Plant Methods

METHODOLOGY

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PlantCareNet: an advanced system to recognize plant diseases with dual-mode recommendations for prevention

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Abstract

Plant diseases adversely affect the agricultural sector by substantially affecting food security and limiting production. We introduce PlantCareNet, a novel, automated, end-to-end diagnostic system for plant diseases that can also offer interactive guidance to users. The system utilizes a dual mode strategy that integrates advanced deep learning algorithms for precise disease diagnosis with a knowledge-based framework guided by experts for preventive measures. The proposed architecture utilizes a convolutional neural network (CNN) to examine images of plant leaves, with the final block flattened and subsequently forwarded to Dense-100 and ultimately Dense-35 for the precise classification of various plant diseases. Subsequently, PlantCareNet promptly offers two types of recommendations: automated suggestions based on identified symptoms and expert-guided advice for personalized treatment. Both categories of recommendations are accessible immediately. The experimental findings indicate that PlantCareNet can accurately diagnose diseases in five well-known datasets, with an accuracy between 82% and 97%, outperforming notable models like Inception and ResNet in most cases. The overall approach demonstrates advancement by surpassing lightweight CNN models with 97% precision and an average inference time of 0.0021 s, hence offering farmers precise and quick actions for remedy. This study emphasises a novel blend of artificial intelligence-driven recognition and expert consultation, which contributes to the advancement of sustainable agriculture practices.

Keywords Plant disease, PlantCareNet, LLM, Recommendation, Prevention

Introduction

The agricultural industry sustains 2.5 billion individuals as their principal source of income, providing a steady food supply, job possibilities, and enhanced global wealth [1]. It constitutes 29% of GDP and 65% of employment in emerging nations, especially in rural areas. The economic importance of agriculture is amplified by its support of ancillary sectors such as textiles, biofuels, and pharmaceuticals. Since 1961, technical advancements have nearly doubled global agricultural output, enhancing access to a broader array of healthier foods [2, 3]. Nonetheless, factors such as economic instability, violence, and climate change jeopardize food systems and exacerbate poverty [4]. By 2050, the global population is projected to reach 10 billion, necessitating sustainable agriculture to fulfill their needs. Agriculture is a fundamental pillar of Bangladesh's economy, employing over 40% of the workforce and contributing 14% to the nation's GDP [5]. Despite challenges such as market fluctuations and

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climate change, it remains essential for rural livelihoods and underpins key sectors that contribute to economic stability and growth [5, 6]. Sustainable methods and technology are essential for the sector's growth and adaptability to ensure food security and resilience.

To optimize agricultural productivity and ensure food security in Bangladesh, prompt diagnosis and treatment of plant diseases are crucial. Agricultural diseases in the region jeopardize the livelihoods of millions, potentially causing output losses of 20–30%, particularly in essential crops such as wheat and rice [7, 8]. Effective early identification and treatment can reduce crop losses by up to 70%, aiding farmers in minimizing reliance on chemical pesticides, which constitute 25–30% of agricultural costs in Bangladesh and adversely affect the environment. Prompt actions are essential for maintaining crop health and enhancing resistance to climate-related stress, hence ensuring sustainable agricultural practices. Recent advancements underscore the need for AI-driven approaches in crop protection, which can improve the efficiency of disease prediction and treatment strategies, ultimately enabling more precise and eco-friendly solutions for a resilient agricultural future [9].

