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CNN-based leaf disease detection for rooftop gardening using multi-species image segmentation

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ABSTRACT

Rooftop gardening is increasingly popular in urban areas with limited agricultural space, but many gardeners abandon it due to the rapid spread of plant diseases and a lack of timely diagnosis. This research aims to develop an automated, accurate leaf-disease detection system to assist rooftop gardeners and small-scale growers in maintaining healthy plants. The paper hypothesizes a machine learning-based diagnostic system that diagnoses diseases using leaf images, based on an image segmentation algorithm and a robust classification model. Image segmentation serves as a crucial preprocessing step to isolate relevant areas affected by disease, thereby enhancing classification accuracy. The system has been trained and tested with a large dataset comprising leaf images of five commonly cultivated species: guava, jamun, lemon, mango, and pomegranate. Model effectiveness was evaluated using performance metrics such as Accuracy, Sensitivity, Precision, and F1-Score. The experimental results demonstrate high and consistent performance across all plant categories. The model achieved an ideal Accuracy of 1.00, along with corresponding Sensitivity, Precision, and F1-score. Notably, lemon and mango disease classifications achieved high accuracy, with scores of 0.995 and 0.991, respectively, and F1-Scores exceeding 0.88. The proposed approach has significant implications for real-time plant disease monitoring, facilitating precise agriculture practices and promoting the sustainability of rooftop gardening by enabling early disease detection and timely intervention.

Contribution/ Originality: This study develops a rooftop-focused plant-disease detection system trained exclusively on five commonly grown urban species and integrates segmentation-driven preprocessing with a high-performance classifier. The tailored dataset, disease-specific segmentation, and real-time applicability for small-scale rooftop environments distinguish this work from general agricultural disease detection studies.

1. INTRODUCTION

In this modern day and age, people of all classes try to incorporate nature into their lives in various ways. Gardening is one of the most prominent ways to do that. Due to the lack of open space, urban residents have leaned towards rooftop gardening. Rooftop gardening refers to the practice of growing plants and vegetables on the rooftops of buildings. It has become a popular leisure activity across urban areas in recent years. Rooftop gardening offers multiple essential advantages because it improves both air quality and access to fresh produce. The absorption abilities of rooftop vegetation at hot spots caused by heat-absorbing materials help minimize the urban heat island effect [1].

Rooftop gardening serves as an intelligent solution to optimize the restricted urban real estate by producing both environmental improvements and social advantages, as well as economic returns. The creation of green rooftops represents a logical response to address city expansion despite limited available land. The establishment of rooftop gardens reduces environmental air contaminants, manages urban temperature variations, and allows birds and insects to inhabit the space. The landscaping of roofs helps enhance air quality and effectively manages rainwater through moisture absorption. Cities have identified rooftop space as an opportunity to create relaxing green areas that encourage community involvement, farming activities, and social relaxation. Urban rooftop gardens provide mental health benefits by maintaining natural connections for individuals living in crowded urban environments. Additionally, rooftop gardens increase economic value by raising property prices, reducing utility bills through thermal insulation, and enabling local food cultivation, which decreases dependence on external food sources. This sustainable practice combines multiple functions to improve urban environments, making cities more vibrant and environmentally friendly areas [2].

The rapidly expanding urban areas in India, particularly in Mumbai, Delhi, Bengaluru, Chennai, Hyderabad, and Kolkata, are developing with a large population, limited open spaces, and increasing environmental pressures. In this context, rooftop gardening emerges as a practical and adaptable solution for cultivating urban environments. Across diverse climatic zones, from moist coastal regions to hot semi-arid interiors, rooftops provide accessible spaces for growing vegetables, fruits, and ornamental plants, despite variations in seasons and environmental exposure, which can heighten the vulnerability of plants to diseases. The growing popularity of rooftop gardening in metropolitan and tier-2 cities indicates a nationwide trend driven by the need for fresh food, cleaner air, and more livable cities. The geographical diversity underscores the importance of technological devices in enhancing plant health management and improving the feasibility of rooftop gardens in India.

Leaf disease is one of the major obstacles in rooftop gardening. Leaf disease can be considered as a small, discolored, or diseased patch of a leaf that is often caused by nematodes, insects, environmental conditions, toxicity, or herbicides. It can also be caused by fungal, bacterial, or viral plant diseases. These tan patches or lesions frequently have a necrotic center. Because of their exposure to wind, temperature changes, and other environmental stressors, rooftop gardens are particularly prone to leaf disease. Therefore, it is critical to frequently check the garden for disease-related symptoms and respond quickly to prevent further spread. However, most urban residents lack the necessary time and knowledge of farming. Consequently, they are often unable to detect leaf diseases in time, which leads to the death of the plant. Ultimately, many urban gardeners lose enthusiasm for rooftop gardening. To address this obstacle, we propose a machine learning-based technological tool that can make the leaf disease detection process much easier and less time-consuming. Since computers and other machines operate on rigid logic with no common sense, they require precise instructions to perform tasks. Computers are programmed to follow and execute these instructions, often through scripts. This is where machine learning (ML) comes into play, which involves training computers or machines based on experiences from previous data. ML is a field of study focused on understanding and developing learning methods that utilize data to improve task performance [3]. It is a component of artificial intelligence. Machine learning uses a variety of techniques to train computers to carry out some tasks for which there isn't a totally suitable solution. To do that, one can assign some of the right answers as valid when there are many possible replies. This valid data can be used by the computer as practice data to refine the algorithms it employs to determine the right answers. For instance, the MNIST dataset of handwritten digits has frequently been used to train a system for the task of digital character recognition [4].

