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Research Article

Deep learning model for smart agriculture: Diagnosing plant diseases on apple leaves

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ABSTRACT

Automatic and early diagnosis of plant diseases is crucial for protecting crops and enhancing agricultural productivity. This paper introduces an efficient and lightweight deep-learning model to detect plant diseases from high-resolution images captured by digital cameras. The proposed model uses a convolutional neural network architecture that obtains high accuracy (96.55%) with significantly fewer parameters, decreasing computational complexity while maintaining strong feature extraction capabilities. To optimize performance, the network is downsampled using a fixed 2×2 MaxPooling2D operation, ensuring minimal loss of critical information. A real-world dataset to classify apple leaf images into diseased or healthy, is used to train a classifier model for specifically detecting Black Rot (Botryosphaeria obtusa), Cedar Rust (Gymnosporangium juniperi-virginianae), and Scab (Venturia inaequalis). Additionally, a mobile application is presented that provides farmers and agricultural workers with real-time disease identification and decision-support tools. The results of the experiments demonstrate that our approach outperformed state-of-the-art models (87.23% accuracy) while maintaining a capability for mobile deployment. These contributions position our model as a practical, accurate, and computationally efficient solution for plant disease detection in agricultural fields.

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INTRODUCTION

Agriculture is the basic sector that meets our nutritional needs, and it is an indispensable area for the continuity of our lives. Providing sustainability in the agricultural sector is very important for the prosperity of the people and developing economies, especially for agricultural countries. In this regard, Agriculture 4.0, also known as "modern agriculture", aims to popularize the use of digital hardware and software products in the agricultural sector and the analysis of data obtained from agricultural products using artificial intelligence (AI). The usage of AI techniques in agriculture

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will increase the welfare and agricultural efficiency of the whole society, especially farmers, facilitate access to safe food and quality nutrition, and contribute to economic sustainability.

Images of plant leaves are captured with cameras and sensors, such as those in smartphones or dedicated imaging devices. The images contain the visual details needed to diagnose diseases, and they make real-time monitoring and portable diagnosis possible. Automatic plant disease diagnosis from images is one of the innovative solutions incorporating AI technology to improve productivity in agriculture. In this regard, the primary goal is to contribute to the agriculture sector by taking photographs of plant leaves and developing an application that detects which disease the plant has. It helps plants grow in a healthy way by detecting plant diseases in the early stage, preventing the spread of diseases, and minimizing the damage that may arise from crop loss. This study aims to eliminate existing knowledge gaps, such as making recommendations to farmers about the treatment of the disease.

Unlike the existing applications in the literature, which were based on basic nutritional foods, this study focuses on apple plants. Because apple plant cultivation is an important agricultural field that is used both in the domestic market as a food source in many countries, such as China, the United States, Poland, Russia, and Turkey, and in the export market that contributes to the economies of these countries. Considering the place and value of the apple plant in the agricultural sector, further studies are required regarding the disease diagnosis of apple plants using the deep learning technique and making a suitable treatment method for this disease by developing a mobile application.

In the context of plant disease prediction, the input data generally comprises images of plant leaves, stems, or other plant tissues. Leaf images show textures, colors, and shapes that change with the health of the plant. Simple linear models cannot capture the complex, non-linear relationships between these features. Non-linear models can, for example by using higher-order terms, powers, or interactions between variables [1-4]. CNNs are well suited to this problem because they learn to map visual patterns, such as marks on a leaf, to a disease status [5-10].

The primary contributions of this study can be summarized as follows. (i) A deep-learning model is introduced to diagnose diseases in plants in the agricultural area accurately (ii) It especially detects apple leaf diseases from the images by designing an efficient CNN architecture with fewer parameters than other deep learning models in the literature, which is suitable for real-time deployment (iii) It presents a mobile application for the early diagnosis of diseases in apple plants, assisting farmers and agricultural workers in monitoring and detecting diseases through a warning system, and making recommendations to them about the treatment of the disease as well. (iv) The experimental results showed that the proposed model (96.55%) demonstrated its superiority over the existing models (87.23%) on average in terms of accuracy.

The proposed system supports data-driven decision-making, minimizes crop loss, optimizes pesticide use, and contributes to sustainable agriculture. The model is small and efficient, so it can be adapted to other crops and run on low-cost hardware. This supports the use of AI in agriculture, since it helps farmers detect diseases early and manage their farms better.

The organization of the remaining paper is as follows. The related work is discussed in the Related Works Section. The method and material are described in the Materials and Methods section, which outlines the proposed deep learning model and dataset used. The experimental results, performance matrix, comparison against the existing models, and the related discussions are given in the Experimental Studies section. Finally, it is concluded with a summary and comments on future research scope in the Conclusion section.

Related Works

Recently, machine learning methods have been used for disease diagnosis of different plants such as tomato [11-13], strawberry [4], corn [6, 13-15], cucumber [16], potato [7, 8, 13], pear [17], peanut [18], soybean [19], pepper [9], and rice [15, 10, 20-21]. In the paper of Sun et al. [18], one of the frequently encountered diseases in peanuts, the severity of southern blight, was focused on determining the level of the aforementioned disease as healthy, mild, moderate, or severe. Fenu and Malloci [17] carried out their studies to detect frequently occurring diseases in the pear plant, including spot, curl, and slug. Resti et al. [14] presented a machine learning model to classify the corn plant diseases and pests into seven different categories, namely nonpathogenic, common rust, blight, downy mildew, Locusta pest, Heliostic Armigera pest, Spodoptera Frugiperda pest. Liu et al. [16] addressed the topic of cucumber disease diagnosis in their study by dealing with the images of bacterial angular spot leaves, downy mildew leaves, and healthy leaves. Restrepo-Arias et al. [11] focused on tomato plants to categorize them into healthy or diseased classes. Their experiments included ten categories considering different disease types. The images of tomato plants in the experiments were made up of early blight, late blight, mosaic virus, bacterial spot, leaf mold, septoria leaf spot, yellow leaf curl, spider mites, target spot, and healthy leaf samples. In another work, Yin et al. [9] developed a search model for hot pepper diseases using the images of 15 classes of hot pepper diseases (i.e., bacterial wilt, canker, gray mold, etc.) and 19 classes of hot pepper pests (i.e., stali, speculum, whitefly, etc.). In the studies of Ali et al. [7] and Shaheed et al. [8], potato diseases were taken into consideration by modeling a classifier to seek three classes of crop leaves: early blight, late blight, and healthy. Sengupta et al. [20] and Latif et al. [10] used machine learning to detect five common rice diseases, including bacterial leaf blight, brown spot, and leaf

blast. In another study [5], strawberry leaf pest classification was concentrated by dividing samples into five classes: normal, mite, cotton aphid, fusarium wilt, and powdery mildew.

