background of Crop Disease Detection

Crop disease detection refers to the process of identifying whether a plant is healthy or affected by a particular disease. Disease symptoms are often visible on plant leaves, making leaf images a useful source of information for automated detection. Earlier computer-based approaches generally depended on manually designed features. Researchers had to identify characteristics such as color, shape, texture, and edges and then provide these features to a machine learning classifier. Deep learning changed this approach by allowing the model to learn useful features automatically from images. Mohanty et al. [6] demonstrated the potential of deep convolutional neural networks for plant disease detection using more than 54,000 leaf images and multiple crop and disease categories. Their work showed that image-based deep learning could achieve high classification performance under controlled conditions. The development of deep learning has therefore made automated plant disease detection an active research area. FineKrop follows this research direction by using crop leaf images as the primary input for disease classification.

2.2 Impact of Crop Diseases on Agriculture

Crop diseases can affect agricultural production by damaging leaves, reducing plant growth, lowering crop quality, and decreasing final yield. When disease symptoms are ignored during the early stages, the infection may spread to other parts of the plant or nearby plants. The impact is not limited to crop production. Disease-related losses can also increase the financial burden on farmers. Farmers may need to spend additional money on disease management, pesticides, labour, and repeated crop monitoring. The problem becomes more difficult when farmers do not have immediate access to agricultural experts. Traditional diagnosis may require the farmer to collect a sample or contact an expert, which can delay decision-making. Therefore, automated image-based disease detection can serve as an initial decision-support mechanism. It does not replace agricultural experts, but it can help users identify possible disease categories quickly and decide whether further expert examination is required.

2.3 Need for Automated Disease Detection

Manual disease detection requires continuous observation of crops. For large agricultural fields, inspecting every plant manually is difficult and time-consuming.

An automated system can process a large number of images in a shorter period. Such a system can provide consistent predictions based on the patterns learned during model training. The need for automation is also supported by previous research. Ferentinos [5] developed CNN-based plant disease detection models using 87,848 images representing 58 plant-disease combinations and reported high classification accuracy on unseen images. However, high laboratory accuracy does not automatically guarantee good field performance. Real agricultural images may contain different backgrounds, lighting conditions, camera angles, overlapping leaves, and other visual variations. Therefore, automated systems must be developed with practical deployment in mind.

2.4 Role of Artificial Intelligence in Agriculture

Artificial Intelligence has become increasingly useful in agriculture because agricultural activities generate large amounts of visual and environmental information.AI can be used in several agricultural applications, including:

- Crop disease detection
- Weed identification
- Pest detection
- Crop monitoring
- Yield prediction
- Soil analysis
- Irrigation management
- Plant growth monitoring

In crop disease detection, AI models can learn relationships between image features and disease classes. Instead of requiring the user to manually define every disease characteristic, deep learning models can learn important visual representations during training. Recent research also demonstrates the use of AI with CNNs, machine learning algorithms, mobile applications, and transformer-based architectures for crop disease identification.

2.5 Role of Deep Learning and CNN

Deep Learning is a branch of machine learning based on neural networks with multiple layers. It is particularly effective for tasks where large amounts of complex data need to be analyzed. A Convolutional Neural Network is one of the most widely used deep learning architectures for image classification. A CNN generally contains convolutional layers, activation functions, pooling layers, and fully connected or classification layers. The convolutional layers identify visual features from images. In the early layers, the network can learn simple patterns such as edges and color transitions. Deeper layers can learn more complex patterns related to shapes, textures, spots, and disease symptoms. CNNs are therefore suitable for crop disease detection because disease symptoms often appear as visual patterns on leaves. Research has demonstrated the effectiveness of CNN-based approaches for plant disease identification.

2.6 Motivation of the Proposed Work

The motivation for FineKrop comes from the need for a simple and accessible crop disease detection system. Many existing research models achieve high accuracy, but several challenges remain. Some systems are developed using controlled datasets, while actual field images may have different backgrounds and lighting conditions. Other advanced models can require considerable computational resources. Recent research has highlighted the gap between laboratory performance and real-world agricultural deployment. The 2026 explainable CNN study specifically notes challenges related to uncontrolled field conditions, computational requirements, scalability, and model interpretability. FineKrop is motivated by the idea of bringing deep learning-based disease detection into a simple user-oriented system. The system is designed to accept a crop leaf image and provide a disease prediction without requiring the user to understand the internal machine learning process.