Traditional manual measurement of plant traits is labor-intensive and inefficient, necessitating automated approaches for large-scale phenotyping [10]. Integrating advanced measurement techniques into diverse agricultural landscapes helps address the challenges of fast and accurate identification, similar to the broader push towards automation and sustainability in Bangladesh's agricultural transformation [11]. By facilitating early and precise identification through image analysis, artificial intelligence (AI) and machine learning technologies are essential to the management of plant diseases [12, 13]. These technologies enable real-time monitoring and timely intervention, reduce the need for chemical pesticides, and enhance crop health and food security [14, 15]. Deep learning techniques, when combined with robust training datasets, facilitate precise trait analysis and decision-making in agricultural settings [16]. Plant disease diagnosis is transforming as a result of machine learning and deep learning replacing time-consuming and tedious manual diagnostic techniques [17]. In order to identify plant diseases, convolutional neural networks (CNNs), a top deep learning architecture, evaluate characteristics including color, shape, and texture [18]. The accuracy of well-known CNN models like ResNet, Inception, and MobileNet frequently surpasses 97% [19–21]. However, environmental considerations including illumination, plant stage, and disease manifestation, as well as significant processing and data requirements, make these advancements difficult to implement in places like Bangladesh [22, 23]. Efficiency and flexibility are crucial when developing models in locations with limited resources. In order to solve these issues and find effective and dependable ways to improve disease control and food security, this study assesses cutting-edge deep learning models within the context of Bangladesh's agricultural industry [24].

The efficient application of machine learning and deep learning for plant disease identification in Bangladesh is hampered by issues including inadequate infrastructure and resources [13, 25]. Leveraging advanced technologies, a recommendation system can provide timely disease predictions and customized treatment strategies [23, 26]. This approach can significantly enhance decision-making and support for farmers in managing plant health. This is illustrated in Fig. 1, highlighting the key benefits of using a plant disease recognition system. Using models trained on local disease data, the system evaluates crops that farmers scan with their phones or PCs. This early intervention strategy lowers pesticide use, increases production, and ensures food security while preventing the start of disease [15, 18]. Large language models (LLMs) contribute by analyzing vast amounts of textual data related to disease symptoms, historical crop health records, and expert knowledge, which further enhances the accuracy and reliability of disease diagnosis and treatment recommendations [27, 28]. Integrating data-driven approaches can help forecast crops and improve decision-making for farmers, bridging the gap between traditional agricultural practices and modern AI-driven solutions to enhance adaptability and effectiveness in diverse environments like Bangladesh [29]. These technologies provide proactive alerts and customized treatment choices by combining historical disease data and weather forecasts, improving sustainable farming practices and assisting farmers in making a living [30].

This study aims to improve the detection and treatment of plant diseases in Bangladesh via the application of machine learning and deep learning techniques. Interventions led by intelligent systems have demonstrated considerable promise in delivering customized solutions, promoting efficiency, and improving decision-making processes across several fields [31–34]. The aim is to enhance the speed and precision of illness diagnosis by developing models that utilize locally pertinent data, such as a tailored dataset for the Bangladeshi context. Traditional monitoring methods, such as machine vision, often struggle with real-time detection due to environmental factors, which can lead to discrepancies and reduced reliability in predicting produce quality [35]. By addressing these challenges, this research aims to decrease crop losses and enhance food security. The creation of a recommendation system that provides farmers with tailored information via mobile devices is an essential component

