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Crop Disease Detection System Using Convolutional Neural Network

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Abstract: *One of the essential and tedious task in agricultural practices detecting of disease on crops. It requires huge time as well as skilled labour. This paper proposes a smart and efficient technique for the detection of crop disease which uses machine learning techniques. Every year India loses a significant amount of annual crop yield due to unidentified plant diseases. The traditional method of disease detection is manual examination by either farmers or experts, which may be time-consuming and inaccurate. It is proving infeasible for many small and medium-sized farms around the world. To mitigate this issue, a computer aided disease recognition model is proposed. It uses leaf image classification with the help of deep convolutional networks. In this paper, CNN was proposed to detect plant disease. It has three processing steps namely feature extraction, downsizing image, and classification. In CNN, the convolutional layer extracts the feature from the plant image. It helps to give personalized recommendations to the farmers based on soil features, temperature, and humidity.*

Keywords: Crop Disease Detection, CNN (Convolutional Neural Network),Agriculture, image Processing

I. INTRODUCTION

Agriculture is a crucial sector for global food security, but it faces numerous challenges, including crop diseases that lead to significant losses in yield and quality. Early and accurate detection of these diseases is vital for effective management and mitigation. Traditional methods of disease detection, which rely on manual inspection and expertise, are often time-consuming, labor-intensive, and prone to error, especially in large-scale farming.Recent advances in machine learning, particularly in the domain of image processing, offer promising solutions to this problem. **Convolutional Neural Networks (CNNs)**, a class of deep learning models, have demonstrated superior performance in analyzing and classifying complex patterns in images. In the context of crop disease detection, CNNs can be trained to recognize visual symptoms of various plant diseases from leaf images with high accuracy. By automating this process, CNNs not only improve the speed and precision of disease identification but also enable scalable monitoring systems for large farms.

This paper explores the application of CNNs for detecting crop diseases, focusing on developing and optimizing models to achieve reliable and efficient disease identification. The research aims to contribute to the growing body of knowledge on using artificial intelligence in agriculture, offering solutions that can help farmers minimize losses and improve crop management practices.

CNNs are particularly well-suited for crop disease detection as they can automatically learn discriminative features from images of infected plant parts, such as leaves. Unlike traditional machine learning models that require manual feature extraction, CNNs operate end-to-end, learning to classify diseases directly from raw image data. This allows them to detect even subtle differences in disease symptoms, leading to highly accurate classifications. By leveraging large datasets of annotated plant disease images, CNN models can be trained to recognize a wide range of diseases, making them a valuable tool for real-time, automated disease monitoring in agriculture.

Several studies have demonstrated the efficacy of CNNs in crop disease detection, achieving high accuracy in recognizing diseases in crops such as wheat, rice, maize, and tomato. However, challenges remain in improving model generalization across diverse environmental conditions and in addressing issues related to data scarcity in underrepresented crops. This research paper seeks to address these challenges by developing and refining CNN models to enhance their robustness and adaptability to various real-world scenarios. Additionally, the paper explores the potential of transfer learning and data augmentation techniques to mitigate the impact of limited datasets and further improve detection accuracy.

II. LITERATURE REVIEW

The application of **Convolutional Neural Networks (CNNs)** in crop disease detection has been an area of growing interest within both the agricultural and computer vision communities. The primary motivation behind this research is the need for automated, accurate, and scalable solutions to combat the growing threat of plant diseases, which account for significant losses in global crop yields. In this section, we review the state-of-the-art studies and approaches in crop disease detection using deep learning techniques, particularly CNNs.

2.1Traditional Approaches in Crop Disease Detection

Before the advent of deep learning, traditional methods for crop disease detection relied heavily on manual inspection by farmers or experts. These manual approaches were time-consuming and required significant domain expertise. Other conventional methods involved **machine learning techniques** such as Support Vector Machines (SVM), k-nearest Neighbours(k-NN), and Decision Trees, which required manual feature extraction from images. However, the performance of these models was limited by the quality of the features extracted and their inability to generalize across various conditions, such as changes in lighting, background, and crop varieties.