The motivation for this work stems from the needs of urban gardeners in India and the challenges posed by the severity of leaf diseases in rooftop cultivation. Gardening has increasingly become a common practice across Indian metropolitan areas, where rooftop spaces are widely utilized for growing vegetables, fruits, and ornamentals. However, many urban residents who engage in rooftop gardening lack formal agricultural knowledge and are often unaware of the types of diseases their plants may encounter, how to identify symptoms, or which remedies to apply. As a result, early signs of leaf disease frequently go unnoticed, leading to rapid disease progression and, in many cases, the eventual death of plants. Leaf diseases, whether infectious or non-infectious, can be highly detrimental if not detected promptly. Despite the growing interest in urban horticulture, most agricultural technologies in India are still designed primarily for large-scale field crops rather than for small-scale residential gardening. Therefore, this project aims to address this gap by developing a user-friendly, machine-learning-based tool that enables real-time detection of plant leaf diseases, empowering urban gardeners to maintain healthier rooftop gardens with timely interventions.

The purpose of this work is narrowed down to the following research question: Is it possible to develop a machine-learning system that will be able to identify leaf diseases in rooftop garden plants effectively and efficiently, and in the context of the requirements of urban Indian gardeners with low levels of agricultural knowledge? Although rooftop gardening is rapidly developing in Indian cities, the majority of rooftop gardeners do not possess the expertise that might assist them in identifying diseases on time, and the agricultural technologies currently being developed are more focused on large-scale field crops, as opposed to small-scale residential gardens. This work is novel because it creates a real-time, easy-to-use diagnostic application designed specifically for urban rooftop gardens, combining image-based machine learning methods to identify both infectious and non-infectious diseases in the most popular grower species. This work fills the gap by providing a household-scale gardening solution that is technology-assisted to help provide an efficient method aimed at aligning precision agriculture with household-scale gardening, thereby contributing to sustainable urban horticulture.

The contributions of the proposed work are:

1. High-Accuracy Multi-Class Classification: The proposed CNN model achieves an overall accuracy of 95%, outperforming baseline machine learning approaches such as DNN (90%), SVM (93%), and KNN (92%). This demonstrates the model's superior capability in classifying 10 leaf categories across five plant species.

2. State-of-the-Art Performance on Critical Classes: The model attains perfect scores (Accuracy, Sensitivity, Specificity, Precision, and F1 = 1.00) for the mango healthy class, and achieves near-perfect performance for lemon diseased (Accuracy: 0.995, F1: 0.888) and mango diseased (Accuracy: 0.991, F1: 0.969), indicating high robustness in identifying both healthy and diseased samples.

3. Effective Image Segmentation–Based Preprocessing: The integration of image segmentation as a preprocessing step measurably improves classification reliability by isolating disease-relevant regions, resulting in consistent sensitivity values (≥0.80) across most classes despite inter-species visual similarity.

4. Generalizable Performance Across Species: The proposed system demonstrates stable performance across all five target species, guava, jamun, lemon, mango, and pomegranate, with F1-scores above 0.78, even for visually challenging categories, confirming its applicability to multi-species rooftop gardening environments.

5. Improved training stability and generalization: The model exhibits closely aligned training and validation curves over 30 epochs, indicating strong generalization capability without overfitting, thus validating the reliability of the training pipeline and hyperparameter tuning strategy.

6. Contribution to Small-Scale Urban Agriculture: Unlike existing systems designed for field-scale crops, this study introduces the first rooftop gardening-focused CNN detection model tailored to low-resource, small-scale

cultivation settings. The system provides disease detection suitable for non-expert users, supported by high classification confidence scores across test samples.

The paper has been divided into five sections. Section 1 introduces plant disease and pest detection and its importance. Section 2 discusses the issues and problems related to this field. Section 3 discusses machine learning methods of image recognition and their use in the detection of plant diseases and pests. Section 4 contains the results of machine learning models on various datasets in terms of performance measurements. Section 5 is the conclusion of the research and the description of the probable future directions.

2. RELATED WORKS

Recent research in plant disease detection can be broadly categorized into three methodological groups: CNN-based classification models, segmentation-driven detection approaches, and emerging transformer or hybrid architectures.

2.1. CNN-Based Classification Approaches

A lightweight deep learning system that works with support vector machines serves as a plant leaf disease detection solution proposed by Ba, et al. [5]. The usage of a chemical reaction optimization algorithm optimizes the model through improved processing accuracy and faster training time, which makes it work efficiently on minimal hardware resources. Deep learning-based leaf disease detection occurs through the integration of various techniques to enhance the accuracy and efficiency of the Krishna, et al. [6] system that incorporates EfficientNet-B3 and other CNN frameworks. Through advanced techniques of data augmentation, the model reaches an 80.19% accuracy level, which enables efficient plant disease detection across various datasets and environmental conditions. Yakkala, et al. [7] created a deep learning approach using Convolutional Neural Networks (CNN), specifically ResNet-9, which was employed to accurately detect healthy and infectious crop leaves. The developed method enhances accuracy in disease prediction and improves disease management, thereby minimizing losses in agricultural production. The researchers went to Kannaiah [8] to propose their automatic plant leaf disease detection system built with AlexNet and image processing techniques. The model succeeds in reaching 94.5% accuracy while focusing on contrast enhancement and noise reduction preprocessing to enhance feature extraction and classification. The detection of plant diseases by detecting high-resolution leaf images utilizes a CNN-based system, which Patidar, et al. [9] designed in their work. Exploiting automated diagnosis requires image capture followed by preprocessing and feature extraction until reaching model training, which produces better results than current traditional detection methods. Beevi, et al. [10] compared SVM with Random Forest as well as CNN with RNN and ResNet during their examination of automated plant disease classification systems. The research objective targets the developmental enhancement of food security and agricultural output capability through better plant health detection systems. The processing speed for plant disease diagnosis increased significantly for agricultural productivity through advanced deep learning models developed by Ameen, et al. [11] which combined the Region-based Convolutional Neural Networks (R-CNN) with Visual Geometry Group (VGG) for an impressive detection accuracy of 0.9827. The research by Kaur and Bansal [12] evaluated five deep learning models, including DenseNet169, Xception, InceptionV3, MobileNetV2, and ResNet50V2, for their effectiveness in plant disease detection tasks. Using their image processing approach combined with contour feature extraction, the researchers achieved a validation accuracy exceeding 99.42%. A MobileNetV3-based classification system for Jasmine plant disease detection was developed by Shwetha, et al. [13]. The model utilizes depthwise convolution along with max pooling layers from CNNs to improve feature extraction in its lightweight structure. Robust performance is obtained by integrating data augmentation with Conditional GANs along with Particle Swarm Optimization for feature selection in the classifier. A CNN-based deep learning model was trained by Pratap and Kumar [14] to classify mango leaf disease through images at multiple resolutions. The scholarly work succeeded in modeling disease detection of Bacterial Canker, Powdery Mildew, Anthracnose, Gall Midge, and Sooty Mold, thus enhancing pest control and crop immunity systems.