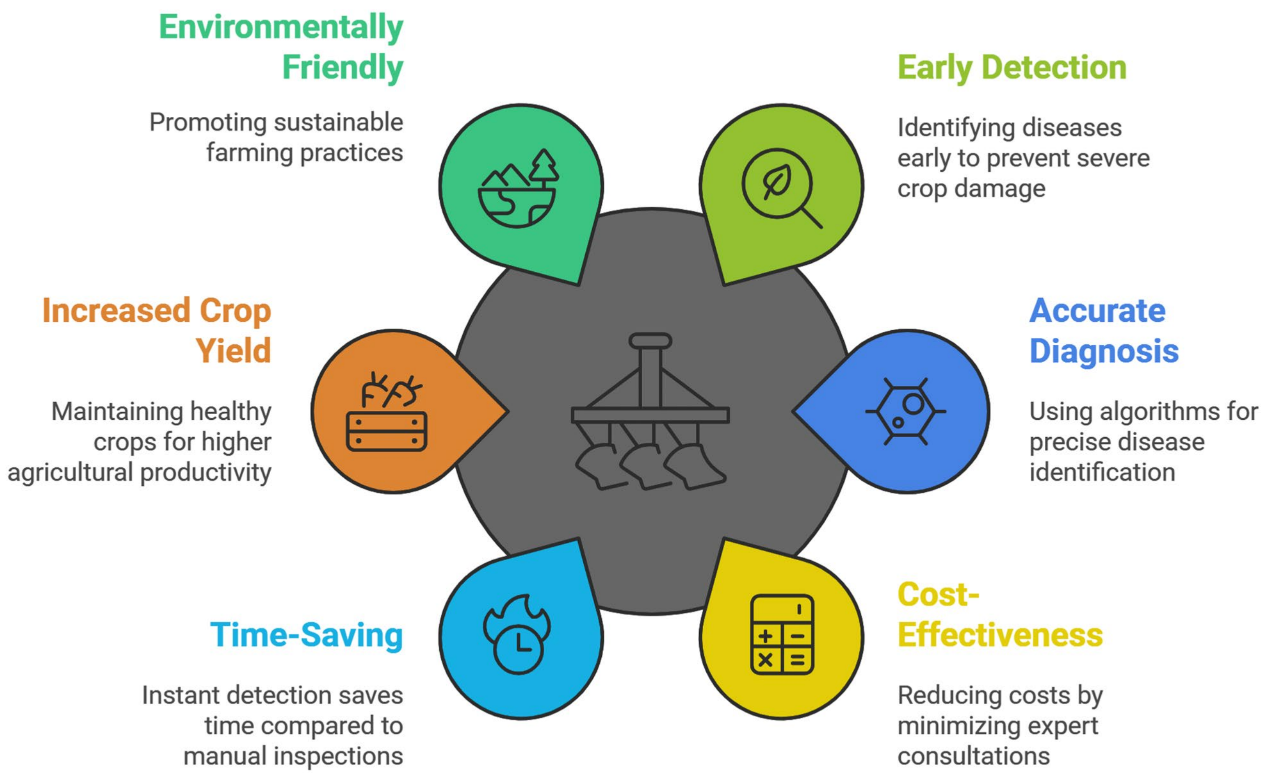

Fig. 1 Benefits of plant disease recognition system

of this research. These insights provide timely interventions and specific care recommendations by aiding farmers in making educated decisions about crop health. This technique aims to enhance agricultural productivity by integrating environmental considerations and reducing reliance on chemical treatments, hence promoting sustainable farming practices. The work has broader implications as it offers a scalable methodology that might inform national policy and foster data-driven agricultural practices, ultimately enhancing food security and sustainable development in Bangladesh.

Figure 2, illustrates the full pipeline of the system, which integrates plant disease detection and a recommendation module. By leveraging deep learning models trained on regionally relevant datasets, the system achieves high accuracy and effective identification of plant diseases in frequently occurring cases. The detection module processes user-uploaded images to classify crop conditions, followed by a recommendation system that provides tailored insights. In Reference Mode, the system delivers concise details about symptoms, prevention, and cure, while the LLM Mode offers dynamic, context-specific recommendations based on advanced language models. This research endeavour seeks to provide a technology-driven strategy for early plant disease diagnosis and control, aiming to influence agricultural practices significantly, particularly in Bangladesh. In a nation where farming is central to the economy and food security, the ability to detect crop diseases with precision and speed empowers smallholder farmers to maximize resources and minimize losses. Addressing challenges like high pesticide costs and limited access to expert advice, this work paves the way for smarter, more efficient agriculture.

The key contribution of this study includes:

1. Comprehensive and Localized Dataset: A key contribution of this research is the creation of a comprehensive dataset comprising over 30,000 annotated images, focusing on 35 plant diseases affecting critical crops such as rice, wheat, tomato, and eggplant. This dataset is unique in that it was created by merging data from local sources and worldwide databases, with a focus on conditions that mostly occur in Bangladesh. By ensuring that the dataset accurately represents the agricultural reality of the area, this method makes it possible to create deep learning models that are both context-specific and useful for addressing the farming difficulties faced by Bangladesh.
2. PlantCareNet Architecture: We demonstrated an innovative CNN that was optimized for mobile devices and maintained a low computing footprint