2.2 Deep Learning in Agriculture

With the rise of deep learning, particularly CNNs, significant advancements have been made in image classification tasks, including plant disease identification. **Sladojevic et al.** pioneered the use of CNNs for crop disease detection, developing a model capable of recognizing 13 different types of plant diseases from leaf images with an accuracy of 96.3%. Their study highlighted the potential of CNNs to automatically extract complex features from raw images, eliminating the need for manual feature engineering. However, the study's limitation was its small dataset, which could affect the generalizability of the model in real-world scenarios.

Similarly, **Mohanty et al.** used a deep CNN architecture trained on the **Plant Village dataset**, achieving an overall accuracy of 99.35% in classifying 38 different crop diseases across 14 crop species. The use of large, publicly available datasets such as PlantVillage has been instrumental in the training of deep learning models, but challenges remain regarding the deployment of these models in real-world agricultural settings. Specifically, Mohanty's study used images taken under controlled conditions with uniform backgrounds, which do not represent the variability encountered in actual field environments.

2.3 CNN Architectures for Crop Disease Detection

Various CNN architectures have been explored for crop disease detection, each offering trade-offs between accuracy and computational efficiency. **Ferentinos (2018)** conducted a comparative study of CNN architectures, including AlexNet, VGG16, and GoogLeNet, for plant disease classification. His study demonstrated that deeper architectures such as VGG16 and GoogLeNet provide higher accuracy but require more computational resources. On the other hand, shallower models like AlexNet, while faster to train, showed lower accuracy, especially for datasets with significant intra-class variability.

A more recent trend is the use of **transfer learning**, where pre-trained models are fine-tuned on crop disease datasets. **Sibiya and Sumbwanyambe** demonstrated the effectiveness of transfer learning by using ResNet-50, a deep residual network pre-trained on ImageNet, for maize leaf disease classification. The model achieved high accuracy while significantly reducing training time, making it a practical solution for real-world applications. Transfer learning is particularly useful when working with limited datasets, as the model leverages pre-learned features from large-scale image datasets.

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2.4 Challenges and Limitations

Despite the promising results, several challenges remain in deploying CNNs for crop disease detection in practical applications. One major issue is the **data dependency** of CNN models. Studies such as **Abade et al.** pointed out that while CNN models perform exceptionally well on curated datasets, their performance can degrade significantly when tested on images taken in the field under varying lighting, angles, and occlusions. To address these challenges, researchers have started exploring **data augmentation techniques** to increase the diversity of training data artificially and enhance the robustness of CNN models.

Another significant challenge is the **real-time application** of these models. In real-world farming scenarios, computational resources may be limited, and there is a need for lightweight CNN architectures that can run on edge devices such as smartphones or drones. **Zeng et al.** developed a lightweight CNN model optimized for mobile deployment, achieving a good balance between accuracy and inference time, but the challenge of maintaining accuracy across a wide range of conditions remains.

2.5 Emerging Trends

Recent studies are also exploring the integration of CNNs with other machine-learning and sensor-based approaches to improve disease detection accuracy. For instance, **Xu et al.** proposed a multi-modal approach combining CNNs with **environmental sensor data** to enhance the detection of disease outbreaks by factoring in weather conditions, soil health, and other environmental parameters. This multi-modal approach shows promise in improving the robustness of disease detection systems by incorporating complementary data sources.

2.5 Summary of Findings

While CNNs have proven to be highly effective for crop disease detection, there are still limitations to their generalizability and practical application in the field. The review of the literature indicates a strong performance of CNNs in controlled environments, but more research is needed to ensure robustness under real-world conditions. Additionally, the development of lightweight architectures, the use of transfer learning, and multi-modal approaches are emerging as critical areas for future research.