3. LITERATURE REVIEW

Deep learning-based plant disease detection has developed significantly over the last decade. Researchers have investigated CNNs, transfer learning, mobile applications, hybrid CNN-transformer models, and explainable AI.

3.1 Deep Learning for Plant Disease Detection

Mohanty et al.[1], Hughes, and Salathé introduced one of the influential studies in image-based plant disease detection in 2016 [1].Their work used a public dataset containing 54,306 images and developed a deep convolutional neural network to identify 14 crop species and 26 disease or healthy categories. The model achieved 99.35% accuracy on a held-out test set. The study demonstrated that deep learning could automatically learn useful visual characteristics from plant leaf images. However, the researchers also showed that performance decreased substantially when the model was tested on images captured under conditions different from the training data. This observation is important because agricultural images captured in real fields are usually more complex than laboratory images. This study established an important foundation for systems such as FineKrop.

3.2 CNN-Based Plant Disease Classification

Ferentinos[2] investigated deep learning models for plant disease detection and diagnosis in 2018 [2]. The study used an open database containing 87,848 images representing 58 plant-disease combinations from 25 plant species. The final model achieved 99.53% accuracy on 17,548 previously unseen images. The study demonstrated the ability of CNN models to classify a large number of plant disease categories. It also showed the importance of having sufficiently large image datasets for training deep learning systems. For FineKrop, this research supports the use of CNN-based image classification as a suitable approach for crop disease identification.

3.3 Deep Learning for Multiple Crop Diseases

A 2022 study titled Plant Disease Identification Using a Novel Convolutional Neural Network [3] proposed a CNN architecture designed to improve classification performance while reducing the number of model parameters. The architecture incorporated an inception layer, residual connections, and depthwise separable convolution. The proposed model was tested using three datasets. It achieved 99.39% accuracy on PlantVillage, 99.66% on a rice disease dataset, and 76.59% on a cassava dataset. The variation in accuracy across the three datasets shows that model performance depends not only on the architecture but also on the characteristics of the dataset. This observation is relevant to FineKrop because the system should not be evaluated only using a single accuracy value. Dataset characteristics and testing conditions should also be considered

3.4 Transfer learning in plant Disease Detection

Transfer learning is another important approach used in plant disease detection. Instead of training a deep network completely from the beginning, a pretrained model can be adapted to a new classification task. Transfer learning can be useful when the available agricultural dataset is relatively small. A pretrained network already contains general visual representations, which can then be fine-tuned using crop images. Research in this area has investigated models such as DenseNet, ResNet, VGG, AlexNet, and other pretrained CNN architectures. Transfer learning can reduce training requirements and may improve performance when the target dataset is limited. However, the selected pretrained architecture, dataset quality, image distribution, and fine-tuning strategy can affect the final results. FineKrop can be extended in the future by comparing a custom CNN with pretrained architectures.

3.5 Mobile-Based Crop Disease Detection

Mobile deployment is important because smartphones can provide farmers with a convenient way to capture crop images.A 2023 study developed a mobile application for tomato disease identification using fine-tuned CNN models [4]. The researchers evaluated five CNN architectures, and DenseNet-121 achieved the best reported accuracy of 99.85%. The application also supported English and two Indian languages. Importantly, the study incorporated real-time field data along with Plant Village images. This research demonstrates that crop disease detection can move beyond laboratory experiments toward user-oriented applications. FineKrop follows a similar direction by providing a simple interface through which a user can submit a crop leaf image. In future development, the system can be extended into a complete mobile application.

3.6 Advanced Deep Learning Approaches

Recent research has started combining CNNs with newer architectures such as Vision Transformers. Meng et al. [6] proposed a dual-branch model that combines CNN and Vision Transformer branches. The CNN branch captures local visual features, while the transformer branch captures global information. The researchers reported 99.71% accuracy on the PlantVillage dataset and 98.78% on the Potato Leaf dataset.

3.7 Explainable AI for Plant Disease Detection

Deep learning models are often considered difficult to interpret because users may not know why a particular prediction was produced. Explainable Artificial Intelligence can help address this problem by showing which areas of an image contributed to a model's prediction. A 2026 Scientific Reports study proposed a lightweight explainable CNN using the study is relevant to FineKrop because it shows that desease detection models can be made both efficient and easier to interpret. However such approaches may require additional computation and have not been fully evaluated under diverse field conditions. The model was evaluated on the PlantVillage dataset containing 54,305 images covering 38 crop diseases from 14 crops and reported a test accuracy of 97.63%.Grad-CAM was used to generate visual heatmaps indicating important image regions. Such explanations can potentially improve user confidence because the system can provide visual evidence associated with its prediction.