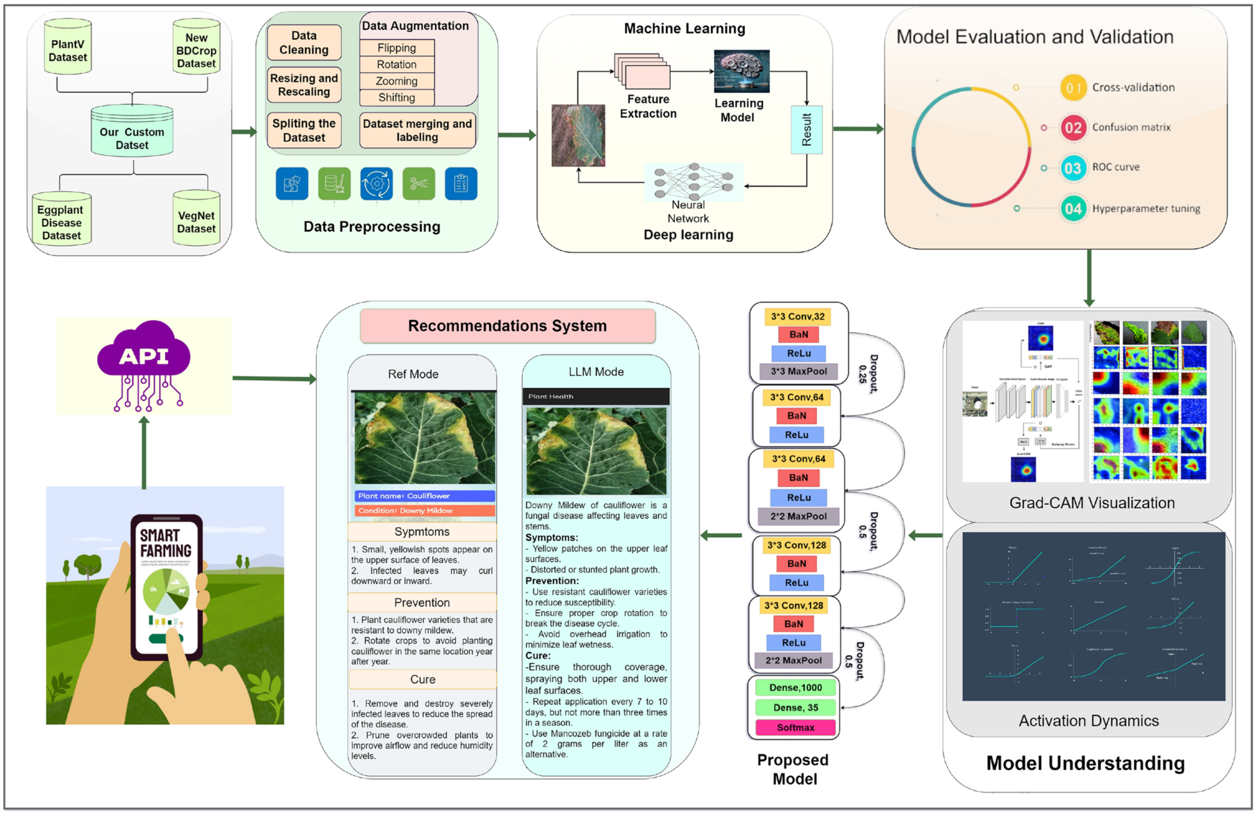

Fig. 2 Overall Workflow Diagram of the Recommendation System

while achieving a high level of accuracy. This architecture makes deployment easier in contexts with limited resources, despite the fact that it sacrifices performance.

3. Smart Agriculture Application: The developed mobile application integrates PlantCareNet to provide real-time diagnosis of plant diseases and actionable care recommendations, enabling farmers to effectively mitigate crop losses. This research significantly advances sustainable agriculture and the democratization of AI-based plant disease management by highlighting scalability and practical implementation.