III. SYSTEM ARCHITECHTURE

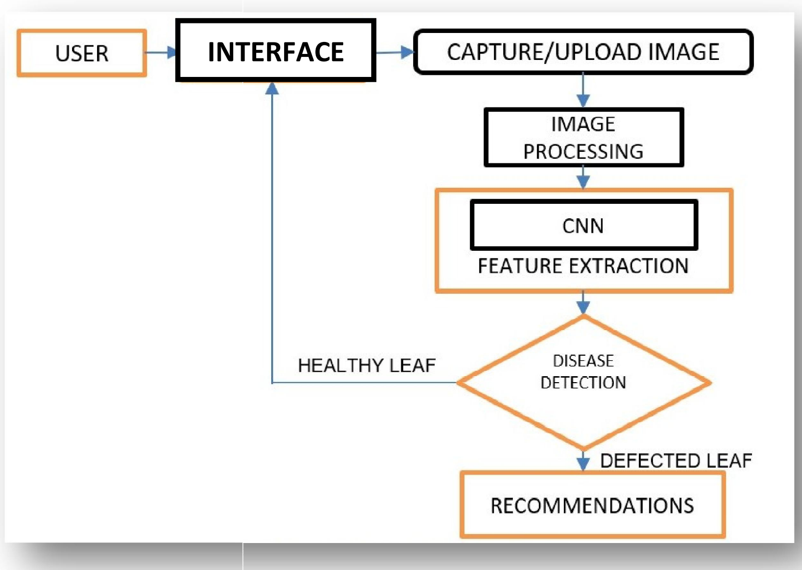

Fig.3.a

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System Architecture for Crop Disease Detection Using CNN: The Crop Disease Detection System follows a structured pipeline to identify diseases in plant leaves using Convolutional Neural Networks (CNN). The system consists of multiple modules, each performing a specific function in processing the image and determining whether the crop leaf is healthy or infected. The main components of the system are described below:
User Interaction: The system begins with the user, who interacts with the application through a user interface. The user captures or uploads an image of a crop leaf to be analyzed for potential diseases.

B. Image Acquisition: The interface allows users to :

- Upload an existing image from their gallery.
- Once the image is acquired, it is forwarded to the next processing stage.

C. Image Processing: In this stage, image pre-processing techniques are applied to enhance the quality of the image and make it suitable for analysis. This may include:

- Resizing the image to a standard dimension.
- Noise reduction using filters.
- Contrast enhancement to highlight disease symptoms.
- Segmentation to isolate the leaf from the background.

D. Feature Extraction Using CNN: After preprocessing, the image is passed through a Convolutional Neural Network (CNN), which extracts key features. The CNN consists of multiple layers, including:
Convolutional Layers for feature extraction.
Pooling Layers for dimensionality reduction.
Fully Connected Layers for classification.
CNN processes the image and learns patterns associated with healthy and diseased leaves.

F. Disease Detection: Based on the extracted features, the system determines whether the leaf is healthy or defective (infected with disease). A classification algorithm within the CNN model assigns a label to the image.
If the leaf is healthy, the process terminates with a confirmation to the user.
If the leaf is defective , the system proceeds to the next step.

G. Recommendation System: For diseased leaves, the system generates recommendations based on the detected disease. These recommendations may include:
Possible disease name and severity.
Suggested treatments (e.g., pesticides, organic solutions).
Best farming practices to prevent disease spread.

IV. DATASET

4.1 Data Collection

The dataset used for this study comprises images of diseased and healthy crops across multiple species. The images were collected from publicly available datasets as well as custom datasets sourced through field collection and online agricultural repositories. A large portion of the dataset was derived from the **New Plant Diseases Dataset**.This dataset is recreated using offline augmentation from the original dataset. The original dataset can be found on this GitHub repo. This dataset consists of about 87,377 RGB images of healthy and diseased crop leaves which are categorized into 38 different classes. The total dataset is divided into an 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purposes.