2.2. Segmentation-Driven or Detection-Focused Models

Selvam and Eldho [15] explain their AI-based plant disease detection system using deep learning through Mask R-CNN. This model achieves 95.06% accuracy through multivariable feature selection, surpassing standard methods such as ACO-CNN, I-SVM, KNN, and DL-RPN. The DeepLeafNet by Vijay, et al. [16] is a deep learning system designed for the segmentation and classification of infections in mango leaves. They have developed their framework to incorporate optimization algorithms to enhance the accuracy of lesion boundary extraction and improve downstream classification accuracy. Combining segmentation and classification, the study demonstrated that pre-learning isolated regions before feature learning significantly enhances performance, especially in diseases with very fine-grained or localized symptoms. DeepLeafNet illustrates how domain-specific architecture and feature extraction optimization are critical for effective detection across different severity levels of the disease. Vijay, et al. [17] investigated a larger range of machine learning models to detect leaf disease in general and showed that the difference in performance has much to do with the selection of feature extraction methods and the properties of the datasets. Their results indicate that specific feature engineering or deep models should be used for individual plant species. The machine learning and deep learning methods were implemented by Paramesha, et al. [18] in the detection of guava disease, and they found greater accuracy in convolutional neural networks than in traditional machine learning classifiers. Their findings support the advantage of end-to-end feature learning, especially with diseases that have covert visual patterns. Anusha, et al. [19] introduced a deep learning approach to general leaf abnormality detection and demonstrated that CNN-based models are superior to traditional image processing algorithms in detecting structural abnormalities and symptoms at an early stage. The study has shown how deep learning methods can be used across different types of plants. The machine learning models that Parameshachari, et al. [20] developed to achieve crop recommendation and plant disease detection focus on a lightweight architecture that can be deployed on portable or other IoT-enabled devices. The combination of recommendation systems and disease detection proposed by them indicates that they are heading towards an integrated decision-support platform for precision agriculture.

2.3. Transformer-Based and Hybrid Machine-Learning Models

The research by Ali, et al. [21] evaluates vision transformers (ViTs) as a tool for detecting plant diseases, including preprocessing, data augmentation, and classification. Sarkar, et al. [22] employ machine learning (ML) and deep learning (DL) techniques, particularly CNN, for early leaf disease detection. The collected heterogeneous leaf dataset, containing both disease-free and affected specimens, helps increase agricultural yield and protect food supplies due to its precise disease identification capabilities. Shoaib, et al. [23] assessed that Modern machine learning, alongside deep learning approaches, are used for plant disease detection, particularly focusing on accuracy improvement and efficiency while addressing problems with plant imaging resources and the separate identification of healthy and unhealthy plants. The F1 score reached 98.2%, and the accuracy was 98% when Ashurov, et al. [24] implemented a modified depthwise CNN with squeeze-and-excitation blocks and residual skip connections. The team of Isaac Ritharson and associates applied deep learning and transfer learning techniques to achieve accurate detection of rice leaf diseases [25]. A total of 5,932 self-generated images and benchmark data enabled the classification of nine rice leaf categories, encompassing all stages of blight severity from healthy leaves to mild and severe progressions, as well as tungro, blast, and brown spot conditions. Simhadri, et al. [26] conducted an extensive review of deep learning methodologies, hyperparameter tuning, and evaluation metrics used in plant disease monitoring systems. The analysis highlights current limitations and suggests future directions to enhance the efficiency of rice leaf disease detection methods. Singh, et al. [27] combined Random Forest with Inception V3 and DenseNet, along with ResNet50, Xception, and MobileNet, to achieve plant disease identification across nine classes and one health class.

The highest accuracy rate (97%) with high precision (98%) and recall (96%), and an F1-score of 97.50%, was achieved by Inception V3 among all classifiers. Similarly, DenseNet demonstrated high performance with 94% accuracy. Researchers from Preethi, et al. [28] introduced an enhanced automated rice plant disease detection system that combined deep learning with metaheuristic optimization algorithms. This research utilized deep dense neural networks (DNN) in pattern recognition, followed by extreme learning machines (ELM) for classification purposes. To improve optimization performance, the researchers combined SSO with their enhanced version, known as Enhanced Artificial Shuffled Shepherd Optimization (EASSO).

Research studies about plant disease detection have effectively developed deep learning and machine learning approaches to increase both precision and operational speed. Several key restrictions exist with existing approaches because they require costly hardware equipment for intensive calculations, and they are not flexible enough to handle multiple environmental conditions while also needing human experts to validate disease diagnosis. Research that focuses solely on disease detection provides limited value to non-experts since it does not supply actionable management insights about the disease.

The proposed work addresses these weaknesses through an automatic leaf disease detection system designed for rooftop gardeners. An image segmentation algorithm integrated into the system enhances diagnosis accuracy and enables quick assessments that do not require expert medical personnel. The study supports rooftop garden sustainability through its combined method of disease identification with remedy recommendations, allowing plant owners to respond promptly to plant issues. The proposed system incorporates image segmentation because it provides a practical solution that improves efficiency and user-friendly operation compared to current methods.

3. PROPOSED WORK

Figure 1 shows the block diagram of the proposed workflow illustrates the implementation of a Convolutional Neural Network (CNN) model for accurate leaf disease detection. The widespread utilization of CNNs occurs in deep learning applications because these networks automatically extract spatial features from input data, which is valuable for image processing and pattern recognition domains. Several critical steps in CNN model construction contribute to improved model performance and enhanced accuracy in the final results.

