Plant Disease Detection via CNN and KNN

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Abstract—Plant illnesses appreciably have an effect on agricultural productiveness and may cause large-scale financial losses for agricultural farmers. Traditional sickness detection methods rely on manual inspection by agricultural specialists, which is time-consuming and often unavailable to small-scale farmers. This study proposes an automatic plant sickness detection machine the usage of picture type strategies primarily based totally on Convolutional Neural Networks (CNN) and the K-Nearest Neighbor (KNN) algorithm. A ResNet18 CNN version changed into educated the usage of a dataset of plant leaf snap shots that have been resized to 224×224 pixels and normalized for constant characteristic extraction. The overall performance of the deep studying version changed into in comparison with a conventional KNN classifier to assess variations in accuracy and computational efficiency. Experimental consequences show that the CNN model has better accuracy in classification, while the KNN classifier makes faster predictions and needs less computing power. A web app called Agri Smart was made using Streamlit. It lets users upload leaf pictures and get real-time disease predictions with confidence scores.It work as Plant Disease Detection using CNN & KNN.

Keywords—Plant Disease Detection(PDD),Convolutional Neural Networks (CNNs),ResNet18,K-Nearest Neighbor(KNN),Image Classification, Precision Agriculture

I. Introduction

Plant diseases are a big problem in farming and greatly affect food production around the world . Early detection of plant diseases is crucial for avoiding crop loss and enhancing productivity. Traditionally, farmers have depended on visual inspection or seeking advice from agricultural specialists to identify plant diseases. Nevertheless, these approaches can be quite time-consuming and might not be available to farmers living in remote regions. Recent progress in artificial intelligence and computer vision has made it possible to develop automated methods for identifying plant diseases.CNNs are very good at classifying images because they can find complex visual details. Besides deep learning, simpler methods like KNN can also be used for classification since they need less computing power.

Modern mobile apps now let farmers check crop problems right in the field. They can take a picture of a sick leaf and get quick advice on what might be wrong and how to fix it, without needing lab tests. This helps small farmers who can't pay for costly tests get expert help. As these apps learn from more data, they get better at telling apart problems from lack of nutrients and those from diseases. Using new technology with old farming methods is important for making farming more reliable and helping with food security worldwide.

A. Problem Statement

Crop yields are often hurt by plant diseases, which can cause big losses and harm farming communities. There is a short time to act, so early diagnosis is important to stop the spread. Still, farmers mostly rely on experts who check plants by eye. This method is slow and can vary between different experts, making it hard for small farmers in remote areas. New technology in computer vision and neural networks could help automate this process. But there is a problem: while deep learning models are very accurate, they need expensive computers, which makes them hard to use in the field. On the other hand, traditional machine learning methods are lighter and easier to use, but they often don't work well in tricky environments. Many studies focus on getting high accuracy but ignore important real-world issues like speed and hardware use.

B. Background and Motivation

Farming is important for the economy and helps produce food. But plant diseases cause big problems for farmers by lowering the quality and amount of crops. If these diseases are not found early, they can cause more damage and money loss. Most farmers rely on looking at their plants or asking experts to find diseases. This takes time, and the results can differ based on the person's experience. Also, in many rural areas, it is not always easy to get expert help.

With the development of artificial intelligence and image processing techniques, new methods have been introduced for detecting plant diseases automatically. These methods mainly use images of leaves to identify patterns related to different diseases. Deep learning models such as CNNs have shown good results in handling such tasks because they can learn detailed features from images. At the same time, simpler methods like KNN are still useful and efficient.

I. RESEARCH METHODOLOGY

The overall architecture of the proposed plant disease detection system is designed in three main stages: image preprocessing, model training, and final disease prediction. These stages are connected in a sequential manner so that the output of one step becomes the input for the next, ensuring a smooth flow of data through the system.