In the literature, different machine learning methods have been used for plant disease diagnosis such as k-nearest neighbors (KNN) [9, 18, 22], naïve Bayes (NB) [14, 23], logistic regression (LR) [19], and support vector machines (SVM) [13, 18, 22]. Resti and colleagues [14] constructed a multinomial NB model by integrating fuzzy discretization into their framework, employing various combinations of membership functions. In another study [19], the disease severity levels of the soybean crop were classified by various machine learning models, from which LR and SVM achieved the most accurate predictions. In addition to individual classifiers, ensemble learning techniques such as random forest (RF) [13, 19], bagging [20], voting [5], and boosting [13, 20] have been frequently performed. Hasan et al. [13] used a two-step approach. First, a simplified visual geometry group (VGG) model extracted the features. Then, two ensemble models, random forest (RF) and extreme gradient boosting (XGB), classified the plant diseases. Sengupta et al. [20] proposed ensemble classification models with RF, AdaBoost, and bagging after applying feature selection using rough set theory in the MapReduce framework. In the paper of Kim and Kim [5], an ensemble learning model combining ResNet and EfficientNet was introduced to identify the disease names of pests. Furthermore, deep learning techniques such as CNN and transfer learning (TL) [5-11, 13, 17, 18] have been broadly applied in many studies because of their capability to automatically discover intricate patterns in data. Several widely utilized CNN architectures in this domain are Resnet [6-9], EfficientNet [5-6, 8, 17], DenseNet [6, 9-10], GoogleNet [10], AlexNet [10], and VGG [6, 9-10, 17]. Table 1 briefly demonstrates some of the related works aiming at detecting plant diseases. The performances of models have been validated using various metrics, including accuracy (Acc), precision (Pr), recall (Rl), sensitivity (Se), specificity (Sp), F1-score (F1), and area under the curve (AUC).

In plant disease diagnosis, machine learning models are expected to perform better with a larger number of image samples compared to a smaller number. Some previous works [18-19] have been performed on relatively small datasets, which affects generalizability since they only allow for a limited number of class distributions. On the other hand, some previous studies [13] have developed plant disease diagnosis systems that can detect more than one plant species, such as corn, potato, and tomato. Although some satisfactory results were obtained in the existing works [5, 18-20], they still need to be improved so as to achieve an accuracy of over 90%. The CNN models are expected to be designed with few layers, parameters, and calculations for improved computational efficiency and to be deployable on tiny hardware platforms. Since some previous studies [5-10, 17] have been conducted on deep CNN architectures, they lead to greater complexity, higher storage requirements, longer processing times, and more advanced hardware platforms for execution.

MATERIALS AND METHODS

Proposed Model

This study proposes an intelligent model to diagnose apple plant diseases using deep learning techniques. As part of the study, the CNN deep learning algorithm was used to identify apple plant diseases. The reason for selecting the CNN model in this study is that it has mostly demonstrated state-of-the-art performance [24, 25] by learning hierarchical features easily from data, especially from images, by having translation invariance due to its convolutional layers, and by using parameter sharing and obtaining reduced complexity. Our study includes efforts to improve the algorithms' diagnostic skills through research and development.

The CNN method is particularly well-suited for plant image classification tasks because it can automatically learn spatial hierarchies of features through multiple layers. In our model, deep learning layers were used to extract localized patterns such as color changes, texture irregularities, and lesion shapes that are indicative of specific plant diseases. This method tends to accomplish non-linearity, prevent overfitting, and improve learning capacity in disease detection in plants.

Figure 1 displays a visual overview of the system being introduced. Initially, users have the option to either upload an image or capture a photo of an apple plant via the mobile application. Images are taken with digital cameras that have high-quality sensors, which capture the details of the plant leaves for analysis. The main goal is to find out whether the submitted image shows a disease such as black rot, scab, or cedar rust. In the background, the app uses a model that is trained on images of healthy and diseased apple leaves. The images are resized, rescaled, and augmented before training, which standardizes the input and makes the model more robust to real-world variation. The model learns the patterns in the leaf images, so a new image can be classified once it is uploaded. The predicted class is shown together with a confidence score for each disease category. Based on the result, the app also gives recommendations, such as treatment options, preventive measures, or links to further reading.

Figure 2 represents the architecture of the proposed model. The algorithm started by reading the input images from the dataset. Data preprocessing was done by resizing, scaling, and augmentation operations to enhance the algorithm's ability to identify key features in images. In the first step of preprocessing, input images were adjusted to a single size of 256x256 by the resizing operation. As the next step, a rescaling operation was performed using the ratio (1/255) to regularize the data distribution throughout the image. First, pixel values were rescaled from the range 0-255 to the

Table 1. Summary of the recent studies in plant disease diagnosis

Ref.	Year	Method	Plant type	Dataset used	Dataset size (number of images)	Result
[18]	2024	CNN, SVM, KNN	Peanut	Collected	590	Acc=82.76% Kappa=0.75
[19]	2024	LR and SVM	Soybean	Collected	300	Acc=~87% Kappa=~80% F1=~93%
[6]	2023	CNN variant with TL	Corn	PlantVillage, PlantDoc	3188	Acc=98.85% Se=98% Sp=98%
[14]	2023	NB variants with fuzzy discretization	Corn	Collected	3172	Acc=98.63% Pr=94.14% Rl=85.94% F1=89.95% Sp=99.21%
[8]	2023	CNN variant with vision transformer	Potato	PlantVillage	3600	Acc=97.6% Se=94% Sp=96% Pr=94.12% F1=96.2%
[5]	2023	Ensemble CNN variants	Strawberry	Collected	10,000	Acc=85.60%
[17]	2023	Ensemble of CNNs	Pear	DiaMOS Plant	3006	Acc=91.14% Pr=89.84% Rl=90.02% F1=89.93%
[16]	2022	CNN variant with additive feature extraction	Cucumber	Collected	2542	Acc=90.2%
[7]	2022	PCA-LDA model using feature fusion with TL	Potato	PlantVillage	1337	Acc=98.21% Se=98.79% Sp=92.67% F1=95.33% AUC=98.46%
[20]	2022	RF, bagging, and AdaBoost with rough set theory-based feature selection	Rice	Rice Leaf Diseases Dataset on Kaggle and collected data	500 (collected) 120 (Kaggle)	Acc=~88%
[10]	2022	CNN with TL	Rice	Rice Leafs 5 Diseases Dataset on Kaggle	2167	Acc=96.08% Pr=96.20% Rl=96.17% Sp=99.21% F1=96.16%
[13]	2021	TL with RF, TL with XGB	Corn, Potato, Tomato	PlantVillage, PlantDoc	4500 (corn) 7698 (potato) 7822 (tomato)	Acc=94.47 (corn) Acc= 98.74 (potato) Acc= 93.91 (tomato)
[9]	2020	KNN with TL	Pepper	Taken from the National Institute of Horticultural and Herbal Science in South Korea	4598	Acc=97.52%

range 0-1. The dataset was then augmented with random rotation and flipping. Rotation was applied with a factor of 0.2, and the images were flipped horizontally and vertically. This added variety to the training set and helped the model generalize. Next, features were extracted with Conv2D layers and ReLU activation, where learnable filters were applied to the images to produce feature maps. Different filter sizes were tried. Since the leaf images are full of fine textures, 3×3 filters gave better results than 5×5 or 7×7 filters, which suit large objects better. While 32 filters of 3x3 size