3.8 Comparative Analysis of Existing Studies

The reviewed studies show a clear development in plant disease detection research.

Year	Approach	Main Contribution
2016	Deep CNN	Demonstrated image-based plant disease classification
2018	CNN models	Large-scale multi-crop disease classification
2022	Improved CNN	Reduced complexity using architectural improvements
2023	Fine-tuned CNN + Mobile App	Practical mobile-based tomato disease detection
2024	ML and DL comparison	Compared CNN, SVM and Random Forest approaches
2025	CNN + Vision Transformer	Combined local and global image features
2026	Explainable lightweight CNN	Combined efficient CNN architecture with Grad-CAM

3.9 Research Gap

Based on the reviewed studies a clear gap remains between high laboratory accuracy and practical field deployment. Many existing models are evaluated using controlled datasets while real field images introduce changes in lighting, background, leaf orientation, and image quality.In addition advanced architectures may require greater computational resources. These limitations motivate the development of FineKrop as a simple CNN-based system that can provide preliminart disease classification through an accessible user interface.

4. PROBLEM STATEMENT AND OBJECTIVES

4.1 Problem Statement

Crop diseases can significantly affect agricultural productivity when they are not identified at an early stage. Traditional disease identification generally depends on manual observation and expert knowledge. This process can be slow and may not always be available to farmers. Although several AI-based disease detection systems have been developed, many existing approaches are trained and tested using controlled image datasets. Their performance can be affected when images are captured under different lighting, backgrounds, and field conditions. Therefore, there is a need for an accessible image-based system that can automatically analyze crop leaf images and provide a preliminary disease classification using deep learning. The proposed FineKrop system aims to address this problem by using a CNN-based model to analyze crop leaf images and predict the corresponding disease category.

4.2 Research Objectives

The main objectives of FineKrop are:

1. To develop an CNN-based system for tomato leaf disease detection.
2. To prepare and preprocess a balanced dataset for model training.
3. To tain the CNN model to classify healthycand diseased tomato leaves.
4. To evaluate the model using accuracy, precision, recall, and F1-score.
5. To provide a simple interface for uploading crop leaf images and viewing predictions
6. To analyze the limitations of the proposed approach under practical conditions.
7. To identify possible improvements for future deployment.

4.3 Scope of the Proposed System

The scope of FineKrop is primarily focused on image-based crop disease detection. The system accepts a crop leaf image as input and processes the image using a trained deep learning model. The model predicts the disease class from the classes included in the training dataset. The current system is intended as a preliminary disease identification tool rather than a replacement for professional agricultural diagnosis.

Future versions can include additional crops, additional diseases, mobile deployment, multilingual support, disease severity estimation, treatment recommendations, and explainable AI.

Leaf Image --> Preprocessing --> CNN Model --> Feature Extraction --> Classification --> Disease Prediction.

4.4 Research Questions

The research is guided by the following questions:

RQ1: Can deep learning be used effectively for crop disease classification from leaf images?
RQ2: How does image preprocessing affect crop disease classification?
RQ3: How accurately can the FineKrop model classify the disease categories included in the dataset?
RQ4: What are the major limitations of image-based crop disease detection?
RQ5: Can the proposed system be extended for mobile and real-time agricultural applications?

5. PROPOSED FINEKROP SYSTEM

5.1 Overview of FineKrop

FineKrop is an AI-powered crop disease detection system designed to identify diseases from crop leaf images. The system follows a simple process. First, the user selects or captures an image of a crop leaf. The image is then provided to the preprocessing module. After preprocessing, the image is passed to the trained deep learning model. The model analyzes the visual patterns present in the leaf and predicts the disease category. The result is then displayed through the FineKrop interface. The overall workflow can be represented as:

Leaf Image → Preprocessing → CNN Model → Feature Extraction → Classification → Disease Prediction

5.2 System Architecture

The FineKrop architecture consists of the following major components:

1. User Interface
2. Image Input Module
3. Image Preprocessing Module
4. Deep Learning Model
5. Classification Module
6. Prediction Output Module

The preprocessing module prepares the image for the model. The CNN model extracts meaningful visual features from the image. The classification layer maps the extracted features to the disease classes. Finally, the prediction module displays the detected disease.