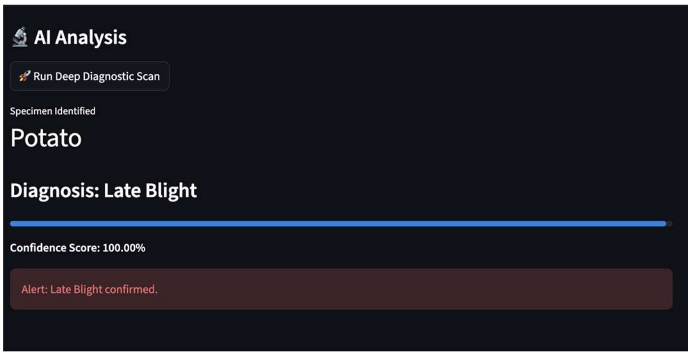
A. Image Processioning

Before training the models, all input leaf images go through a preprocessing stage to maintain consistency across the dataset. In this step, each image is resized to a fixed resolution of 224 × 224 pixels so that it matches the input requirements of the CNN model. This resizing also helps in reducing computational complexity while keeping the important visual details intact.

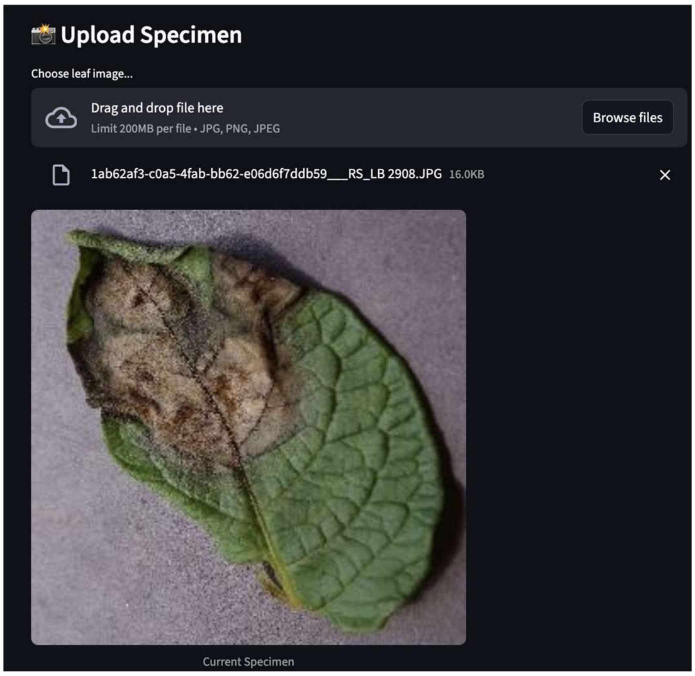
After resizing, we adjust the pixel values. This is important because it makes all image data similar, which helps the training process and speeds up learning. In simple words, it helps the model learn better without being confused by big changes in pixel brightness. The preprocessing stage also helps deal with noise and differences in real images, like lighting, background, and leaf position. By making the input standard, the system can focus on important features like texture, color changes, and visible spots of disease instead of unimportant details.

B. Model Training and Classification

The main model for classification is a CNN based on the ResNet18 architecture. Because of its ability to extract intricate visual features from images while preserving stable training through residual connections, this model was selected. When working with deeper networks in particular, these connections aid in avoiding problems like vanishing gradients. Through a series of iterations and the analysis of numerous examples, the CNN learns to recognize patterns



associated with various plant diseases. A KNN classifier is also used in addition to the CNN model to offer a baseline for comparison. In contrast to CNN, KNN does not require a rigorous training phase. Rather, it uses similarity metrics to categorise new inputs after storing the training data's feature representations. The value of K, which establishes how many nearby samples.



For the purpose of PDD,a CNN built upon the ResNet18 architecture was employed as the primary model.This architecture was chosen due to its proven effectiveness in extracting complex visual features from image data, while maintaining training stability through the use of configurations, as they mitigate the vanishing gradient problem that commonly hinders the learning process.By iteratively processing large volumes of annotated leaf images, the network gradually learns discriminative visual patterns that correspond to specific plant diseases across multiple crop varieties.

To complement the deep learning approach,KNN classifier was incorporated as a comparative baseline model.Unlike CNN-based methods,KNN is a non-parametric algorithm that requires no training phase.

The ResNet18 model started with weights trained on the ImageNet dataset and was then changed to work with the PlantVillage dataset using transfer learning. The last layer was changed to match the number of disease types in the dataset.