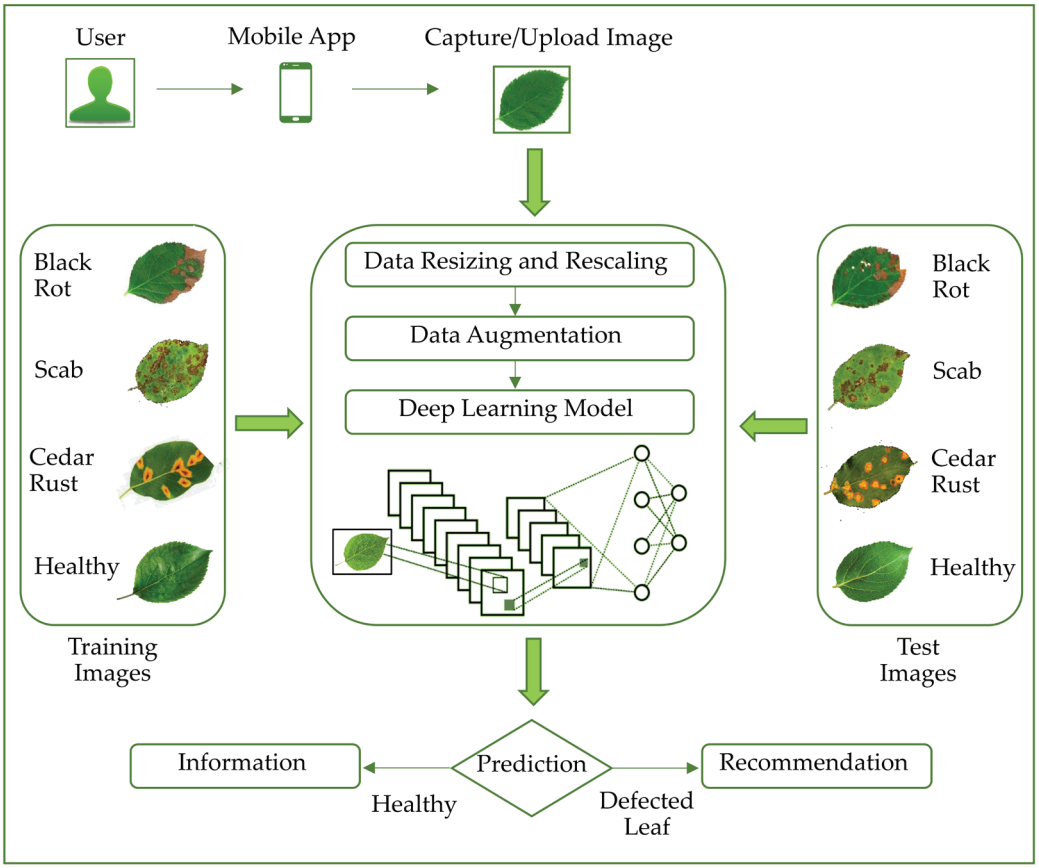


Figure 1. An overview of the general structure of the proposed framework.

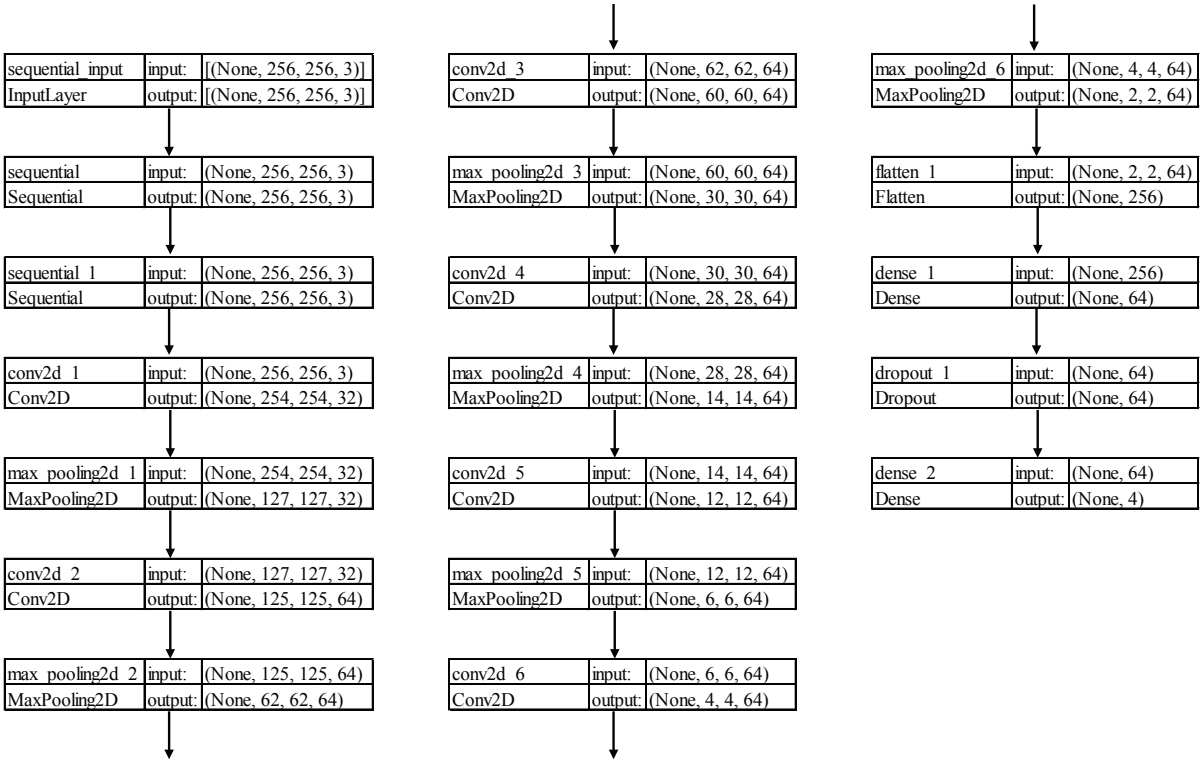


Figure 2. Proposed CNN architecture for apple plant leaf disease diagnosis.

were used in the first layer, 64 filters of 3x3 size were used in the other layers. To reduce the computational complexity of the network and preserve important features, the network was repeatedly decreased by operations represented as MaxPooling2D. Based on performance, the max pooling size was fixed as 2x2. In this way, reduced complexity in terms of trainable parameters and model size enhanced the effectiveness of the model prediction process.