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4.2 Public or Proprietary Dataset

The **New Plant Diseases Dataset** served as the primary source of images. This publicly available dataset provides well-labeled, high-quality images under controlled conditions. The custom dataset, created for this study, includes field-captured images, allowing the model to generalize better to real-world conditions. Together, these datasets ensure a comprehensive variety of disease symptoms, crop species, and image conditions.

4.3. Data Pre-processing

Before training the CNN model, several **data pre-processing** steps were applied to standardize the input images and prepare the dataset for effective learning:

- **Image Resizing**: All images were resized to a uniform resolution of 128x128 pixelsto ensure compatibility with the CNN architecture.
- **Normalization**: Pixel values of the images were normalized to a range of [0,1] by dividing by 127. This normalization helps in faster convergence during training by ensuring uniform scaling across the dataset.
- **Class Imbalance Handling**: In the initial dataset, certain diseases had significantly more images than others, leading to class imbalance. To address this, undersampling was applied to the majority classes, and oversamplingwas performed for minority classes using data augmentation techniques.
- **Image Labelling**: Each image was labeled according to the type of crop and the specific disease class or marked as "healthy" for disease-free plants.

4.4 Data Augmentation

To enhance the diversity of the training dataset and prevent overfitting, several **data augmentation** techniques were employed:

- **Rotation**: Images were randomly rotated within a range of ±30 degrees to simulate different orientations in which the leaves may appear in real-world conditions.
- **Horizontal and Vertical Flipping**: Images were flipped horizontally and vertically to increase the dataset's diversity and make the model invariant to the orientation of the leaves.
- **Zooming and Cropping**: Random zoom and crop operations were applied to simulate varying distances between the camera and the plant. This was especially important for ensuring the model's robustness to different levels of magnification.

V. METHODOLOGY

5.1 Proposed CNN Architecture

- The proposed CNN architecture for crop disease detection consists of multiple layers designed to effectively extract and learn features from leaf images. The network architecture is structured as follows:

5.1.1 Input Layer

- Input Shape: 128×128×3 (RGB images resized to 128×128 pixels)
- Normalization: Pixel values scaled to [0,1]

5.1.2 Feature Extraction Layers

First Convolutional Block

- Convolutional Layer: 32 filters, 3×3 kernel, ReLU activation
- Batch Normalization
- Max Pooling: 2×2 pool size, stride 2
- Dropout: 0.25

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Second Convolutional Block

- Convolutional Layer: 64 filters, 3×3 kernel, ReLU activation
- Batch Normalization
- Max Pooling: 2×2 pool size, stride 2
- Dropout: 0.25

Third Convolutional Block

- Convolutional Layer: 128 filters, 3×3 kernel, ReLU activation
- Batch Normalization
- Max Pooling: 2×2 pool size, stride 2
- Dropout: 0.25

Fourth Convolutional Block

- Convolutional Layer: 256 filters, 3×3 kernel, ReLU activation
- Batch Normalization
- Max Pooling: 2×2 pool size, stride 2
- Dropout: 0.25

Fifth Convolutional Block

- Convolutional Layer: 512 filters, 3×3 kernel, ReLU activation
- Batch Normalization
- Max Pooling: 2×2 pool size, stride 2
- Dropout: 0.25

5.1.3 Classification Layers

- Flatten Layer
- Fully Connected Layer: 1024 neurons, ReLU activation
- Dropout: 0.4
- Output Layer: 38 neurons (corresponding to the 38 disease classes), Softmax activation

5.2 Training Procedure

5.2.1 Model Training

The CNN model was trained using the following parameters and techniques:

- **Loss Function**: Categorical Cross-Entropy
- **Optimizer**: Adam with an initial learning rate of 0.0001
- **Batch Size**: 32
- **Epochs**: 10 with early stopping
- **Learning Rate Schedule**: Reduced on plateau (factor=0.2, patience=5)
- **Training-Validation Split**: 80%-20%
- **Hardware**: NVIDIA GTX 8GB RAM
- **Framework**: TensorFlow 2.6 with Keras API