Related works

Numerous researches have addressed important issues in agriculture by advancing the area of plant disease classification through the use of deep learning and image processing techniques. CNNs, K-means clustering, and histogram analysis were used by Harakannanavar et al. [36] to classify tomato diseases, with an astounding 99.6% accuracy rate. However, the actual usefulness of their technology is limited due to its dependence on high-quality photos and resource-intensive processing. On cauliflower datasets, Kanna et al. [37] investigated transfer learning models, such as EfficientNetB1, and achieved an impressive validation accuracy of 99.90%; nevertheless, issues like tiny datasets and high computing needs still exist. Similar to this, Pandian et al. [38] observed challenges with dataset quality and hyperparameter optimisation in multi-GPU systems, but they also presented a 14-layer DCNN using sophisticated data augmentation techniques, attaining 99.95% accuracy. Hossain et al. [39] designed an optimized model utilizing the transformer architecture, achieving an accuracy of 99.75% in identifying mango leaf diseases. Using Inception ResNet V2 and Inception V3 models, Saeed et al. [40] detected tomato leaf disease with 99.22% accuracy, highlighting the need of different datasets to improve generalisability. Islam et al. [41] used ResNet-50 to obtain 98.98% accuracy on the PlantVillage dataset; nevertheless, real-world scalability and limited dataset diversity are still issues. Bhuiyan et al. [42] developed Banana-SqueezeNet to identify three prominent banana leaf diseases using the BananaLSD dataset [43] with an accuracy of 96.25%. With a 98.49% accuracy rate, Trivedi et al. [44] developed a CNN-based model for tomato disease detection, but they also emphasised the necessity of scalability testing. Rashid et al. [45] combined CNNs and YOLOv5 for the diagnosis of potato disease, attaining 99.75% accuracy; nevertheless, scalability and regional applicability across crops are still difficult. The DTComp CNN model using class decomposition approaches was lastly introduced by Gulame et al. [46]. It achieved 98.30% accuracy and was compatible with real-time systems, but it was limited by biases in the dataset and problems with image quality. Together, these works show a great deal of advancement in the use of deep learning for plant disease diagnosis while pointing out important areas for further study, such as computational efficiency, real-world scalability, and dataset variety.

The study investigates the application of machine learning and artificial intelligence technologies for suggestion creation. Using Random Forest for crop selection and CNN for disease diagnosis, Diwakar et al. [47] developed an online application that smoothly integrates crop recommendation and plant disease detection. Though it emphasises the need for larger datasets and more flexibility across a variety of crops, this real-time, data-driven approach gives farmers practical information. Kumar et al. [48] presented an open-source online platform that includes disease forecasts and an interactive news feed in addition to conventional crop and fertiliser advice. By using interpretability approaches for transparent disease identification, this technology not only improves sustainability but also productivity.

Choudhary et al.'s study [49] concentrated on using economic and environmental analysis to optimise crop choices. This method solves issues related to food security while also increasing yields. They can provide farmers with early treatments since their approach includes a diagnostic component for plant diseases. To identify plant diseases, Suma et al. [50] used image processing techniques. There were five thousand photos in the dataset. They employed convolutional and semi-supervised learning techniques to create effective solutions that might boost agricultural productivity. To give customised solutions, Isinkaye et al. [51] created a smartphone-based system that integrates a content-based filtering algorithm. CNN, ANN, and KNN are also used by the system to accurately diagnose illnesses and offer treatments. Patil et al. [52] achieved an astounding 97.53 percent disease detection accuracy by successfully using artificial intelligence (AI) in agriculture via the use of Deep Convolutional Neural Network (CNN) models like Sequential and VGG-16. Before generating suggestions, its content-based filtering approach considers things like location, season, and climate to produce personalised crop recommendations. To tackle the issue of connection, Omara et al. [53] developed a field-based recommendation system. This technology provides advisory services and real-time input on crop disease detection. It does this by combining methods from natural language processing and machine learning.

Arvind et al. developed an explainable AI pipeline [54]. This pipeline has good F1 score accuracy and emphasised automated diagnosis. For the pipeline, EfficientNet B5 and transfer learning on tomato leaves were utilised. Users may upload photographs online or via mobile devices to this technology to rapidly and reliably diagnose ailments and provide recommendations. These studies improve disease detection, crop recommendations, and decision-making, boosting agricultural productivity. Their downsides include the need for larger datasets, scalability, and real-time application in agriculture. These disadvantages imply some areas require additional research and development.