Dropout was applied after the convolution and pooling steps to prevent overfitting. During training, some of the units were randomly set to zero. The dropout rate was set to 0.5 after empirical tuning, a value that is also common in CNN studies. The feature maps were then flattened into single-column vectors and passed to the fully connected layer, a Dense layer with 64 neurons. Classification was finally performed with a softmax activation function, which gives a probability between 0 and 1 for each class. The sum of the estimated probabilities must be 1. The class with the highest probability was marked as the predicted outcome. It can be noted here that the "Adam" optimizer was used for the optimization of variables.

The proposed methodology consists of the following steps:

- *Input layer*: Preprocessed images of healthy or diseased apple leaves are fed into the network.
- *Convolutional layers*: Several stacked convolutional layers are used to extract features such as color, texture, and shape, which help separate healthy leaves from diseased ones.
- *Activation function*: ReLU is applied after the convolutions to add non-linearity, so that more complex patterns can be learned.
- *Pooling layers*: Feature maps are downsampled with pooling layers. This reduces computation and the risk of overfitting while the most important features are kept.
- *Flatten layer*: The two-dimensional feature maps are converted into a one-dimensional vector.
- *Dropout layer*: A fraction of the units is randomly dropped from the current layer during training with a probability between 0 and 1, which helps prevent overfitting.
- *Fully connected layer*: The extracted features are mapped to the disease categories.
- *Output layer*: Softmax is used to assign a probability to each class: healthy, black rot, scab, or cedar rust.

The CNN models are expected to be designed with fewer parameters for efficiency and deployment on low-cost hardware platforms. Training and classification times are highly dependent on the number of parameters of a CNN architecture since the number of parameters is proportional to the network size, the number of operations, and the inference time. As the network goes deeper, it will result in many parameters, increased complexity, a high storage capacity, increased running time, and demanding complex hardware platforms for execution. Our research takes into consideration minimizing the complex nature of CNN architecture. As given in Table 2, our CNN architecture has a a much smaller parameter count than VGG-19 and ResNet-50, two commonly used CNN models. Because

Table 2. The output size and the number of parameters for each layer in the proposed model

Layer (type)	Output shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(32, 256, 256, 3)	0
conv2d_1 (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d_1 (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_2 (Conv2D)	(32, 125, 125, 64)	18,496
max_pooling2d_2 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_3 (Conv2D)	(32, 60, 60, 64)	36,928
max_pooling2d_3 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_4 (Conv2D)	(32, 28, 28, 64)	36,928
max_pooling2d_4 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_5 (Conv2D)	(32, 12, 12, 64)	36,928
max_pooling2d_5 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_6 (Conv2D)	(32, 4, 4, 64)	36,928
max_pooling2d_6 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16,448
dropout (Dropout)	(32, 64)	0
dense_1 (Dense)	(32, 4)	260
Total params		183,812

our model has only 6 layers while VGG-19 and ResNet-50 have 19 layers and 50 layers, respectively, and more layers usually mean more parameters. Moreover, the models may tend to cause overfitting as they have a large number of parameters. Using imagery along with mobile devices, our model is computationally less demanding, so it can be accessible from a wide range of agricultural applications.

Mobile Application

Considering the environmental impact, providing a decision-support tool without leading to job displacement, and protecting privacy for collected/stored data are key ethical considerations that are addressed in the adoption of AI in agriculture.

The main objective of this study is to develop an innovative mobile application that can identify diseases in apple plant species early on. This user-friendly application can facilitate farmers and agricultural workers in monitoring and detecting diseases, and will guide them with a warning mechanism for certain diseases. It serves as a digital innovator by extending the application of technology to farming operations. Additionally, the application makes recommendations about the treatment of disease to the agricultural community by increasing farmer awareness of agricultural issues. Our application can operate stably even in remote areas thanks to the popularity of mobile internet services in recent years.

The mobile app is meant to help farmers make better decisions in the field. By catching diseases early, it can limit their spread, reduce product losses, and improve the quality and amount of the harvest. Sustainability in agriculture is also one of the main goals of this study. When a disease is found early, farmers can act before it spreads, so less chemical treatment is needed. This lowers environmental pollution and supports more sustainable food production.

Figure 3 shows the main interfaces of the mobile application that the user can run on their devices, including the home page, the diagnosis and suggestion page, and the image storage page. When the application is opened on a mobile device, first the user is prompted to either upload a picture from the device gallery or immediately snap a photograph from an apple plant, as shown in Figure 3a. In other words, the "Home Page" was designed to guide users through the process of capturing or uploading a leaf image. Once the image has been uploaded or snapped, the application immediately starts processing the image for the diagnosis of the plant disease. The image is then processed at the backend with the constructed model for disease classification, and after that, the user should receive the diagnostic results, as shown in Figure 3b. In the "Diagnose Page", the predicted disease name is displayed as the output with a suggestion for treatment. In addition to the symptom type label, the user can now see information about the disease, like the causes and how to control it. Here, recommendations for avoiding infection (e.g., organic methods) or suggestions for actions the user can take (e.g., proper watering techniques, crop rotation) are displayed. In the "My Plants" page, all images according to their categories are also provided for the user as a list for a further view, as shown in