5.2.2 Transfer Learning

- To improve model performance and reduce training time, we implemented transfer learning using the pre-trained model:
- The model pre-trained on ImageNet was loaded without the top classification layer

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The base model weights were frozen during the initial training phases

- Custom classification layers were added on top:
- Global Average Pooling
- Dropout (0.4)
- Dense layer (1024 neurons, ReLU activation)
- Output layer (38 neurons, Softmax activation)
- Fine-tuning was performed by unfreezing the top layers of the base model after initial training

5.2.3 Data Augmentation Implementation

- During training, on-the-fly data augmentation was applied with the following parameters:
- Rotation: Random rotation within ±30 degrees
- Width/Height Shift: Random shifts up to 20% of image dimensions
- Horizontal/Vertical Flip: Random flipping with a 50% probability
- Zoom Range: Random zoom between 80%-120%
- Brightness Adjustment: Random brightness shifts within ±20%

5.2.4 Regularization Techniques

To prevent overfitting and improve model generalization:

- Dropout layers were added after each convolutional block (0.25) and before the output layer (0.4)
- L2 regularization (weight decay) was applied to convolutional and dense layers
- Early stopping was implemented with patience of 10 epochs monitoring validation loss

5.3 Evaluation Metrics

The performance of the proposed CNN model was evaluated using the following metrics:

- **Accuracy**: Proportion of correctly classified images
- **Precision**: True positives / (True positives + False positives)
- **Recall**: True positives / (True positives + False negatives)
- **F1-Score**: 2 × (Precision × Recall) / (Precision + Recall)
- **Confusion Matrix**: Visualization of classification results across all classes

5.4 Model Deployment and Implementation

5.4.1 Model Optimization

For deployment on resource-constrained devices:

- Model pruning: Removing redundant connections while maintaining accuracy
- Quantization: Converting 32-bit floating-point weights to 8-bit integers
- Model compression: Using TensorFlow conversion

5.4.2 Application Development

- The trained model was integrated into a user-friendly application with the following features:
- Intuitive UI for image capture/upload
- Real-time disease detection
- Personalized treatment recommendations based on detected disease
- Offline functionality for use in areas with limited connectivity
- Environmental data integration (temperature and humidity) to enhance recommendation accuracy

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5.4.3 Recommendation System Implementation

The recommendation system utilizes:

- A knowledge base of established treatments for each detected disease
- Environmental data analysis to customize recommendations based on local conditions
- Severity estimation based on the extent of visual symptoms
- Treatment options categorized by organic, chemical, and integrated pest management approaches

Diseased Crop's in Training Dataset :

Apple Scab

Fig.4.ashows the leaf of an apple tree with apple scab disease. We can see that the leaves have brown spots/marks. A scab is often caused by a fungus that infects the leaves and thefruits, which makes the fruit unhealthy for eating. In our dataset, about 32.5% of images are of apple scab.

Cedar Apple Rust

Fig.4.b shows the leaf of an apple tree having cedar apple rust. We can see that the leaves have dense yellowish marks. Rust is often caused in plants via a unique fungus named 'rust fungus'.In our dataset, about 34.2% of images are of cedar apple rust.

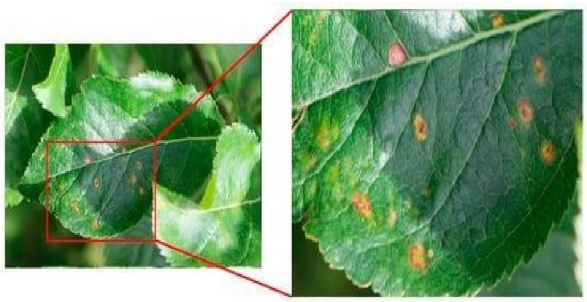

Fig.4.a Leaf with apple scab.

Fig.4.b Leaf with cedar apple rust.