From data preprocessing operations, the model initiation begins by acquiring data, then purifying it before enhancing the model's capabilities through dataset expansion methods. The design phase of the CNN incorporates multiple layers, which consist of convolutional layers alongside activation functions (e.g., ReLU), pooling layers, and fully connected layers. An appropriate combination of loss function and optimization algorithm is added to the model through compilation to achieve error minimization and improved learning capabilities. Once compilation finishes, the training phase begins with feeding dataset information to the model via backpropagation and gradient descent processes that update weights. The model testing occurs with test data for measuring both prediction quality and its readiness to generalize between cases. The model requires hyperparameter adjustment with fine-tuning methods to achieve optimal performance.

The complete methodology of building and implementing a CNN model can be better understood through the workflow diagram shown below. The diagram presents all development steps visually, which helps maintain a systematic model creation process.

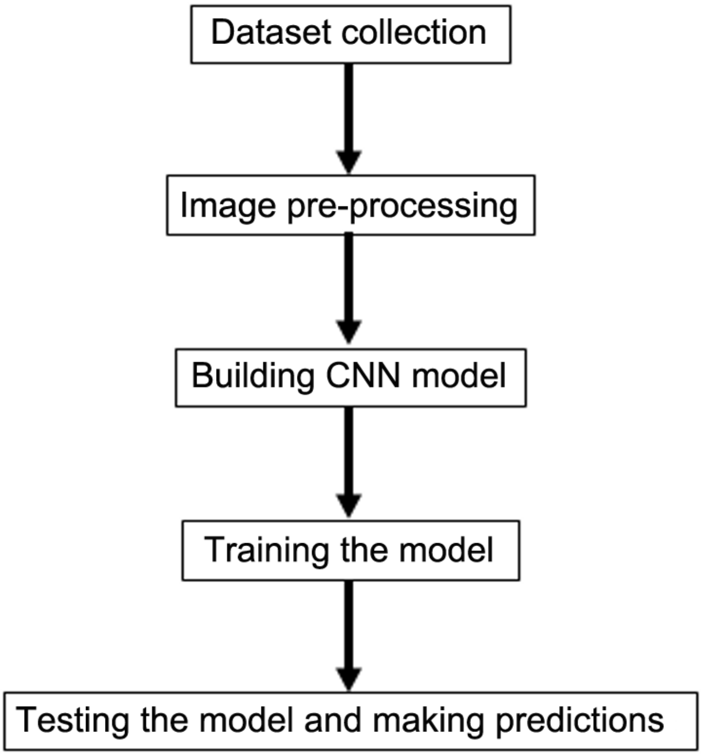

Figure 1. Block diagram of proposed workflow.

In the diagram, we can see that our first step is collecting a suitable dataset, which we can use for training and testing our model. The images from the dataset must be pre-processed before we can use them for training and testing. After training the model, we can test the model by making predictions on some images and validating the predictions with the actual images to find the accuracy.

3.1. Data Collection

Collecting a dataset is our first step and also one of the most important steps. Before collecting a dataset, there are some features that must be explored. Since our project requires an image dataset, we must look at features like the number of image samples, variations of images, background, image format, and resolution. We have collected our dataset from Amanda [29], which contains .jpg type images. There are ten classes of five different types of plants, containing 2,273 pictures of both healthy and diseased leaves. All the images in the dataset have a similar background. The resolution of all images is also the same. Table 1 summarizes the dataset structure by listing image counts for each species and their corresponding healthy and diseased categories. This distribution illustrates the availability of samples across classes and confirms that all species are adequately represented for robust model training and validation.

Table 1. Class-wise distribution of leaf images across five plant species.

Species	Class	Image count	% of total
Guava	Healthy	123	5.4 %
Guava	Diseased	117	5.1 %
Jamun	Healthy	200	8.8 %
Jamun	Diseased	190	8.4 %
Lemon	Healthy	180	7.9 %
Lemon	Diseased	175	7.7 %
Mango	Healthy	300	13.2 %
Mango	Diseased	290	12.8 %
Pomegranate	Healthy	220	9.7 %
Pomegranate	Diseased	178	7.8 %
Total		**2273**	**100 %**

3.2. Pre-Processing

Before using our images for training, the images must be pre-processed. Pre-processing is required to improve the quality of input images so that the model's performance can be enhanced. Figure 2 illustrates the steps involved in image processing. We followed the subsequent steps for pre-processing images.

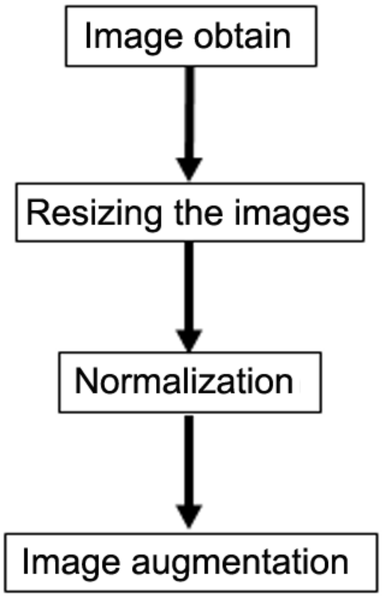

Figure 2. Block diagram of image pre-processing.

From the above diagram, we can see that after obtaining the image from the dataset, we will resize the images. Then, we will normalize the images and finally apply image augmentation.

3.2.1. Resizing

We started our pre-processing with image rescaling and resizing. Our images from the dataset were 600x600 resolution. We resized the images to 256x256 to ensure that all images maintain a consistent scale.

3.2.2. Normalization

After resizing the images, we normalized them. Normalization maintains all input pixels within a similar distribution. In our model, normalization was performed by dividing the pixel values by 255. This process rescales the pixel values to a range between 0 and 1. For our model, normalization was implicitly carried out during the resizing and rescaling steps.