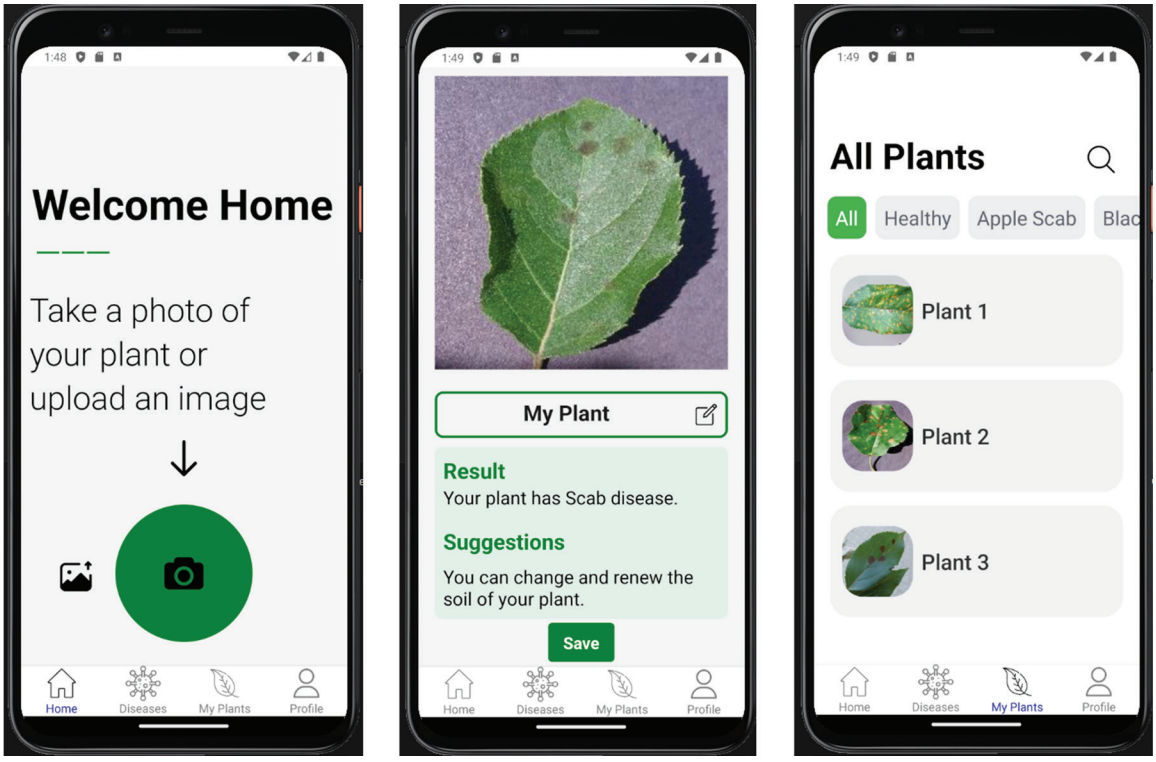


Figure 3. The main user interfaces of the mobile application.

Figure 3c. This image gallery allows user to save their personal history for later reference and view previous images to track the health of their plants over time. In summary, users can easily organize their actions by pressing the buttons at the bottom of the pages, including "Home", "Diagnose", "My Plants", and "Profile".

The mobile application was developed by taking into consideration the necessary key factors related to architecture and performance, such as low latency, device compatibility, usability, scalability, and efficient resource usage. It is designed to give a response to the users within a few seconds for interactive tasks. The application can provide a compatible experience for a wide range of users, regardless of their device type (Android, iOS, etc.), as well as different device hardware (smartphones and tablets). With the aid of a well-trained model (96.55%), robust and precise outcomes can be produced by the application. However, providing a high-quality image is essential for successful disease recognition. The camera allowance is the necessary permission that should be asked to the user.

In the current phase, direct user feedback or real-world testing results were not conducted for the mobile application; however, this tool was developed with user-centric features to address common challenges faced by farmers. The app was designed after looking at how disease detection is usually done, so that it fits what users need. The app was designed to be easy to use, so people with little technical background or little experience with smartphones can work with it comfortably. Its icons, text labels, and menus were streamlined to keep users from getting lost. Data can be entered easily, results are shown in real time, and decision-support tools are provided, which saves time and effort in farm management. Since the model performs well, the app is expected to help with crop monitoring, resource use, and productivity.

Dataset Description

In this study, the proposed deep learning model was tested on the PlantVillage dataset [26] (https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset). It is a public dataset that contains labeled leaf images of different plants, such as tomato, pepper, and potato. The images were captured by Penn State University in the USA to provide a large-scale resource for agricultural research, particularly for plant disease diagnosis. The diseases were named and labeled by experts in plant pathology according to plant species. The dataset includes 3,171 images of healthy and diseased apple leaves, which were collected under controlled conditions. The images of apple leaves are categorized into four groups: "Healthy", "Scab", "Black Rot", and "Cedar Rust". Figure 4 shows the sample apple leaf images for all four classes. All the original images in the dataset are 256x256 pixels with an RGB color space.

A brief description of the apple leaf diseases is given in Table 3. Besides, the main characteristics of diseases are summarized below:



Figure 4. Sample images from the dataset. (a) Scab Leaf (b) Cedar Rust Leaf (c) Black Rot Leaf (d) Healthy Leaf.

Table 3. Description of apple leaf diseases

Disease	Type	Related pathogen	Symptoms/Characteristics
Scab	Fungal	Venturia inaequalis	During the starting stage, light-green radial or round spots are formed on the leaf surface. As the infection spreads, the spots can cover the whole leaf and cause the leaves to turn brown.
Cedar Rust	Fungal	Gymnosporangium juniperi-virginianae	At an early stage, pinhole-sized pale-yellow spots appear on leaves. As the disease continues, they gradually expand and become round orange-yellow, and edged in red.
Black Rot	Fungal	Botryosphaeria obtusa	Initially, symptoms appear as round purple-black (frog-eye) spots on leaves. Later, it expands in size and causes the leaves to turn brown in color, as well as black patches on the fruit.

Scab: Scab is one of the most frequent leaf diseases in apple trees. This is caused by a fungus called venturia inaequalis. It is a serious infection that can attack both the fruits and leaves of the tree. Disease symptoms appear as light-green radial or round marks on the leaf's upper surface of the infected leaf and as velvety or olive-colored lesions on the lower surface. Spots can merge with each other and show big lesions. The severely infected leaf turns yellow, ranges in size (curls up, becomes smaller and thicker), and drops prematurely. As the infection spreads, more and more leaves fall off, which weakens the apple tree.

Black Rot: It is also a fungal infection and is caused by a fungus known as Botryosphaeria obtuse that attacks trees mainly in humid and warm areas. Initially, symptoms appear as small and purple-black (frog-eye) spots on the upper surface of the leaf and enlarge to round contusions 3 mm to 6 mm in diameter. The center of the lesion turns tan or brown; however, the margins of it remain purple, resembling frog eyes. As the lesion ages, higher severity can cause defoliation that eventually weakens the apple tree. The "black rot" disease affects both the leaves and fruits of the tree (black patches on the fruit).

Cedar Rust: It is likewise a fungal disease triggered by a pathogen called Gymnosporangium juniperi-virginianae. Initially, pinhole-sized pale yellow spots appear on the upper surfaces of leaves and gradually expand and become bright orange-yellow spots with a red border. As the illness continues, lots of disease spots appear on a leaf, and it can be destructive to the trees. The disease can damage both leaves and fruits. When the disease gets severe, the worst-affected leaves can turn yellow and fall off early.