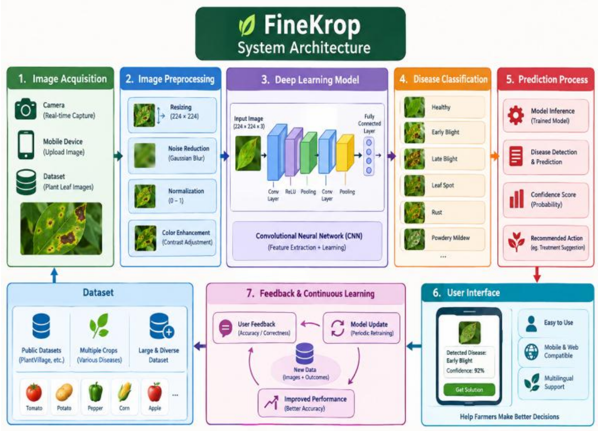


Figure 1: FineKrop System Architecture

Fig. 1. FineKrop system Architecture

5.3 Image Acquisition

Image acquisition is the first stage of the FineKrop system. The system accepts crop leaf images obtained from the selected dataset or user-provided images. For a research experiment, all images should be stored with their corresponding class labels. The image collection should contain both healthy and diseased samples where applicable. The quality and diversity of images are important because the model learns directly from the available training examples.

5.4 Image Preprocessing

Raw images may have different dimensions, brightness levels, orientations, and image quality. Therefore, preprocessing is performed before the images are given to the CNN model.

For example, all input images are resized to 150×150 pixels so that they have a common input dimension. The pixel values are normalized to the range **[0,1]** before being provided to the CNN model.

5.5 Deep Learning Model

The core of FineKrop is a custom Convolutional Neural Network (CNN) developed for four-class leaf disease classification. The input images are resized to 150 × 150 pixels with three RGB channels. The model consists of two convolutional layers with 32 and 64 filters respectively, each followed by a 2 × 2 max-pooling layer. The extracted feature maps are then flattened and passed through a fully connected layer containing 64 neurons with ReLU activation. A dropout layer with a rate of 0.5 is used to reduce overfitting. The final dense layer contains four neurons with Softmax activation, corresponding to the four classification categories: healthy, early blight, late blight, and Tomato Yellow Leaf Curl Virus.

Input size --> RGB channels --> two convolution layers --> 32 and 64 filters --> pooling -->64-neuron dense layer --> ReLU --> dropout 0.5 --> softmax --> four classes

The final classification layer produces probabilities for the disease classes.The predicted class is selected based on the highest model probability.

5.6 Disease Classification

Disease classification is the final machine learning stage. After feature extraction, the model generates an output corresponding to the classes used during training. For example, the model was trained to classify four categories: healthy, early blight, late blight, and Tomato Yellow Leaf Curl Virus. Therefore, the final classification layer produces four output values. The class with the highest predicted probability is selected as the model's final prediction.

Predicted Class: Early Blight
Confidence: 64.26%

5.7 Prediction Process

The prediction process consists of the following steps:

1. User uploads a crop leaf image.
2. The system receives the image.
3. The image is resized according to the model's input requirement.
4. Pixel values are normalized.
5. The processed image is passed to the trained CNN.
6. The CNN extracts important visual features.
7. The classification layer predicts the disease class.
8. The highest-probability class is selected.
9. The prediction is displayed to the user.

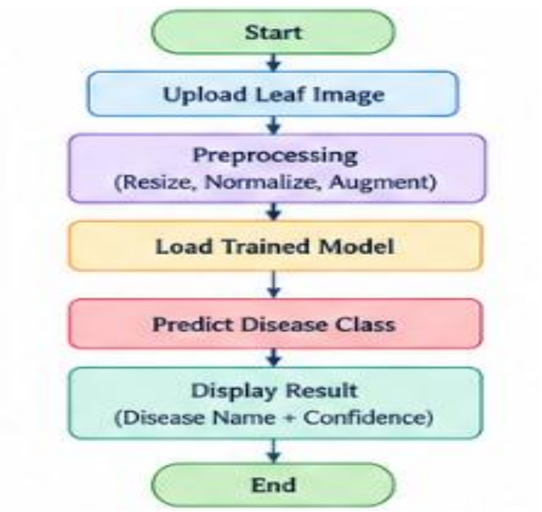


Fig. 2. CNN model workflow

This process allows disease identification to be performed automatically without requiring the user to manually analyze the leaf symptoms.