This paper presents an advanced method for identifying plant diseases that addresses computational and scalability challenges. It enables swift intervention and effective illness management by integrating AI-generated recommendations with real-time data analysis. This approach provides pragmatic recommendations tailored to diverse environmental conditions, enhancing agricultural productivity and ensuring food security.

Materials and methods

By developing a real-time disease monitoring system, this research aims to build sustainable farming practices. Through a straightforward smartphone application, the device will give farmers and practitioners instant disease recommendations. The first goal of this effort is to create a dataset on agricultural diseases that is mostly related to crops grown in Bangladesh. Subsequently, we will develop a disease classification model that is as lightweight as possible, aiming for deployment in a mobile application. Ultimately, we will develop a system capable of promptly diagnosing a plant's state.

Data collection

The initial phase of this research was the compilation of a dataset pertinent to the categorization of plant diseases affecting significant crops in Bangladesh. The data was obtained from four esteemed public databases: PlantVillage [55], VegNet: Cauliflower Disease [56], the New Bangladeshi Crop Disease dataset [57], and the Eggplant Disease Recognition dataset [58]. The PlantVillage collection has 14 crop varieties and 38 categories, with images of both healthy and damaged leaves. Essential crops pertinent to Bangladesh include rice, tomato, potato, and maize, which are crucial to the nation's agriculture. The information include critical diseases like bacterial spots, blights, molds, and viruses. VegNet: Comprises one crop (cauliflower) with four categories, addressing illnesses such as black rot, downy mildew, and bacterial spot, in addition to a healthy category. The New Bangladeshi Crop Disease Dataset includes healthy specimens and include diseases such as brown spot, blast, late blight, and leaf curl virus across four crops (rice, tomato, potato, and maize), including over 12 categories. Eggplant Disease Recognition Dataset: Comprises a single crop (eggplant) categorized into six classifications, including bacterial wilt, fruit rot, phomopsis blight, and a healthy category.

During the data collecting process, we prioritized four essential criteria to guarantee that the dataset correctly represents Bangladesh's agricultural environment. Rice, maize, wheat, potato, tomato, cauliflower, and eggplant are seven widely farmed crops in Bangladesh that hold considerable economic significance. The main aim of this study was to highlight the cultivation of particular crops that are strategically significant for focused agricultural enhancements. The purpose of this technique was to guarantee the dataset's applicability for agricultural researchers and local farmers. Secondly, to augment the dataset's pertinence to the unique agricultural difficulties in Bangladesh, we incorporated 35 disease classifications based on their occurrence and effect within the region's distinctive climate and environment. To guarantee effective model transfer to real-world situations, we selected photographs that depict diverse phases of disease development, environmental circumstances, and viewpoints (from close-ups to expansive vistas). Ultimately, we maintained a limited number of pictures per class to reduce any bias in the model, despite some disease categories being underrepresented in the original datasets. Therefore, the paradigm would be applicable to all diseases.

The sample images of each of the 35 classes are shown in Fig. 3. The collection consists of 30,578 images of these crops captured under various conditions and disease stages. Specifically, there are 643 images of rice across four categories, 3,852 images of maize across four categories, 3,780 images of wheat across three categories, 2,152 images of potatoes across three categories, 18,146 images of tomatoes across ten categories, 640 images of cauliflower across four categories, and 1,374 images across seven categories. Table 1 illustrates the quantity of classes and the aggregate number of images inside each crop class. The dataset highlights specific crop production and addresses the unique agricultural issues encountered in Bangladesh, designed to support local farmers and agricultural research. We ensured that the photographs depicted a variety of environmental contexts, encompassing both close-ups and broader landscape vistas, as well as various stages of the disease's progression, from first symptoms to advanced stages. Furthermore, we ensured that each class had a minimum of 100 images to mitigate bias and ensure the model's applicability across diverse agricultural contexts.