Table 4 displays the number of sample apple diseases for each class and their distribution within classes. The training set has 2,218 images, the validation set has 634, and the test set has 319. Therefore, the dataset was split into three parts: training (70%), validation (20%), and test (10%).

The dataset is a good fit for practical use for three reasons:

- *Disease stages*: The images cover Scab, Cedar Rust, and Black Rot at early and advanced stages, so the model can learn to spot both. This helps with monitoring in real time.
- *Real-world relevance*: These three diseases cause serious losses in apple production worldwide, so the model addresses problems that farmers and agronomists actually face.
- *Mobile use*: The images were taken with digital cameras similar to those in smartphones, so the model should work with photos farmers take on their own phones.

The PlantVillage dataset is clean and well annotated, but it does not reflect the variety of real fields. According to Hughes and Salathé [26], the leaves were photographed in controlled conditions, against plain grey or black backgrounds, under consistent lighting, and were then cropped and aligned in the same way. This makes training easier, but it can cause problems outside the lab. Real fields have soil, pests, other plants, changing light, and leaves seen from many angles, none of which appear in the dataset. Because of this, a model trained only on PlantVillage may not generalize well to real farming conditions.

Experimental Studies

This study aims to precisely diagnose apple plant diseases using the deep learning technique. To reach this goal, a CNN architecture was designed, trained with the annotated images, and used as a classifier. The proposed model was implemented in Python, using Keras on top of TensorFlow.

In order to judge the performance of the method, a number of evaluation metrics, such as accuracy (Acc), recall (Rl), precision (Pr), and F1-score (F1), were used as given in Equations (1) to (4), in the same order:

$$\mathrm{Acc} = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TN} + \mathrm{TP} + \mathrm{FN} + \mathrm{FP}} \tag{1}$$

$$\mathrm{Pr} = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP}} \tag{2}$$

$$\mathrm{Rl} = \frac{\mathrm{TP}}{\mathrm{FN} + \mathrm{TP}} \tag{3}$$

$$\mathrm{F1} = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FN} + \mathrm{FP}} \tag{4}$$

where TP (true positives) are the positive cases the model identified correctly by the CNN classifier. On the other hand, TN (true negative) refers to the number of instances correctly detected as negative. FP (false positive) refers to the negative instances, which were tested as positive, but

Table 4. Number of sample apple leaf images for each class

Dataset	Scab	Black Rot	Cedar Rust	Healthy	Total
Train Dataset	441	434	192	1151	2218
Validation Dataset	126	124	55	329	634
Test Dataset	63	63	28	165	319
Total	630	621	275	1645	3171

which are actually negative. In contrast, FN (false negative) indicates the count of wrongly predicted positive instances. These metrics are commonly used to judge how well a classifier separates the classes.

RESULTS AND DISCUSSION

This section reports how the proposed model performed on a real-world image dataset is presented in detail. The model was first trained and then tested on the apple leaf image data. In the test set, the proposed model achieved 96.55% accuracy for apple disease diagnosis. Figure 5 plots the model's accuracy and loss on the training and validation sets across 50 epochs. As can be seen, classification accuracy increased as the number of epochs increased. Additionally, the figure displays that the presented model produces loss that keeps decreasing across epochs.

Table 5 presents the recall, precision, and F1-score values obtained on a per-class basis. All the values are over 0.86, and most of them are very close to 1, indicating that the classification model is very confident in diagnosing apple diseases. The F1-score ranges between 0.92 and 0.98, which shows that the model can reliably tell apart diseases. The overall precision, recall, and F1-score metrics were calculated as 0.97, 0.95, and 0.96, respectively.

Figure 6 shows the confusion matrix produced by the CNN model trained on the apple leaf image dataset. It summarizes the counts of right and wrong predictions to provide a comprehensive view of categorization efficacy. Low non-diagonal cells and high diagonal cells of the matrix (63, 27, 164, and 54) for each class indicate the good performance and reliability of the model for diagnosing apple plant leaf diseases. The matrix shows that the model revealed only 11 misclassifications out of 319 predictions. It is clearly seen that the proposed model generally managed to detect the plant disease types reliably. For instance, 164 out of 165 cedar rust diseases were detected correctly; nevertheless, only 1 of them was classified incorrectly. These findings point to the model's strength in diagnosing apple plant diseases.

At the feature level, understanding the reasons behind misclassification is related to input characteristics (color, texture, shape, spectral signatures, etc.) that influence the predictions of a machine learning model. The main reason is the feature similarity across classes since some plant diseases manifest with visually similar symptoms (e.g.,

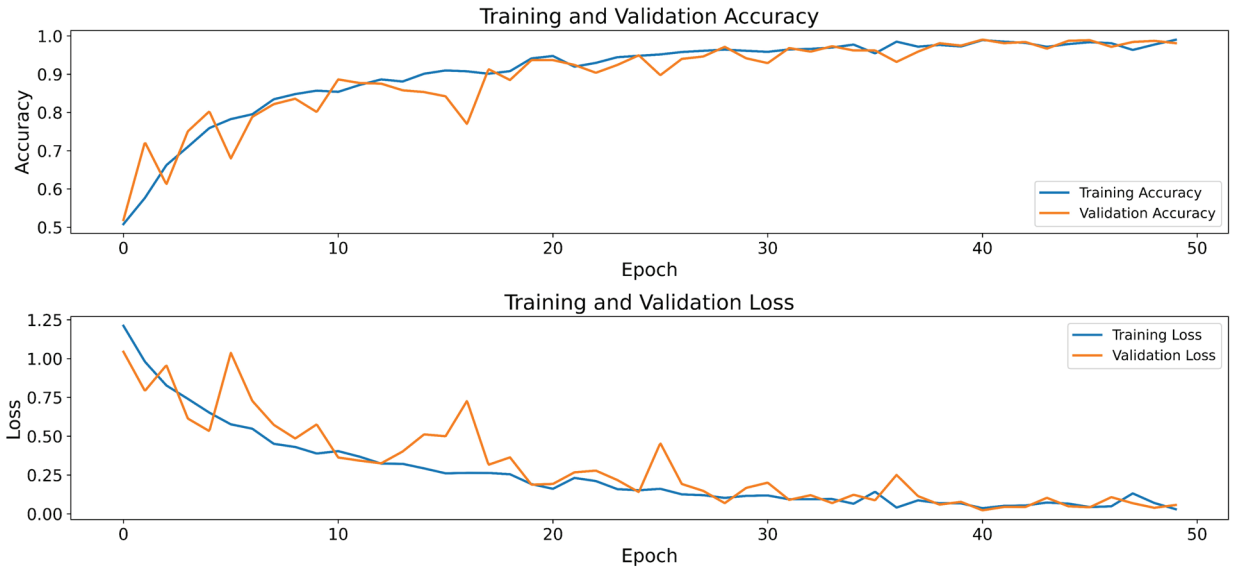


Figure 5. Training & validation accuracy and loss graphs of the proposed model.