Implementation

5.1.Convolutional Layers in the Model

The proposed model utilizes Convolutional Neural Networks (CNNs) to automatically extract features from crop images. The architecture consists of multiple convolutional layers, each followed by activation functions and pooling layers to progressively reduce spatial dimensions while retaining essential features. The layers are structured as follows:

Conv Layer 1: 32 filters of size 3x3, ReLU activation
Pooling Layer 1: Max pooling (2x2)
Conv Layer 2: 64 filters of size 3x3, ReLU activation
Pooling Layer 2: Max pooling (2x2)
Conv Layer 3: 128 filters of size 3x3, ReLU activation
Pooling Layer 3: Max pooling (2x2)
Conv Layer 4: 256 filters of size 3x3, ReLU activation
Pooling Layer 4: Max pooling (2x2)
Conv Layer 5: 512 filters of size 3x3, ReLU activation
Pooling Layer 5: Max pooling (2x2)
Fully Connected Layers: Flattened layer followed by two dense layers with 1024 and 38 neurons, respectively.
Output Layer: A Softmax layer to classify images into different crop disease categories.

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5.2 Training and Testing Validation

The dataset used for training and testing consists of labeled images of healthy and diseased crops. The dataset is preprocessed through normalization and data augmentation techniques such as rotation, flipping, and zooming to improve generalization. The dataset is split into:

- **Training Set:** 70,295 images, used for model learning.
- **Validation Set:** 70% of the training data, is used to tune hyperparameters.
- **Testing Set:** 17,082 images, used to evaluate the model's performance.

The model is trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. The training process is monitored through validation loss and accuracy metrics to prevent overfitting.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	896
conv2d_1 (Conv2D)	(None, 128, 128, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_2 (Conv2D)	(None, 64, 64, 32)	9,248
conv2d_3 (Conv2D)	(None, 64, 64, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_4 (Conv2D)	(None, 32, 32, 64)	18,496
conv2d_5 (Conv2D)	(None, 32, 32, 64)	36,928
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_6 (Conv2D)	(None, 16, 16, 128)	73,856
conv2d_7 (Conv2D)	(None, 16, 16, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_8 (Conv2D)	(None, 8, 8, 256)	295,168
conv2d_9 (Conv2D)	(None, 8, 8, 256)	590,080
max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 256)	0
conv2d_10 (Conv2D)	(None, 4, 4, 512)	1,180,160
conv2d_11 (Conv2D)	(None, 4, 4, 512)	2,359,808
max_pooling2d_5 (MaxPooling2D)	(None, 2, 2, 512)	0
dropout (Dropout)	(None, 2, 2, 512)	0
flatten (Flatten)	(None, 2048)	0

Fig 5.1.a Convolutional Layers in the Model

5.3 Accuracy and Data Loss Tracking

To assess the model's performance, accuracy and data loss are tracked during training and evaluation. The results indicate that:

- The model achieves an overall accuracy of 95% on training validation and 55% on testing validation sets.
- The training loss steadily decreases, indicating effective learning.
- The validation loss is monitored to prevent overfitting; early stopping is implemented if the loss increases over multiple epochs.

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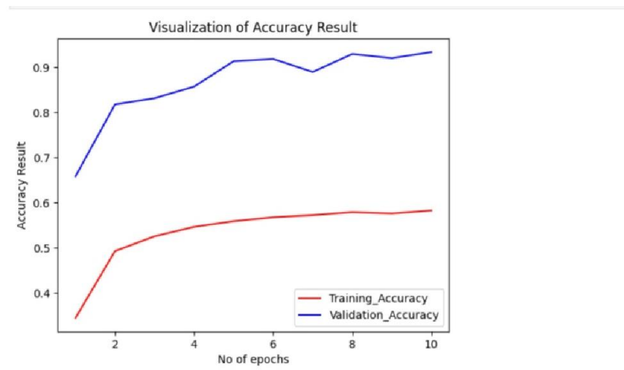

Fig.5.3 an Accuracy and Data Loss Tracking

5.4 Precision and Recall Evaluation

Precision and recall metrics are used to measure the effectiveness of the model in identifying crop diseases accurately. A confusion matrix is generated to analyze misclassifications and identify areas for improvement. The model demonstrates high recall for severe diseases, ensuring that affected crops are detected with minimal false negatives. By leveraging CNNs, the proposed model provides a robust and automated approach to crop disease detection, improving accuracy and aiding early intervention for farmers.