Data preprocessing

Following data collection, we meticulously preprocessed the dataset to ensure its suitability for plant disease classification within a Bangladeshi agricultural framework. Initially, all images were resized to 640×640 pixels to standardize dimensions across different sources, ensuring uniformity and facilitating seamless integration into the dataset. Prior to feeding the images into the deep learning models, they were further resized to 75×75 pixels to align with the input requirements of our custom model, optimizing computational efficiency without compromising critical visual features. Furthermore, pixel intensity values were normalized to a [0,1] range to mitigate illumination variations and stabilize model training, facilitating more effective feature extraction and improving overall model generalization. This normalization process not only accelerates convergence during training but also enhances the model's robustness to varying lighting conditions, ensuring more consistent predictions across diverse real-world scenarios.

To enhance the model's resilience, data augmentation was systematically applied across all ailment categories. The used approaches included random rotations with a tolerance of $\pm 25°$, alterations in width and height of ±10%, shear transformations of 0.2, zoom modifications of ±20%, and horizontal flips (Fig. 4). These enhancements improve the model's ability to generalize across various agricultural settings by replicating diverse real-world scenarios, including changes in size, orientation, and perspective. Real-time augmentation was applied during training, where each batch was augmented dynamically in every epoch. This method ensures that no additional physical images are added to the dataset while creating diverse and varied images in each epoch, which strengthens the model's ability to handle different variations in the data.

Finally, we divided the dataset into training and test sets 85/15. This let us train the model with the most data while preserving a strong evaluation representation. This division allows extensive validation of the model, which is trained using a large dataset that correctly replicates real-world settings. After these preparations, the curated data will be ready for reliable, region-specific plant disease categorization for various Bangladeshi crops.

Model selection

In this research, we introduce PlantCareNet, a convolutional neural network (CNN) specifically designed to properly and quickly categorize plant disease in Bangladeshi agricultural crops. The proposed model is tailored

Table 1 Overview of the Combined Crop Disease Dataset

Name	Classes	Healthy/Disease Classes	No. of Images	Total Images
Cauliflower	4	1. Bacterial spot rot	168	640
		2. Black Rot	102	
		3. Downy Mildew	169	
		4. Healthy	201	
Corn	4	5. Cercospora leaf spot(Gray leaf spot)	513	3852
		6. Common rust	1192	
		7. Healthy	1162	
		8. Northern Leaf Blight	985	
Eggplant	7	9. Healthy Leaf	200	1334
		10. Insect Pest Disease	199	
		11. Leaf Spot Disease	199	
		12. Mosaic Virus Disease	190	
		13. Small Leaf Disease	194	
		14. White Mold Disease	195	
		15. Wilt Disease	197	
Potato	3	16. Early blight	1000	2152
		17. Healthy	152	
		18. Late blight	1000	
Rice	4	19. Bacterial leaf blight	132	634
		20. Brown spot	107	
		21. Healthy	267	
		22. Leaf smut	128	
Tomato	10	23. Bacterial spot	2127	18146
		24. Early blight	1000	
		25. Healthy	1585	
		26. Late blight	1901	
		27. Leaf Mold	952	
		28. mosaic virus	373	
		29. Septoria leaf spot	1771	
		30. Spider mites Two-spotted spider mite	1676	
		31. Target Spot	1404	
		32. Yellow Leaf Curl Virus	5357	
Wheat	3	33. Brown Rust	1128	3780
		34. Healthy	1496	
		35. Yellow Rust	1156	

for mobile devices, enabling seamless accessibility for local farmers and agricultural professionals, as it strikes a compromise between diagnostic precision and computing efficiency. The network employs Rectified Linear Unit (ReLU) activation functions across many convolutional layers to provide effective feature extraction using non-linear transformations. Batch normalization used after each convolutional layer during training, ensures stability and accelerates convergence. Max-pooling layers provide reduced processing complexity via dimensionality reduction while maintaining essential attributes. The use of dropout layers, which mitigate overfitting, enhances the model's capacity to generalize across many situations. The final softmax layer of the research enables multi-class categorization across 35 disease categories, essential for targeted agricultural applications. The model architecture of PlantCareNet is depicted in Fig. 5.