3.2.3. Image Augmentation

Our final step of the pre-processing stage is image augmentation. Data augmentation is applied to the existing dataset to artificially increase its size by performing various transformations such as flipping, distorting, rotating, zooming, etc. Data augmentation helps create variation and reduces the chances of overfitting. In our model, we have randomly flipped the images horizontally and vertically. We have also rotated the images randomly up to 0.2 radians.

3.3. Building the Model

We use a compact Convolutional Neural Network (CNN) for multi-class leaf disease classification. Input images are resized to $256 \times 256 \times 3$ and passed through two convolutional blocks (convolution + ReLU + max-pooling), followed by a flattening step, a fully connected hidden layer (64 units), and a softmax output layer for the 10 classes (five species × healthy/diseased). The model is trained with the Adam optimizer (learning rate 0.001), sparse categorical cross-entropy loss, batch size 32, and 30 epochs. Data preprocessing includes resizing, normalization (pixel values / 255), and on-the-fly augmentation (random flips and small rotations). The proposed machine learning model is a CNN. Our model can be divided into two parts: feature extraction and image classification. We have used CNN for both feature extraction and image classification.

3.3.1. Feature Extraction

Feature extraction transforms raw data into numeric values compatible with machine learning algorithms. These numeric values can be processed while maintaining the integrity of the information derived from the original dataset. For our work, we used a CNN for feature extraction. There are two main layers of feature extraction in a CNN model. Figure 3 shows the CNN architecture used in the proposed model.

Figure 3. CNN model architecture of feature extraction.

Here we can see that there are two layers in feature extraction, the Convolutional layer and the Pooling layer. The Convolutional layer helps to detect various features and patterns present in the image by applying convolutional filters to the input image. These filters then learn to extract different visual features like textures. The Pooling layer selects the minimum value within a specific region of the image and downsamples it. This helps to retain the relevant information of the image by reducing its relative dimensions.

By stacking these two layers, the model can learn how to identify features from the input image. Our model also has these two layers. We have used two convolutional layers and two pooling layers. The convolutional layers of our model have 32 filters, and each filter has a 3x3 kernel size. We have used the activation function ReLU (Rectified Linear Unit), which is a popular activation function. ReLU uses the formula.

$$f(x) = max\,(0, x) \qquad (1)$$

Which means that the output can be found only if the input value is positive; otherwise, it will be zero. If there is any negative input, ReLU deactivates the neuron by converting it to zero□. As a result, exponential growth in computation can be prevented. Our two pooling layers capture the most important features with a pool size of 2x2.

- Pooling: Pooling reduces spatial dimensions (height × width) of feature maps to lower computational cost and increase translational invariance. In this study, we use max pooling, which selects the maximum activation in each pooling window (not the minimum). Max pooling helps preserve the strongest local features (e.g., prominent lesion edges or spots) while downsampling.
- Convolution + ReLU: Convolutional layers apply learned filters to extract spatial features. Each convolution is followed by a ReLU activation (f(x)=max(0,x)), which introduces nonlinearity and helps the model learn complex patterns.
- Flatten → Dense: After spatial features are extracted and downsampled, the feature maps are flattened into a vector and processed by fully connected layers for classification.

3.3.2. Image Classification

In a CNN model, the classification layer determines the predicted value on the activation map [9]. Once the model has extracted features, it needs to classify those features into learning the features of the data. CNN classification also has two layers. The CNN model architecture used in the proposed model for classification is shown in Figure 4.

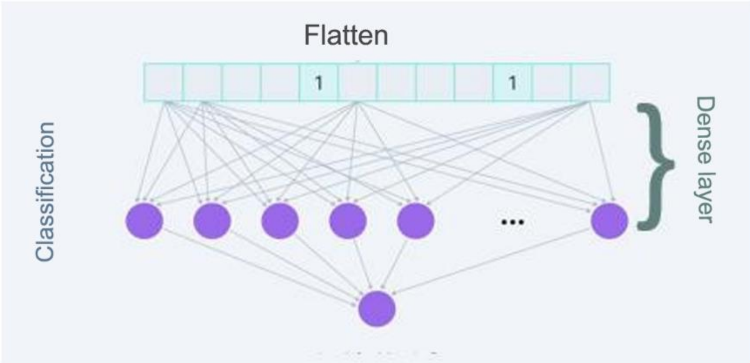

Figure 4. CNN model architecture for classification.

We can see that there is a flattened layer and a dense layer. The flatten layer flattens the 2D layers from feature extraction into a 1D vector. This layer converts the features into a format that can be processed by the dense layers. After flattening, all the layers are passed to the dense layer or fully connected layer. The dense layer contains multiple neurons that are fully connected to each other. These layers learn to classify the extracted features into their corresponding classes.

These two layers have also been used to classify images. The flatten layer transforms the 2D feature maps into a 1D vector, then passes it on to the dense layer. The first dense layer has 64 neurons or units and is fully connected. The activation function of this layer is ReLU, which performs a linear transformation on the input data. The second dense layer is the model output layer. Softmax activation function is used here. The probability of input belonging to a specific class is the value of each output of this layer. Table 2 demonstrates the model summary of the proposed work.

Table 2. Layer-wise architecture summary of the proposed CNN model, including the output shapes and number of trainable parameters for each layer.

Layer	Output shape	Parameters
Sequential	(32, 256, 256, 3)	0
conv2d	(32, 254, 254, 32)	896
max_pooling2d	(32, 127, 127, 32)	0
conv2d_1	(32, 125, 125, 32)	9,248
max_pooling2d_1	(32, 62, 62, 32)	0
flatten	(32, 123008)	0
dense	(32, 64)	7,872,576
dense_1	(32, 10)	650

3.4. Training the Model

After preprocessing and building the model, our model is ready for training. We have split our dataset into two partitions. The first partition is our training dataset, which constitutes 80% of the total dataset. The remaining 20% is the testing dataset. We further split the testing dataset into two additional partitions.