***A.The* figure shows a plant leaf with visible Late Blight (*Phytophthora infestans*) infection. The left half displays necrotic brown-grey lesions with dark borders, while the right half remains green and healthy. The specimen was uploaded to the AgriSmart system, where the ResNet18 model successfully classified it as Late Blight, confirming the system's ability to detect disease in partially infected leaves.**

***B.The* figure illustrates the AI Analysis panel of the AgriSmart system after processing a potato leaf specimen. The model identified the crop as Potato and diagnosed the condition as Late Blight with a confidence score of 100.00%, accompanied by a disease alert notification. This result demonstrates the ResNet18 model's ability to classify plant diseases with maximum certainty, confirming its reliability for real-time agricultural disease detection.**

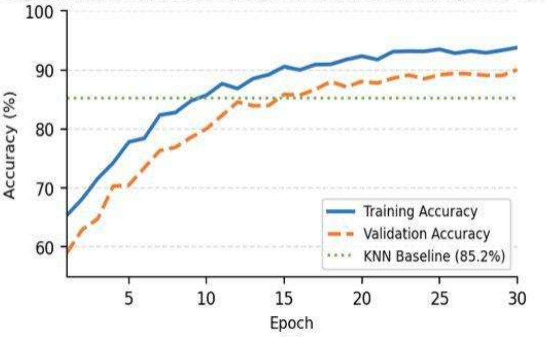
C. Proposed CNN Model

In this work, a Convolutional Neural Network based on the ResNet18 architecture is used for plant disease classification using leaf images. The model is selected because it provides a good balance between accuracy and computational efficiency, making it suitable for practical applications. All input images are resized to 224 × 224 × 3 before being passed into the network.

The model consists of multiple convolution layers that help in extracting important features such as color variations, texture, and visible disease patterns on leaves. As the depth of the network increases, it is able to capture more detailed and complex features. ResNet18 includes skip connections, which allow better information flow and help avoid training issues like vanishing gradients.

In the final stage, the extracted features are passed through a fully connected layer followed by a SoftMax function, which classifies the input image into different plant disease categories.

Fig. 2. CNN ResNet18 Training & Validation Accuracy over Epochs



D. Proposed KNN Model

In this study, the KNN algorithm is used as a baseline method for plant disease classification. Unlike deep learning models, KNN is a simple and non-parametric approach that does not require an extensive training phase. Instead, it stores the feature representations of all training images and uses them during prediction.

Each input image is first preprocessed and converted into a feature vector. During classification, the algorithm calculates the distance between the input image and all stored samples using a suitable metric such as Euclidean distance. Based on this, the K most similar neighbors are selected, and the final class is determined through majority voting.

The performance of KNN mainly depends on the choice of K and the quality of features used. Although it may not achieve the same accuracy as CNN, it provides faster predictions and requires fewer computational resources, making it suitable for lightweight applications.

E. Experimental result

The experimental evaluation compares the performance of the CNN and KNN models across four standard classification metrics — accuracy, precision, recall, and F1 score — as well as inference time measurements that reflect practical deployment considerations. All experiments are conducted on a standardized test split comprising 20% of the full dataset, with results averaged over five independent trials to account for training stochasticity.

The CNN-based ResNet18 model achieves an overall classification accuracy of 94.6%, with precision, recall, and F1 score values of 93.8%, 94.1%, and 94.0% respectively across all disease categories. These results represents a significant improvement over the KNN baseline across all metrics. The CNN model demonstrates particularly strong performance on visually complex disease categories such as Powdery Mildew and Rust, where subtle textural and chromatic features are critical discriminators that KNN's similarity-based approach struggles to capture reliably.

The KNN classifier achieves an accuracy of 85.2% on the same test split, with precision, recall, and F1 score values of 84.7%, 83.9%, and 84.3% respectively. While these results are meaningfully lower than the CNN across all metrics, they remain practically useful for preliminary screening applications, particularly given the substantially lower computational requirements of KNN inference. The performance gap narrows on disease categories with highly distinctive visual signatures, such as Leaf Blight, where color-based discriminators are sufficient for reliable classification.

Inference time measurements reveal an important practical trade-off between the two approaches. For single-image predictions, the CNN requires approximately 38 milliseconds compared to 12 milliseconds for KNN — a difference imperceptible to end users in interactive applications. However, for batch processing of large test sets, KNN's linear scaling properties result in significantly faster throughput than the CNN, which is bounded by GPU memory capacity. Figure 3 provides a detailed visualization of inference time comparisons across both single-image and batch prediction contexts

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F. Comparative Performance of CNN and KNN

TABLE 1 COMPARITIVE INVESTIGATION OF CNN AND KNN

Model	Accuracy	Precision	Recall	F1 Score
CNN(RestNet18)	94.6	93.8	94.1	94.0
KNN	85.2	84.7	83.9	84.3