5.8 User Interface

The FineKrop user interface is designed to keep the disease detection process simple.

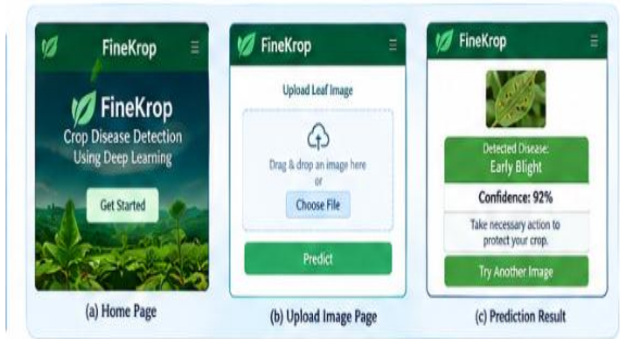


Fig. 3. User Interface

A typical workflow contains:

- Image upload option
- Image preview
- Prediction button
- Disease prediction
- Confidence/result display

The interface should be understandable even for users who do not have technical knowledge.

6. METHODOLOGY

6.1 Dataset Description

The dataset used for FineKrop was prepared from the PlantVillage dataset. For this study, four tomato leaf categories were selected: healthy, early blight, late blight, and Tomato Yellow Leaf Curl Virus. To maintain a balanced experimental dataset, 1,000 images were selected for each category, resulting in a total of 4,000 images. The dataset was divided into training, validation, and testing subsets using a 70:15:15 split, containing 2,800, 600, and 600 images respectively.

6.2 Dataset Preparation

Before training, the dataset is organized according to disease classes. The images are divided into separate subsets for training, validation, and testing.
For example:

- Training set: 70% (2,800 images)

- Validation set: 15% (600 images)
- Testing set: 15% (600 images)

The training set is used to learn the model parameters.

6.3 Image Preprocessing Techniques

Image preprocessing ensures that the input data is suitable for deep learning. The main preprocessing operations used in FineKrop are:

1) **Image Resizing:** Images were resized to a fixed dimension required by the model.
2) **Normalization:** Pixel values are normalized so that the input values are within a suitable numerical range.
3) **Data Organization:** Images are organized according to their disease labels so that the model can learn the relationship between images and classes.

6.4 Model Development

The model is developed using a CNN-based deep learning approach. During development, the input images are passed through convolutional layers to extract visual patterns. Pooling layers were used to reduce spatial dimensions of feature maps while retaining important visual information. The extracted features are then passed to classification layers. The final layer uses an appropriate activation function to generate class probabilities.

6.5 Model Training

During training, the CNN learns from the labelled training images. The model parameters are updated by minimizing the selected loss function. The CNN model was trained for 5 epochs using a batch size of 10. The Adam optimizer was used with categorical cross-entropy as the loss function. During training, the model learned from 2,800 training images, while 600 validation images were used to monitor its performance. The training accuracy increased from 54.39% in the first epoch to 89.61% in the fifth epoch. Validation accuracy reached a maximum of 88.83% in the fourth epoch.

6.6 Model Testing and Validation

After training, the model was evaluated using 600 unseen test images. These images were kept separate from the training and validation datasets and were not used to update the model parameters. The validation set contained 600 images and was used to monitor model performance during training. If the final accuracy of 88.17% was obtained using the fifth-epoch model so. If you selected the fourth-epoch model because it had the highest validation accuracy. The final test accuracy was 88.17%. Precision, recall, F1-score, and confusion matrix analysis were also used to provide a more detailed evaluation of classification performance.

6.7 Disease Prediction Workflow

The complete FineKrop prediction workflow is:

Step 1: Upload leaf image.
Step 2: Validate the image.
Step 3: Resize the image.
Step 4: Normalize the image.
Step 5: Pass the image to the trained CNN.
Step 6: Extract disease-related visual features.
Step 7: Calculate probabilities for disease classes.
Step 8: Select the class with the highest probability.
Step 9: Display the predicted class.