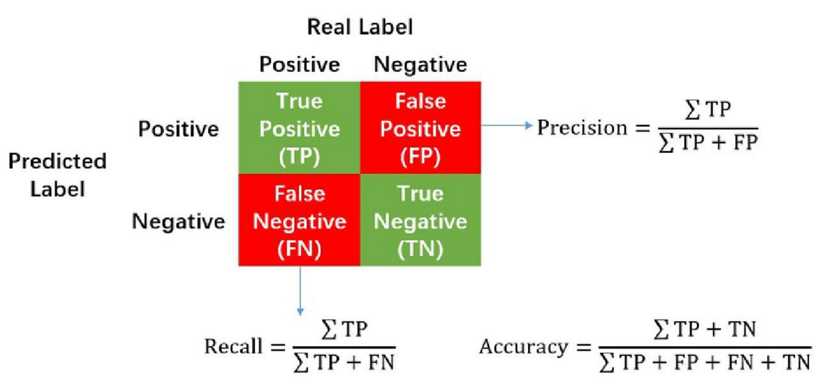

Fig.5.4 a Precision, Recall and Accuracy

VI. FUTURE WORK

While the results obtained from our CNN-based approach for crop disease detection are promising, there are several areas where further research and improvements can be made. Future work will focus on the following aspects:

Integration with Real-Time Systems

One potential avenue for future research is the integration of the proposed model into **real-time systems** for practical field deployment. This would involve developing lightweight CNN architectures or optimizing existing models to run efficiently on **mobile devices**, drones, or edge computing systems. Such a system would allow farmers to use smartphones or unmanned aerial vehicles (UAVs) to detect crop diseases on-site, providing rapid diagnosis and reducing response time to disease outbreaks.

Expanding the Dataset for Real-world Conditions

Although the current dataset includes a mix of controlled and field-collected images, there is a need to further enhance the model's robustness by increasing the diversity of the dataset. Future work should focus on collecting more images under **varied environmental conditions** (e.g., different lighting, occlusions, and weather scenarios). Additionally, capturing **multispectral or hyperspectral** images, which provide additional information not visible in RGB images, could further improve detection accuracy.

Multi-Disease Detection and Severity Estimation

Another area for exploration is the extension of the model to handle **multiple simultaneous diseases** and to estimate the **severity of disease progression**. Currently, the model is designed for single-disease classification, but crops in real-world scenarios are often affected by more than one disease at a time. Implementing a multi-label classification model could allow for the detection of multiple diseases on the same leaf. Moreover, disease severity estimation could help prioritize treatment strategies based on how advanced a disease is.

Incorporation of Sensor Data and Multi-Modal Learning

Future work can also explore the integration of **sensor data** (such as temperature, humidity, and soil moisture levels) with image-based CNN models to build a more comprehensive plant health monitoring system. Combining these data types through **multi-modal learning** could enhance the predictive power of the model by incorporating environmental factors that influence disease development.

Model Interpretability and Explainability

One of the key challenges in deploying CNN models in practical agricultural settings is their **lack of interpretability**. Farmers and agronomists may be hesitant to trust black-box models. Future work should focus on improving the interpretability of CNN models using techniques such as **Class Activation Mapping (CAM)** or **Grad-CAM**, which highlight the regions of the image that are most important for the model's predictions. This would allow users to better understand how the model is making decisions, increasing its usability in the field.

