International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 1, Jan-Feb-2025, ISSN (Online): 2395-566X

Crop Disease Detection System

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Abstract- One of the important and tedious tasks in agricultural practices is the detection of disease on crops. It requires time as well as skilled labor. This paper proposes a smart and efficient technique for the detection of crop disease which uses computer vision and 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 farmers based on soil features, temperature, and humidity.

Index Terms- 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.

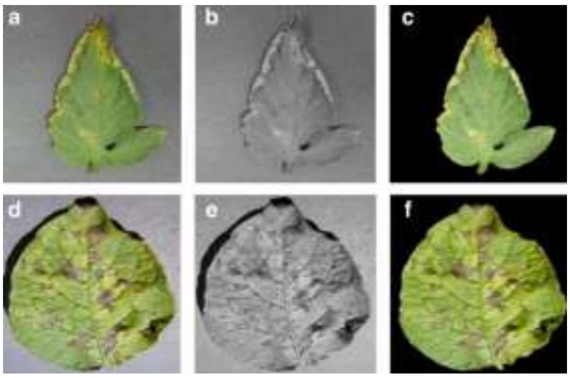

Fig. 1 Crop Diseases

Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated superior performance in analyzing and classifying complex patterns in images [1,2]. 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 [3].

This approach is more efficient compared to traditional methods of disease detection, which are often infeasible in small- and medium-scale farms due to resource constraints [5].

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 [7].

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 [6]. However, challenges remain in improving model generalization across diverse environmental conditions and in addressing issues related to data scarcity in underrepresented crops.

This research 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 [2,6].

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.

1. Traditional 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 timeconsuming 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. 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. (2016) 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. (2016) 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 Plant Village 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.

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 finetuned on crop disease datasets. Sibiya and Sumbwanyambe (2019) demonstrated the effectiveness of transfer learning by using ResNet-50, a deep residual network pretrained on ImageNet, for maize leaf disease classification. The model achieved high accuracy while significantly reducing training time, making it a practical solution for realworld applications. Transfer learning is particularly useful when working with limited datasets, as the model leverages pre-learned features from large-scale image datasets. D.

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. (2021) 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. (2020) 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.

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. (2020) proposed a multimodal 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 multimodal approach shows promise in improving the robustness of disease detection systems by incorporating complementary data sources. F. Summary of Findings

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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 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. DATASET

1. Dataset 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 Plant Village dataset [1], which includes over 50,000 images of healthy and diseased plant leaves. The dataset covers a wide range of crops, including maize, tomato, potato, wheat, and soybean, among others, with various disease classes such as leaf rust, blight, early blight, late blight, and mosaic virus.

In addition to the Plant Village dataset, a custom dataset was created by manually capturing images from local farms using smartphones under real-world conditions. This custom dataset includes varying lighting conditions, occlusions, and environmental backgrounds to ensure the model's robustness in practical applications.

2. Public or Proprietary Dataset

The Plant Village dataset [1] served as the primary source of images. This publicly available dataset provides well-labelled, highquality 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.

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 224x224 pixels to ensure compatibility with the CNN architecture, particularly for pre-trained models like VGG16 and ResNet.
- **Normalization:** Pixel values of the images were normalized to a range of [0,1] by dividing by 255. 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, under sampling was applied to the majority classes, and oversampling was performed for minority classes using data augmentation techniques (described in section D).
- **Image Labelling:** Each image was labelled according to the type of crop and the specific disease class or marked as "healthy" for disease-free plants.

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.

IV. METHODOLOGY

In this section, we describe the approach and techniques used for crop disease detection using Convolutional Neural Networks (CNNs). The methodology is divided into key stages: CNN architecture selection, data preprocessing, training, and evaluation of the model.

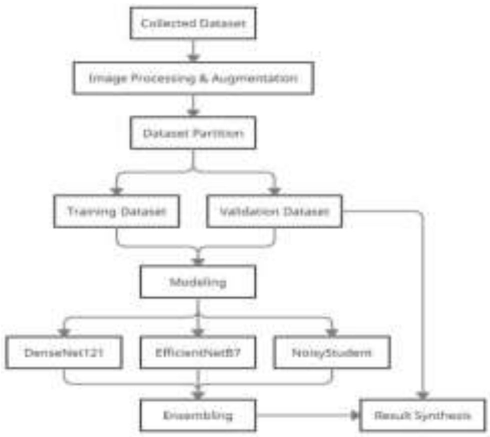

Fig. 2

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A. CNN Architecture The proposed system for crop disease detection is based on a Convolutional Neural Network (CNN), which is highly effective in image classification tasks due to its ability to automatically extract spatial hierarchies of features from input images. For this study, we experimented with both a custom CNN model and pre-trained models through transfer learning.

Custom CNN Model: A custom CNN architecture was designed with multiple convolutional layers, followed by max-pooling and fully connected layers. The architecture consisted of:

Three convolutional layers with 64, 128, and 256 filters, respectively. Each layer was followed by a ReLU activation function to introduce non-linearity, and max-pooling was applied to reduce the spatial dimensions. Flattening layer to convert the 2D feature maps into a 1D vector.

Fully connected layers with 512 and 256 neurons, followed by a softmax layer for multi-class classification.

Dropout regularization was applied after each fully connected layer to prevent overfitting.