Table 5. Per-class results of the proposed model on each class separately

Dataset	Precision	Recall	F1-score
Black Rot	0.97	1.00	0.98
Cedar Rust	0.96	0.96	0.96
Healthy	0.96	0.99	0.98
Scab	0.98	0.86	0.92

yellowing, spotting, or curling of leaves). For instance, as given in Figure 6, one case of black rot was mistakenly predicted since some black rot lesions may have a reddish tint or irregular edges, causing confusion with cedar rust. Another cause of misclassification from a feature perspective is that the same disease can present differently depending on the plant age or environmental conditions. Leaves in the same class can look quite different, which makes classification harder. One cedar rust leaf was predicted as healthy, probably because it was lighter than usual. Early cedar rust has only small yellow spots, which look like normal discoloration. In six cases, healthy leaves were predicted as cedar rust, most likely because some healthy leaves have natural blemishes that look like early symptoms. Two healthy leaves were predicted as scab, probably for a similar reason: mild discoloration or small imperfections were read as disease. Healthy leaves were also predicted as black rot in some cases, likely because dark spots or shadows on the leaf looked like black rot lesions. In short, the model struggles when diseases and healthy leaves look alike in color and texture.

The number of images for each disease type, especially for underrepresented categories, can be increased to improve classification accuracy and reduce misclassifications by ensuring the dataset includes angles, varied lighting conditions, and leaf positions to improve generalization. Besides, more images showing different disease stages (early, moderate, severe) can be collected to help the model learn progressive symptoms.

Figure 7 presents several sample apple leaf images that were selected from the test dataset randomly and classified by our model. As seen in the figure, the constructed model can accurately identify apple diseases. For instance, the Black Rot disease in the third sample image was predicted correctly. Similarly, the Scab and Cedar Rust diseases were labeled correctly from the fourth and fifth images.

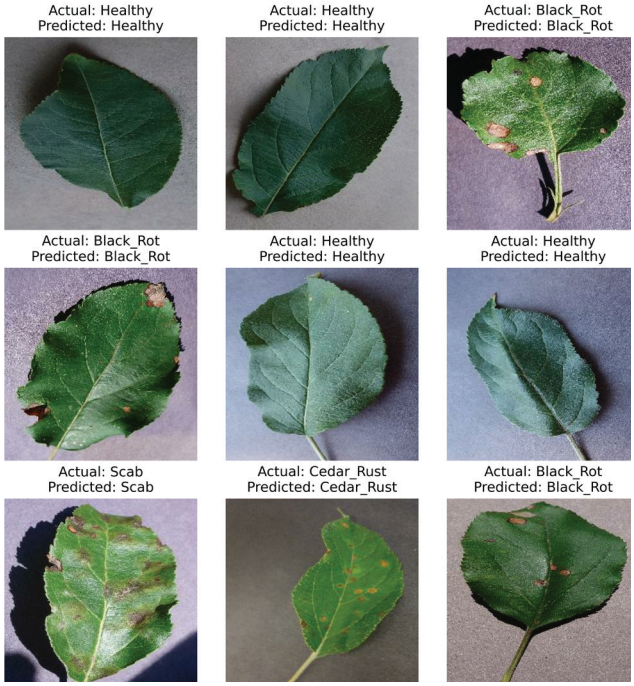


Figure 7. Sample prediction outputs for apple leaf images.

Table 6 shows the findings of earlier studies [27-41] that were reported on the same dataset. According to the table, our model (96.55%) came out ahead of the earlier approaches (87.23%) on average. Therefore, it exhibited remarkable improvement (9.32%) in accuracy. For example, it achieved higher accuracy than the conventional machine learning methods such as KNN (91.25%) [39], SVM (96.21%) [34], artificial neural network (ANN) (85%) [39], decision tree (DT) (87.53%) [28], and multilayer perceptron (MLP) (72.00%) [37]. Additionally, our model performed better than the ensemble-learning-based models, such as gradient

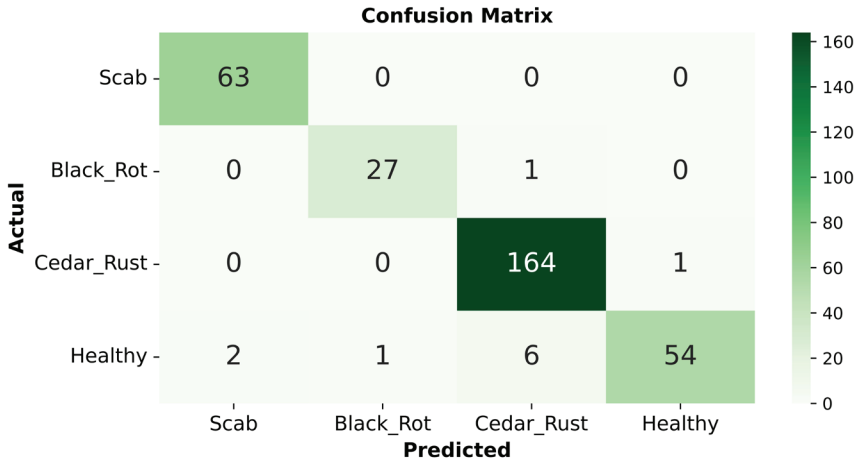


Figure 6. Confusion matrix of the proposed model on the test set.