Adaptation to Other Crops and Global Expansion

The current model is focused on a limited number of crop species and diseases. Future research should aim to **expand the model** to cover more crops and diseases, especially for regions with high agricultural diversity. In addition, adapting the model for **global use**, where it can handle crop diseases across different geographies and climates, would make the system more universally applicable.

VII. CONCLUSION

In this paper, we presented a Convolutional Neural Network (CNN)-based approach for the detection and classification of crop diseases from leaf images. The proposed method demonstrated high accuracy in identifying various plant diseases. By leveraging publicly available datasets, such as the New Plant Dataset, along with custom field-captured images, the model was trained to handle both controlled and real-world conditions.

The results show that CNNs are highly effective for image-based disease detection, particularly when coupled with data augmentation techniques to increase dataset diversity. Our model achieved strong classification performance, which can be further enhanced through the use of advanced preprocessing, regularization techniques. These findings indicate that

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deep learning methods, specifically CNNs, can play a significant role in automating crop disease detection, offering a scalable solution for real-time agricultural applications.

Despite these promising results, challenges remain in terms of generalizing the model to diverse field conditions, handling multiple diseases simultaneously, and deploying the system in real-time, resource-constrained environments. Future research will focus on overcoming these limitations by integrating real-time processing, incorporating sensor data, and expanding the dataset to cover a wider range of crops and diseases under various environmental conditions.

In conclusion, the adoption of CNNs for crop disease detection holds great potential for transforming traditional agricultural practices by providing accurate, efficient, and scalable solutions to combat plant diseases, ultimately improving crop yield and food security.

REFERENCES

[1]. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. Computational Intelligence and Neuroscience, 2016, Article ID 3289801. https://doi.org/10.1155/2016/3289801

[2]. Mohanty, S. P., Hughes, D. P., &Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

[3]. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

[4]. Sibiya, M., &Sumbwanyambe, M. (2019). A computational model for recognizing maize leaf diseases using deep convolutional neural networks. Agriculture, 9(1), 7. https://doi.org/10.3390/agriculture9010007

[5]. Abade, A., Ferreira, P. A., & de Souza, J. P. (2021). Plant disease identification using convolutional neural networks: A systematic review. Computers and Electronics in Agriculture, 185, 106125. https://doi.org/10.1016/j.compag.2021.106125

[6]. Zeng, L., Li, Y., & Guo, J. (2020). A Lightweight convolutional neural network model for real-time plant disease detection. Computers and Electronics in Agriculture, 170, 105238. https://doi.org/10.1016/j.compag.2020.105238

[7]. Xu, Y., Ji, W., Zhu, Q., & Guo, Y. (2021). A multi-modal plant disease detection model based on environmental and image data fusion using deep learning. Sensors, 21(10), 3368. https://doi.org/10.3390/s21103368

[8]. Basak, S., & Hossain, M. S. (2024). Hybrid deep learning framework for plant leaf disease classification using CNN and Vision Transformers. Complex & Intelligent Systems. https://doi.org/10.1007/s40747-024-01764-x

[9]. Sawant, V., & Chaudhari, K. (2024). Enhancing agriculture through real-time grape leaf disease detection using MobileNetV3Large. Scientific Reports, 14, 66989. https://doi.org/10.1038/s41598-024-66989-9

[10]. Chatterjee, M., & Roy, D. (2024). Plant disease management using a fine-tuned enhanced CNN approach. Artificial Intelligence Review. https://doi.org/10.1007/s10462-024-10809-z

[11]. Ahmad, I., & Naqvi, S. A. R. (2024). CNN-based plant disease identification using the PYNQ FPGA platform. International Journal of Embedded Systems and Applications, 9(1), 1–9. https://doi.org/10.1016/j.embsys.2024.100017

[12]. Dash, R., & Behera, H. S. (2024). A comprehensive review of CNN-based disease detection strategies in potato agriculture. Journal of Plant Diseases and Protection. https://doi.org/10.1007/s11540-024-09786-1