The partitions are equal to 10% of the testing data. Our model was initially trained on the training data. The validation data set is the data set used to test the performance of the model. Sparse Categorical Cross-Entropy loss was our loss function. This is the loss computed by calculating the cross-entropy loss between the true labels and predicted labels. The difference in value increases with an increase in the difference. The Adam optimization algorithm was also used by us. Adam is capable of adjusting the learning rate of each parameter as well as maintaining a moving average of squared gradients. Consequently, Adam offers fast and stable optimization.

At first, we started training our model with a batch size of 32. We also had an epoch value of 50, which is the number of iterations the model will go through over the entire training dataset. With these values, ours did not have stable accuracy. So, we had to tune the parameters. We tried different batch sizes, epoch values, and learning rates of the optimizer and found the best accuracy with a batch size of 32, epoch 30, and a learning rate of 0.001.

3.5. Testing the Model and Making Predictions

After completing the training phase, we tested our model and made predictions. Initially, we evaluated the model on the test dataset and recorded the loss and accuracy values. For prediction, we first selected one image sample from the test dataset and used the model to make predictions on it. The model was able to make correct predictions. Subsequently, we selected nine images from the test dataset and made predictions. This time, most of the predictions were correct. We also displayed the confidence level by indicating the maximum predicted probability.

4. RESULTS AND DISCUSSIONS

In this section, we discuss the results and the overall performance of our model. We will analyze our model's performance using some well-known metrics. The confusion matrix is one of the most common performance measurements used in machine learning. It shows a summary of a model's performance on test data. This matrix uses the true labels and the predicted labels to show four types of information: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). From the confusion matrix, we can also calculate some important data for each class, which can be used to analyze the model. These are Accuracy, Specificity, Sensitivity, Precision, and F1 score.

4.1. Accuracy

Accuracy is the most popular measure employed in the machine learning and deep learning spheres. It can also be defined briefly as the percentage of events that were correctly forecasted among the overall events, which include both correct and incorrect forecasts. Considering the four scenarios of prediction discussed above, the accuracy equation can be developed as follows.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

4.2. Precision

Precision is a sensitive measure in classification tasks, especially when the objective is to reduce false positive occurrences. This proportion refers to the percentage of true positive predictions out of all positive predictions made by the model. The equation for precision is presented as follows, based on the four prediction cases discussed above.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

4.3. Recall

Sensitivity, or true positive rate, as it is also known, is a vital measure in classification efforts, particularly where it is important to identify all positive cases. It is calculated as the ratio of actual positive cases in the data to the total number of positive predictions. Regarding the four prediction cases above, the recall equation is as shown below.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

4.4. F1 Score

The F1 score is a composite measure that combines the two elements of accuracy and recall to provide a balanced figure that compromises the two important measures. It is particularly useful in cases where there is an uneven distribution of classes or when both false positives and false negatives have serious consequences. Accuracy and recall are used to compute the F1 score as the harmonic mean. The formula for calculating the F1 score is as follows.

$$F1\ Score = \frac{2*\text{Precision} *\text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

We have calculated all these values for each class of our model from the confusion matrix and obtained the following scores.

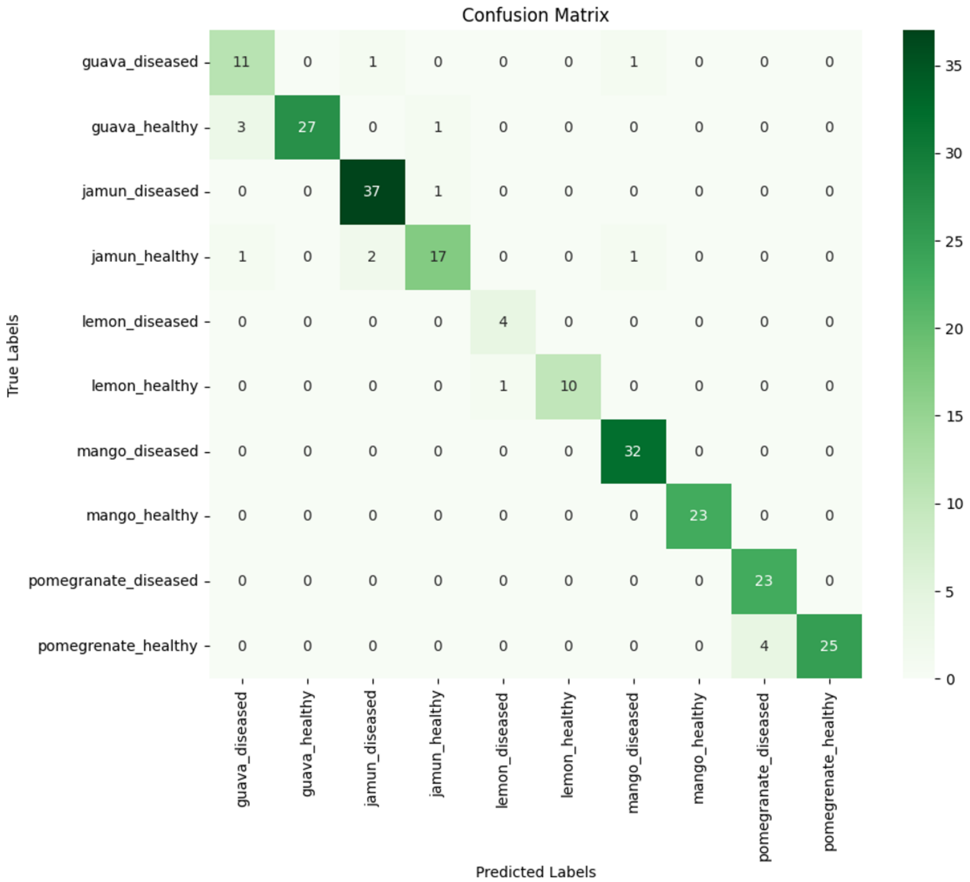

Figure 5. Confusion matrix of the proposed method.