Transfer Learning (Pre-Trained Models): We also employed VGG16 and ResNet50, pre-trained on the ImageNet dataset, to leverage the general features learned from millions of images. Only the final classification layer was replaced and finetuned on our crop disease dataset. Transfer learning significantly reduced the training time and improved performance, especially on small datasets.

Data Pre-processing
Before training the model, several data preprocessing steps were applied to the images, as discussed in the dataset section. The key preprocessing steps included resizing all images to 224x224 pixels, normalizing pixel values, and augmenting the data to improve the model's generalization.

Model Training
The CNN models were trained on the preprocessed dataset using the following parameters:

- **Loss Function:** We used categorical cross-entropy as the loss function, which is appropriate for multi-class classification tasks.
- **Optimization Algorithm:** The model was trained using the Adam optimizer, which combines the advantages of both the Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation
- **(RMSProp).** The learning rate was set to 0.001, with a decay rate of 1e-6 to allow for fine-tuning over time.
- **Batch Size and Epochs:** The models were trained with a batch size of 32 and for 50 epochs. Early stopping was implemented to halt training if the validation accuracy did not improve for 10 consecutive epochs, to avoid overfitting.
- **Regularization Techniques:** Dropout was used with a rate of 0.5 after each fully connected layer to prevent overfitting by randomly dropping neurons during training.L2 regularization was applied to the weights to reduce overfitting by penalizing large weights.
- **Data Augmentation:** As mentioned earlier, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments were applied during training to artificially expand the dataset and reduce overfitting.

Diseased Crop's in Training Dataset
Apple Scab Fig. IV.II shows 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 the fruits, which makes the fruit unhealthy for eating. In our dataset, about 32.5% of images are of apple scab.

Fig. 3 Leaf with apple scab.

Cedar Apple Rust
Fig. IV.II 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.

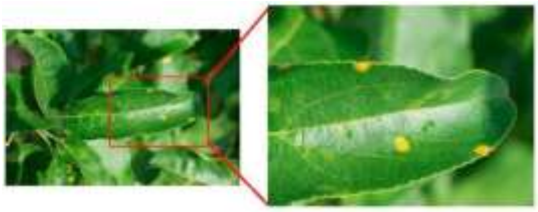

Fig. 4 Leaf with cedar apple rust.

Web Application Work Flow
The working algorithm of our system is summarized in the following points—

User visits our web application and uploads the image of apple leaf. All this takes place at the frontend.

The image uploaded is then sent to the backend, where it is fed to the CNN model. At the backend, we have stored the

weights of our proposed model in the form of an HDF5 file . The model is loaded from this HDF5 file. Before feeding the image to the model, the image is first trimmed into the required shape of 512 × 512.The result returned by our model is a NumPy array of size (4,1), which includes the probability of the four classes. The class with the maximum probability is extracted.The results are shown to the user at the frontend, and the image is stored in our database to enhance our model.
Technologies Used

Our web application has a simple frontend designed using Javascript, CSS, and HTML. The backend of our application uses Ruby on Rails which is a server-side web application framework. The backend of our application maps the frontend to our deep learning model. The proposed model uses technologies such as Python, Keras, Tensorflow, NumPy and Pandas, etc. to store the images in a database to make them available for future training; we have used MySQL, an open-source RDBMS.

Fig. 5

Future Work
While the results obtained from our CNNbased 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 realtime 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 MultiModal 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.

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.

V. 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, utilizing both custom CNN architectures and transfer learning with pre-trained models such as VGG16 and ResNet50. By leveraging publicly available datasets, such as PlantVillage, along with custom field-captured images, the model was trained to handle both controlled and realworld 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, and transfer learning. These findings indicate that deep learning methods, specifically CNNs, can play a significant role in automating crop disease detection, offering a scalable solution for real-time agricultural applications.

REFERENCES

1. S. Mohanty, D. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, p. 1419, 2016. doi: 10.3389/fpls.2016.01419.
2. A.Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018. doi: 10.1016/j.compag.2018.01.009.
3. A.G. K. Agrawal and S. Kumar, "Plant disease detection using deep learning techniques: A review," Artificial Intelligence Review, vol. 53, no. 6, pp. 4025-4054, 2020. doi: 10.1007/s10462-019-09744-5.
4. L. G. Barbedo, "Digital image processing techniques for detecting, quantifying and classifying plant diseases," SpringerPlus, vol. 5, no. 1, p. 919, 2016. doi: 10.1186/s40064016-2954-3.
5. H. Wang, W. Zhan, X. Liu, and Y. Wang, "A survey on deep learning for plant disease detection," Biosystems Engineering, vol. 179, pp. 62-76, 2019. doi: 10.1016/j.biosystemseng.2018.10.008.
6. H. X. Zheng, S. Li, C. Yang, and L. Zhang, "Detection of crop diseases based on improved YOLOv4 model," Computers and Electronics in Agriculture, vol. 195, p. 106785, 2022. doi: 10.1016/j.compag.2022.106785.
7. P. M. M. Ferreira, A. G. P. Da Silva, A. C. R. A. De Oliveira, and M. R. A. Santos, "Convolutional neural networks for plant disease detection: A review," Applied Sciences, vol. 11, no. 19, p. 8902, 2021. doi: 10.3390/app11198902.