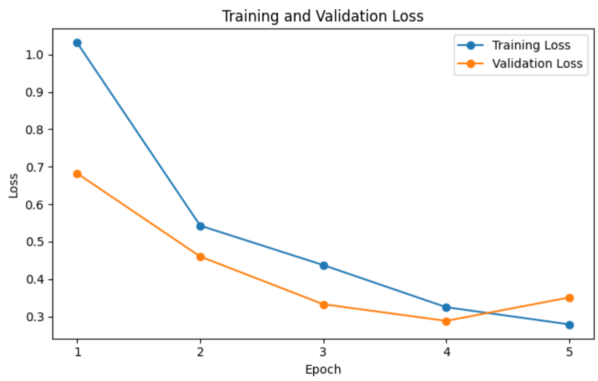
7. RESULTS AND DISCUSSION

7.1 Experimental Setup

The FineKrop model was trained and evaluated using the prepared crop leaf image dataset.

7.2 Training and Validation Results

The training and validation performance of the FineKrop model was evaluated using accuracy and loss measurements across five training epochs. During training, the model learns patterns from the training images. Training accuracy generally increases as the model learns. Validation accuracy provides an indication of how



well the model performs on data that was not directly used to update its parameters.

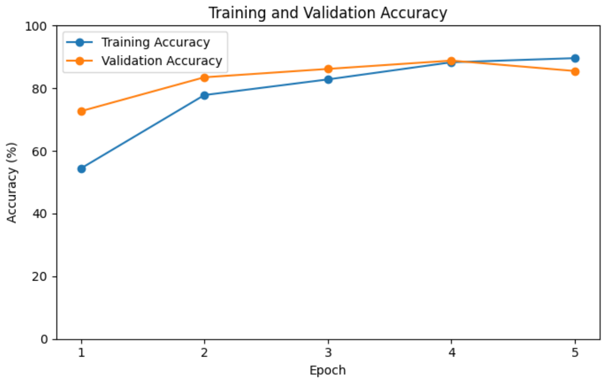


Fig. 4. Training and Validation Accuracy

7.3 Accuracy Analysis

The final testing accuracy of FineKrop was:

Testing Accuracy: 88.17%

The obtained accuracy indicates the percentage of test images correctly classified by the model. However, accuracy alone is not sufficient to evaluate a multi-class disease detection system. Therefore, precision, recall, F1-score, and confusion matrix results should also be considered. The result should also be compared carefully with previous research. Direct comparison is meaningful only when datasets, classes, testing procedures, and experimental conditions are sufficiently similar.

7.4 Precision, Recall and F1-Score

The model's performance for each disease class can be reported using precision, recall, and F1-score.

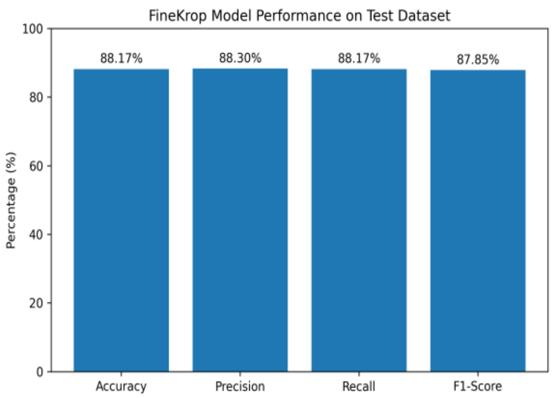


Fig. 5. Confusion Matrix

Disease Class	Precision	Recall	F1-Score
Early Blight	0.88	0.69	0.78
Healthy	0.91	1.00	0.96
Late Blight	0.80	0.88	0.84
Tomato Yellow Leaf Curl Virus	0.94	0.95	0.95
Weighted Average	0.88	0.88	0.88

These results help identify classes that are easier or more difficult for the model to recognize. For example, a class with high precision but lower recall may indicate that the model makes relatively few false positive predictions but misses some actual samples.

7.5 Sample Prediction Results

The following sample predictions demonstrate the classification performance of FineKrop on selected test images.

Input Image	Actual Class	Predicted Class	Confidence
Early Blight	Early Blight	Early Blight	64.26%
Healthy	Healthy	Healthy	100.00%
Late Blight	Late Blight	Late Blight	96.10%
Tomato Yellow Leaf Curl Virus	Tomato Yellow Leaf Curl Virus	Tomato Yellow Leaf Curl Virus	77.77%
Early Blight	Early Blight	Early Blight	98.88%

The sample results provide a visual demonstration of the system's ability to classify crop leaf images.