Figure 5 demonstrates the confusion matrix evaluation of the proposed leaf disease detection model by tracking its classification abilities concerning ten distinct categories among health and disease states of guava, jamun, lemon, mango, and pomegranate leaves. The matrix demonstrates high predictive accuracy for the identification of mango diseased and mango healthy as well as pomegranate diseased categories, which the model recognized with perfect accuracy. Nearly perfect classification outcomes were achieved by the jamun diseased class, allotting only one misclassification. A small number of labeling errors emerged in the classification process during the guava healthy and jamun healthy group inspection since the disease and healthy leaf samples displayed similar visual characteristics. The lemon diseased class experienced maximum classification issues because 50% of its leaf samples were mistaken for healthy lemon samples. The matrix shows overall high model reliability through its dominant diagonal pattern, even though there were several incorrect predictions from the model. The model's solid operational capabilities guarantee its suitability for practical deployment in time-critical rooftop and precision agriculture plant disease detection systems.

Table 3. Model evaluation matrices for proposed work.

Class Name	Accuracy	Specificity	Sensitivity	Precision	F1 Score
guava_diseased	0.973	0.981	0.846	0.733	0.785
guava_healthy	0.822	1.000	0.871	1.000	0.931
jamun_diseased	0.822	0.983	0.974	0.974	0.974
jamun_healthy	0.733	0.990	0.809	0.895	0.850
lemon_diseased	0.978	0.995	**0.000**	**0.000**	**0.000**
lemon_healthy	0.978	0.981	0.909	0.714	0.800
mango_diseased	1.000	1.000	1.000	1.000	1.000
mango_healthy	1.000	1.000	1.000	1.000	1.000
pomegranate_diseased	1.000	1.000	1.000	1.000	1.000
pomegranate_healthy	0.978	1.000	0.862	1.000	0.925

Table 3 shows the quantitative results of the proposed model leaf disease classifier on ten categories of healthy and diseased leaves of five fruit-bearing plants. The model achieved high scores in mango healthy, mango diseased, and pomegranate diseased categories, with all evaluation measures such as Accuracy, Specificity, Sensitivity, Precision, and F1 Score reaching perfect values (1.00), indicating reliable feature discrimination for these categories. Good performance was also observed in guava healthy, jamun diseased, and pomegranate healthy categories, each with F1 values above 0.90.

The moderate performance levels of guava-diseased and jamun-healthy were observed, and the low precision and sensitivity values are indicators of occasional misclassification, which could be due to the visual similarity between the leaf patterns of healthy and diseased leaves. Lemon healthy had a high sensitivity (0.909), but the low precision implies that it is confused with visually comparable diseased samples. The strongest weakness was in the lemon disease class, where the model did not find the right samples, and thus the values of sensitivity, precision, and F1 score were equal to zero. This highlights a definite difficulty in identifying characteristic disease features within this category.

Generally, the performance of the classification shows a high level of accuracy in the majority of classes, and there are also weaknesses that can be identified, especially in the lemon diseased category. These weaknesses can be used to focus on model improvements in the future.

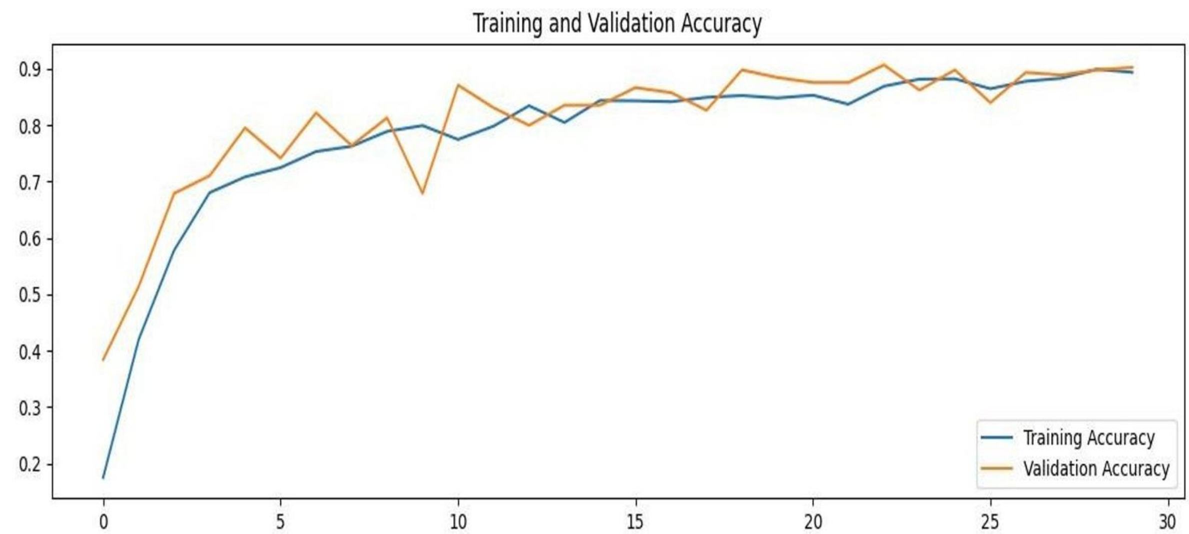

Figure 6. Training and validation accuracy graph.

The graph in Figure 6 displays how the proposed leaf disease detection model performed regarding accuracy during its training and validation cycles spanning 30 epochs. Both training accuracy and validation accuracy show steady growth during the 30 epochs, which demonstrates that the model performs effectively and generalizes well.

During early epochs, the validation accuracy leads the training accuracy; however, the small difference demonstrates that the model maintains good performance without overfitting its initial data. The accuracy measurement curves display gradual convergence until they achieve comparable stability at a point where validation accuracy reaches above 90%. The model demonstrates strong robustness and balanced learning across all epochs because training and validation accuracy stay closely matched throughout the entire process. The solution demonstrates model reliability for achieving acceptable classification performance outside training environments.