Table 6. Comparison of our model w.r.t. the state-of-the-art models on the same dataset

Ref.	Year	Method	Accuracy (%)
Jain et al. [27]	2024	CNN	93.81
Priyaradhikadevi et al. [28]	2023	DT	87.53
		Gradient Boosting	94.59
Santhoshkumar et al. [29]	2022	AlexNet	93.31
		VGG-16	94.80
		PLDP Net-RF	95.53
Sahitya et al. [30]	2022	VGG-19	86.67
Monowar et al. [31]	2022	Bootstrap Your Own Latent	88.70
		Simple Siamese Networks	87.70
		Cross Iterative Kernel K-means enhanced with Image Classification and Similarity Measurements	83.70
		Self-Supervised Clustering Method	88.40
Kurmi and Gangwar [32]	2022	Image Recognition-based Plant Disease Detection	77.20
		Machine Learning-based Plant Disease Diagnosis	90.70
		Automated Crop Disease Management Techniques	85.40
		K-Means Clustering-based Semi-Automatic Method	79.20
		Multi-Level Learning-based Features for Classification	85.90
		Genetic Algorithm-based Features for Apple Disease Classification	85.70
		Bag of Visual Words + Fisher Vectors + Hand-crafted Feature + SVM	94.80
		Bag of Visual Words + Fisher Vectors + Hand-crafted Feature + LR	90.80
		Bag of Visual Words + Fisher Vectors + Hand-crafted Feature + MLP	93.70
Joshi et al. [33]	2022	RF	91.00
Javidan et al. [34]	2022	SVM	96.21
Ghosh and Roy [35]	2022	ANN	94.79
Kulkarni et al. [36]	2021	RF	91.00
Ahil et al. [37]	2021	MLP	72.00
		CNN	90.84
Xiong et al. [38]	2020	MobileNet CNN	83.30
Bracino et al. [39]	2020	KNN	91.25
		Gaussian Process Regression	82.50
		ANN	85.00
		DT	65.00
		SVM	83.30
Usman [40]	2019	Decision-Level Fusion	76.50
Mukherjee et al. [41]	2017	GoogleNet	85.04
		Average	87.23
Proposed		Convolutional Neural Networks	**96.55**

boosting (94.59%) [28] and RF (91.00%) [33]. Evaluation of the proposed CNN model also demonstrated its superiority over the previous deep learning models such as AlexNet (93.31%) [29], VGG-16 (94.80%) [29], VGG-19 (86.67%) [30], MobileNet (83.30%) [38], and GoogleNet (85.04%) [41]. Since it achieved a greater accuracy rate in plant disease identification against the existing solutions, it provides technical contributions in the field of agriculture. Most of the referenced studies (approximately 10-11 out of 15) do not report precision, recall, and F1-score values. Additionally, the confusion matrices were not fully provided, making it impossible to derive these metrics accurately. Given this limitation, considering current studies, in [29], they stated that AlexNet managed to obtain 92.11% precision, 93.36% recall, and 92.41% F1-score, while VGG-16 had 95.32% precision, 94.89% recall, and 94.89% F1-score. The best model was

Plant Leaf Diseases Prediction Net-Random Forest (PLDP Net-RF) with 96.66% precision, 96.54% recall, and 96.53% F1-score. In [30], VGG-19 obtained precision, recall, and F1-score as 89.32%, 85.40%, and 87.32%, respectively. RF in [33] had 92% precision, 90% recall, and 91% F1-score, while in [36], only F1-score was mentioned as 91% by RF. Our model scored best among the compared models: 97% precision, 95% recall, and 96% F1-score.

Many deep learning models use very large networks. Ours uses fewer parameters and still reaches high accuracy, which also helps reduce overfitting. We used MaxPooling2D layers with a fixed 2×2 pool size to shrink the feature maps while keeping the details that matter for telling diseases apart. To get stable training, we tuned the learning rate and added batch normalization and dropout. We also tried different network depths, activation functions, and optimizers to find the combination that worked best.

Recent compact CNNs such as MobileNetV3 and EfficientNet-Lite perform very well. They use techniques like neural architecture search, inverted residual blocks, and squeeze-and-excitation modules. However, these models are fairly complex and can be hard to retrain or interpret when the dataset is small and resources are limited. We took a different route and designed our architecture by hand. It is simpler, easier to understand, and easier to deploy, which matters in agriculture, where many farmers use low-end phones. Our model also reaches 96.55% accuracy, which is comparable to or higher than these models, while being lighter.

The proposed deep learning model, designed for diagnosing apple leaf diseases, has several critical applications in smart agriculture. The model uses a CNN to separate healthy apple leaves from diseased ones, so problems can be caught early. A farmer can photograph a leaf with a phone and check it for scab, cedar rust, or black rot. The app returns a result within moments, along with some basic information about the disease and suggested treatments. Catching a disease early should mean less crop loss and less pesticide, and probably a better yield. With 96.55% accuracy, the model can also help experts follow how diseases develop over time. We trained it only on apple leaves, but the same approach could be adapted to rice, tomatoes, or corn. The model is also small. It has fewer parameters than many standard deep learning networks, so it should run on phones and cheap hardware. Taken together, the results suggest that this kind of diagnosis could be used on real farms and not only in the lab.

CONCLUSION

Plant disease diagnosis is a crucial task for increasing crop quality and cultivation yield in agriculture. The development of leaf disease identification systems by using machine learning techniques is significant to achieve precise and robust predictions for sustainable agriculture. Our paper reports a deep-learning model which accurately detects apple plant diseases from images without requiring an extensive list of hyperparameters, with results that compare well with other deep learning methods in the literature. A new convolutional neural network architecture was designed for the correct classification of three types of apple diseases: Scab, Cedar Rust, and Black Rot. In addition, a mobile application was built to provide agricultural workers and farmers with information to help make decisions when identifying and monitoring diseases. The experiments conducted on a dataset demonstrated that the proposed model (96.55%) was ahead of the state-of-the-art models (87.23%) on average across the accuracy metric. Compared to the results of the previous studies, the performance was improved by 9.32% on average. The proposed model strikes a strong balance between performance and low computational cost, so it can be deployed on mobile devices in agricultural settings.

Future research will focus on cross-crop adaptation of the model to other types of plants, including potato, tomato, and grape. Analyzing images of other plants' symptoms will be useful to enable early disease detection in various species. The model will have the capability of detecting key visual patterns such as texture variations, color changes, and lesion formations—common indicators of plant diseases across different species. To make the system work for other crops, we will add new datasets of crop disease images and retrain the model. The CNN architecture stays the same. Thanks to transfer learning, we only need to fine-tune the existing layers, so the model picks up the disease patterns of a new crop quickly and with less training time. The mobile app will also get a crop selection step: the user picks the plant type before scanning, and the app uses the matching disease detection model. This makes the system easier to scale and useful for more farmers.

Our model has only been tested on PlantVillage images, which were taken in a controlled setting. Field images look different. The light changes during the day, the weather is not always clear, and leaves sit among soil, grass, and other plants. We don't know yet how well the model handles this, so the next step is to test it on photos taken in real orchards. We would need to collect these ourselves. Drones could help here, since they can cover a large area quickly, and farmers would notice an outbreak before it spreads. Treatment could then be limited to the affected trees. Another idea is to add temperature and humidity data to the app, because these two have a big effect on how diseases develop. Integrating environmental sensors with disease prediction models will be useful for better monitoring and early warning systems. Future work will also include collecting user feedback and conducting on-field trials to comprehensively evaluate the performance and effectiveness of the mobile application in real-world agricultural settings.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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