7.6 Comparison with Existing Methods

FineKrop can be compared with existing research approaches.

Study	Year	Method	Reported Performance
Mohanty et al.[1]	2016	Deep CNN	99.35%
Ferentinos[2]	2018	CNN models	99.53%
Novel CNN study[3]	2022	Improved CNN	99.39% on PlantVillage
Mobile tomato study[4]	2023	Fine-tuned CNN	99.85%
I2CT study[5]	2024	ML and DL	Promising results
Meng et al.[6]	2025	CNN + ViT	99.71%
Ray et al.[7]	2026	Explainable	97.63% test

		CNN	accuracy
FineKrop	2026	Custom CNN	88.17%

The values reported for previous studies should not be interpreted as a direct ranking because the studies used different datasets, disease classes, model architectures, and experimental conditions.

7.7 Discussion of Results

The experimental results show that the FineKrop CNN model achieved an overall test accuracy of 88.17% on 600 unseen test images. The model obtained a precision of 88.30%, recall of 88.17%, and F1-score of 87.85%. Among the four classes, the healthy class achieved the strongest performance, with 1.00 recall and 0.96 F1-score. Tomato Yellow Leaf Curl Virus also showed strong classification performance, with a precision of 0.94, recall of 0.95, and F1-score of 0.95. Late blight achieved a recall of 0.88, while early blight was comparatively more difficult to classify, with a recall of 0.69. The confusion matrix shows that several early blight images were classified as late blight, indicating visual similarity between these disease categories.

The results show that proposed CNN can classify the four selected tomato leaf categories reasonably well under the tested dataset conditions. However, this performance should not be taken as evidence that the same accuracy will be achieved in real agricultural fields. The PlantVillage images are collected under relatively controlled conditions, while real agricultural images can contain variations in background, lighting, camera quality, leaf orientation, and disease severity. Therefore, further evaluation using field-collected images is required before claiming reliable real-world deployment.

8. FUTURE SCOPE

8.1 Real-Time Disease Detection

In future work FineKrop can be extended to support additional crops and desease categories. A larger dataset containing field images can also be used to improve robustness under different lighting and background conditions.

8.2 Mobile Application Integration

FineKrop can be developed as a dedicated Android or cross-platform mobile application. A mobile version would make the system more accessible to farmers and field workers. The application could provide:

- Camera-based image capture
- Disease prediction
- Confidence score
- Disease information
- Prediction history
- Offline prediction support

8.3 More Crop and Disease Classes

The current system can be expanded by adding additional crop species and disease categories. A larger and more diverse dataset can improve the ability of the system to handle different types of plants and disease symptoms. Future research can also investigate cross-crop disease recognition.

8.4 Multilingual Support

Agricultural users may prefer to interact with applications in their local language.Therefore, future versions of FineKrop can provide multilingual support, including regional Indian languages.The interface can display disease names, explanations, and instructions in the user's selected language.

8.5 Explainable AI Integration

Explainable AI can be added to show why the model produced a particular prediction. For example, Grad-CAM can generate a heatmap showing the regions of the leaf that influenced the CNN prediction. Recent research has demonstrated the use of Grad-CAM together with lightweight CNN architectures for explainable crop disease detection. This feature could make FineKrop more transparent and useful for farmers, students, researchers, and agricultural experts.

9. CONCLUSION

Crop diseases are an important challenge in agriculture because delayed identification can lead to crop damage, reduced productivity, and financial losses. This research presented FineKrop, a deep learning-based crop disease detection system that uses crop leaf images for automated disease classification. The proposed system combines image preprocessing, CNN-based feature extraction, disease classification, and a simple user interface.

The implemented CNN model was trained and evaluated on a balanced dataset of 4,000 tomato leaf images covering four categories: healthy, early blight, late blight, and Tomato Yellow Leaf Curl Virus. The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio. On the 600-image unseen test set, the model achieved an accuracy of 88.17%, precision of 88.30%, recall of 88.17%, and F1-score of 87.85%. The results indicate that the proposed model can effectively classify the selected tomato leaf categories under the tested dataset conditions.

The result show that a custom CNN can provide useful classification performance for the selected tomato leaf categories. At the same time the evaluation highlights the limitation of using controlled datasets for real-world agricultural applications

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