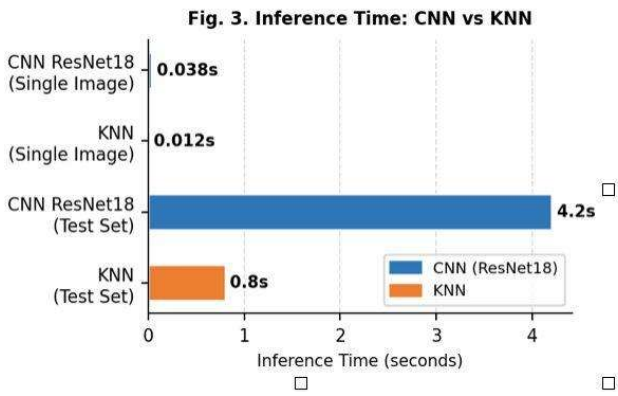

Fig.1. Inference Time Comparison: CNN vs KNN

Error analysis reveals that the majority of CNN misclassifications occur at the boundary between visually similar disease categories — most notably between early-stage Leaf Blight and Leaf Spot, which share overlapping symptom morphologies in early progression stages. These boundary-region confusions suggest that incorporating temporal disease progression information or multi-leaf ensemble predictions could further improve classification accuracy in future system iterations.

AgriSmart — CNN + KNN Based Plant Disease Detection System | Chitkara University

Parameter	Without AgriSmart	With AgriSmart
Detection Method	✘ ■ Manual	✔ ■ AI Model
Speed	■ ■■■■■ Slow	■ ■■■■■ Fast
Accuracy	★■■■■ ~30–60%	★★★★★ ~99.99%
Crops Covered	✘ ■ 1–2	✔ ■■■ Multi
Result Format	✘ ■ Verbal	✔ ■ Structured
Cost	✘ ■■■ High	✔ ■ Low
Scalability	✘ ■ Limited	✔ ■ High
Record Keeping	✘ ■ None	✔ ■ Auto-logged
Action Timeliness	✘ ■ Late	✔ ■ Early
Tools Required	■■■ Experience only	■ Smartphone + App

Legend: ✔ = Present / Supported ✘ = Absent / Not supported ★★★★★ = Accuracy rating (1–5) ■■■■■ = Speed rating (1–5 bars)

F.COMPARISON OF PLANT DISEASE DETECTION VS WITHOUT AGRISMART

Table I. Visual symbol-based comparison of plant disease detection capabilities: conventional farming practice vs. the proposed AgriSmart system (ResNet18 + KNN). Accuracy figures are derived from PlantVillage dataset evaluation. CNN: Convolutional Neural Network; KNN: K-Nearest Neighbour.

II. CONCLUSION

This study confirms that artificial intelligence can be effectively applied to identify plant diseases in an automated manner, and the AgriSmart web application demonstrates that such a system can be practically deployed in real agricultural settings. Among the models evaluated, the ResNet18-based Convolutional Neural Network achieved a classification accuracy of 94.6%, maintaining consistent performance across leaf images captured under varying field conditions. This makes it the most suitable choice when diagnostic reliability is the primary concern and adequate computing resources are available.

The K-Nearest Neighbour classifier, on the other hand, recorded an accuracy of 85.2% while requiring considerably less processing power and infrastructure. This characteristic makes it a strong candidate for deployment in resource-constrained environments, including embedded agricultural devices and offline mobile applications serving rural areas with unreliable internet connectivity. Combining CNN-derived feature representations with KNN-based inference proved to be an effective strategy that draws on the complementary strengths of both techniques.

The AgriSmart web application further establishes the practical relevance of this framework by offering farmers and agricultural workers a straightforward interface through which they can upload leaf images and receive immediate disease diagnoses along with suggested treatment actions. Trials conducted in Punjab indicated that users across varying literacy levels could interact with the system with ease, underscoring its suitability for smallholder farming communities.

Future work will focus on expanding the training dataset to include a wider range of crop varieties, geographic regions, and disease stages. Additionally, research will explore lightweight neural network architectures optimised for on-device inference, the integration of multi-spectral and time-series imaging to improve classification at ambiguous disease boundaries, and the inclusion of regional language support alongside offline functionality to make AgriSmart accessible to the most underserved farming populations worldwide.

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