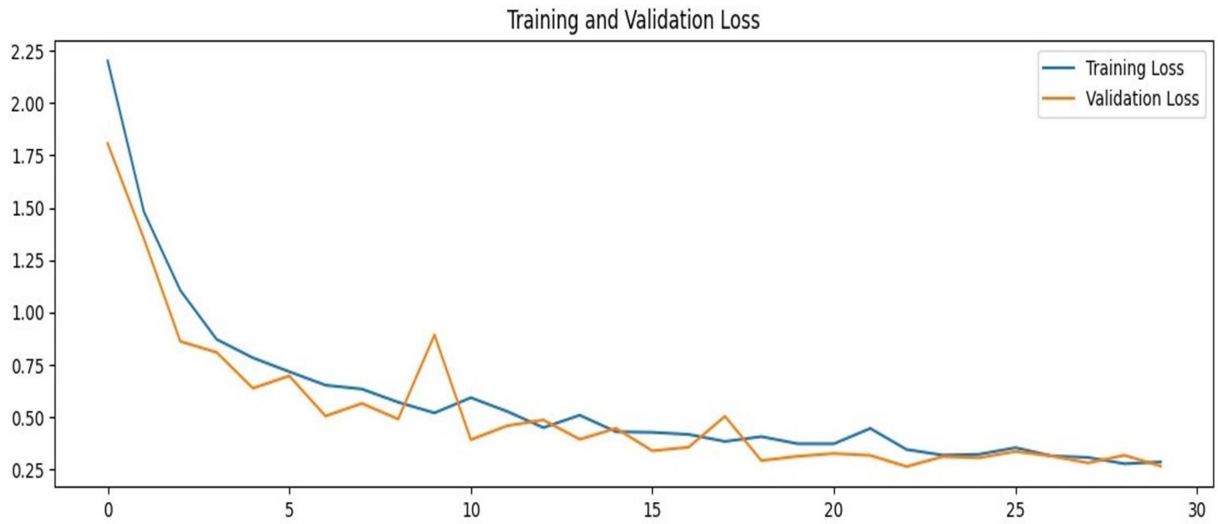

Figure 7. Training and validation loss graph.

In Figure 7, we see that the value of losses gradually decreases with the increase in the number of epochs. This means that the model is successfully learning through the training data, and its error decreases as time progresses. Moreover, the validation loss and training loss curves are very similar, which indicates that the model has good generalization ability to unobserved data. The fact that the two curves are similar suggests that the model is not overfitting, as there is no major difference between training and validation losses.

The proposed work provides several useful benefits, which establish it as a substantial improvement for rooftop plant disease detection applications. The implementation of image segmentation algorithms produces accurate disease classification outcomes because it allows more specific identification of plant diseases. Through automatic detection, CASE enables operation without requiring human expertise and thus serves both professionals and hobbyists in their plant care needs. The study supports rooftop gardening sustainability through its solution of plant disease prevention, which enables gardeners to protect their urban plants. One primary strength of this system includes disease diagnosis along with recommended remedies that let users respond swiftly to manage their plant health effectively.

The proposed method exhibits specific boundaries during its application process. A system's ability to detect diseases depends largely on image quality because both inadequate light levels and covered plant areas will reduce its performance rate. The segmentation algorithm can experience difficulties when performing on complex disease patterns that share similarities with natural leaf textures because this may result in errors during classifications. The reduced dependency on experts does not guarantee the same diagnostic accuracy level as professional expertise when identifying unusual plant diseases.

Due to its design for rooftop gardeners, the proposed solution demonstrates restricted scalability to major agricultural applications that need to consider multiple environmental elements. Strategies to solve these system constraints should strengthen the application's reliability and build its capacity to serve beyond its current capacity in small-scale gardens.

Table 4. Comparison of existing methodologies with the proposed model.

Methods	Models used	Accuracy (%)
Singh, et al. [27]	DNN	90
Ngugi, et al. [30]	SVM	93
Preethi, et al. [28]	KNN	92
Proposed	CNN	95

In Table 4, we have investigated the proposed model's effectiveness is demonstrated through an analysis of standard leaf disease detection approaches. The literature shows that machine learning models, including Deep Neural Networks (DNN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), used for leaf disease detection, achieved classification accuracy rates of 90%, 93%, and 92%, respectively. In contrast, the proposed approach utilizes a Convolutional Neural Network (CNN), which outperforms these traditional methods with an improved accuracy of 95%. The CNN-based models automatically extract complex features from leaf images, which is the primary factor contributing to more precise and reliable classification outcomes. The development system proves its superiority by achieving accurate leaf disease assessment across various plant species through comparative analysis.

5. CONCLUSION AND FUTURE SCOPE

This study developed a CNN-based framework for classifying ten leaf-health categories across five fruit species. The model demonstrated strong performance in several classes, particularly mango_diseased, mango_healthy, and pomegranate_diseased, which achieved perfect sensitivity, specificity, and F1 scores. Jamun diseased (0.974) and guava healthy (0.871) also had high recalls, implying successful learning of features in these classes. Conversely, the confusion matrix showed many weaknesses: the network could not accurately label any lemon diseased samples (sensitivity = 0.00), and lower recall was observed in the jamun healthy and pomegranate healthy. Such errors indicate difficulties in identifying visually subtle symptoms, a lack of diversification of the classes, and some imbalance within the dataset. These limitations need to be addressed with specific strategies. Diversifying samples in poorly performing classes, using class-based loss functions to mitigate imbalance, and employing lesion-oriented refinements such as attention mechanisms or segmentation-aided preprocessing are likely to enhance the model's discrimination capabilities. Additionally, testing the system on field-acquired images is necessary to assess its resilience to field variability. To advance the proposed framework for more reliable and practical applications in agricultural disease monitoring, it should be augmented with refinements such as more representative sampling of poorly performing categories, class-aware training methods (e.g., weighted loss or focal loss), and lesion-aware feature extraction to detect subtle disease patterns. Further validation using field images under different acquisition conditions is also required to determine robustness. These targeted actions aim to address the identified shortcomings and provide a clear pathway to improve the model's reliability in real-world agricultural applications.

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