We placed a high priority on striking a compromise between classification accuracy and computational efficiency when developing PlantCareNet, especially in order to enable real-time performance on mobile devices with limited resources. Without imposing additional complexity, the design makes use of conventional multi-scale convolutional layers to efficiently

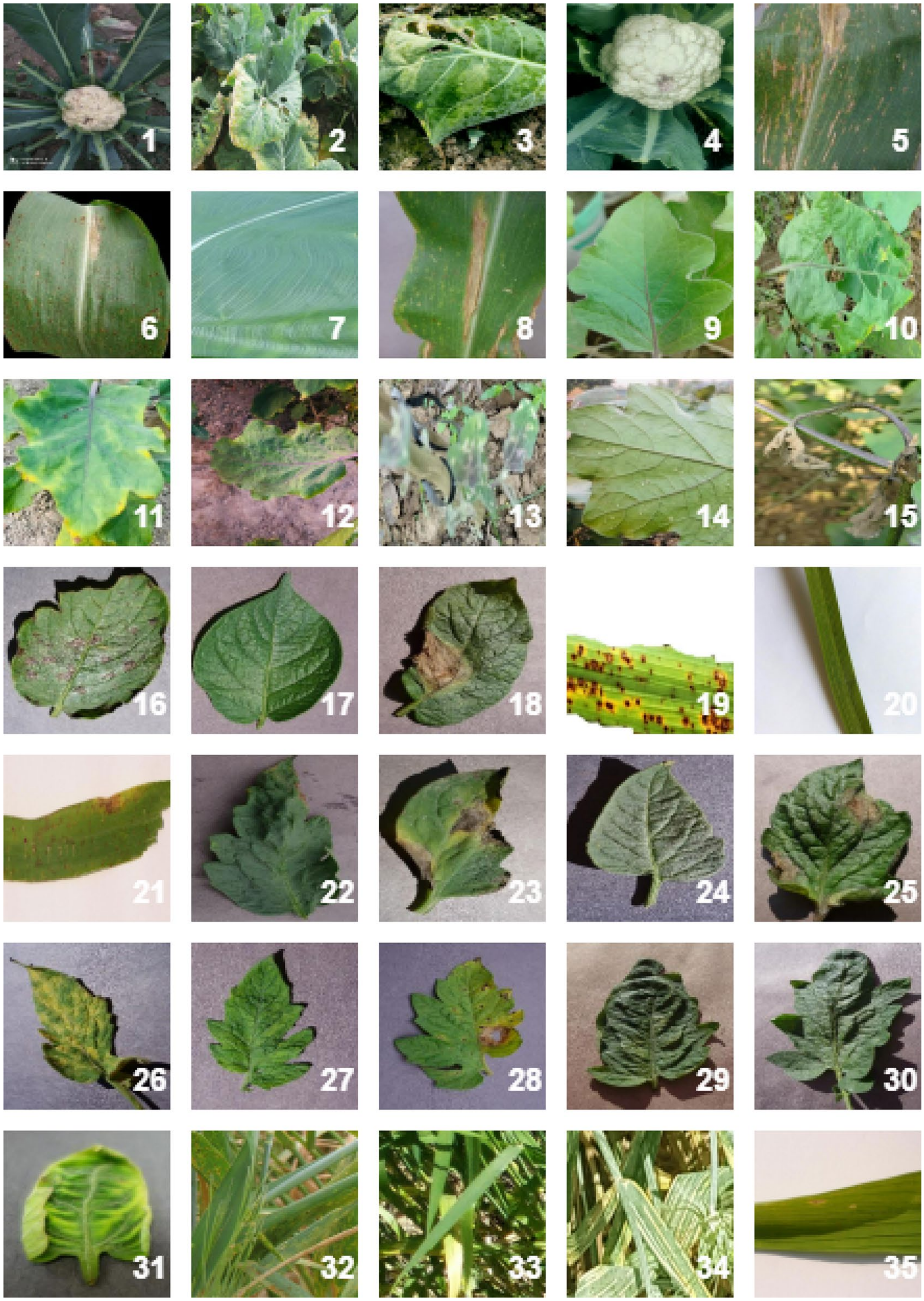

Fig. 3 Sample Images Representing Each Class in the Dataset

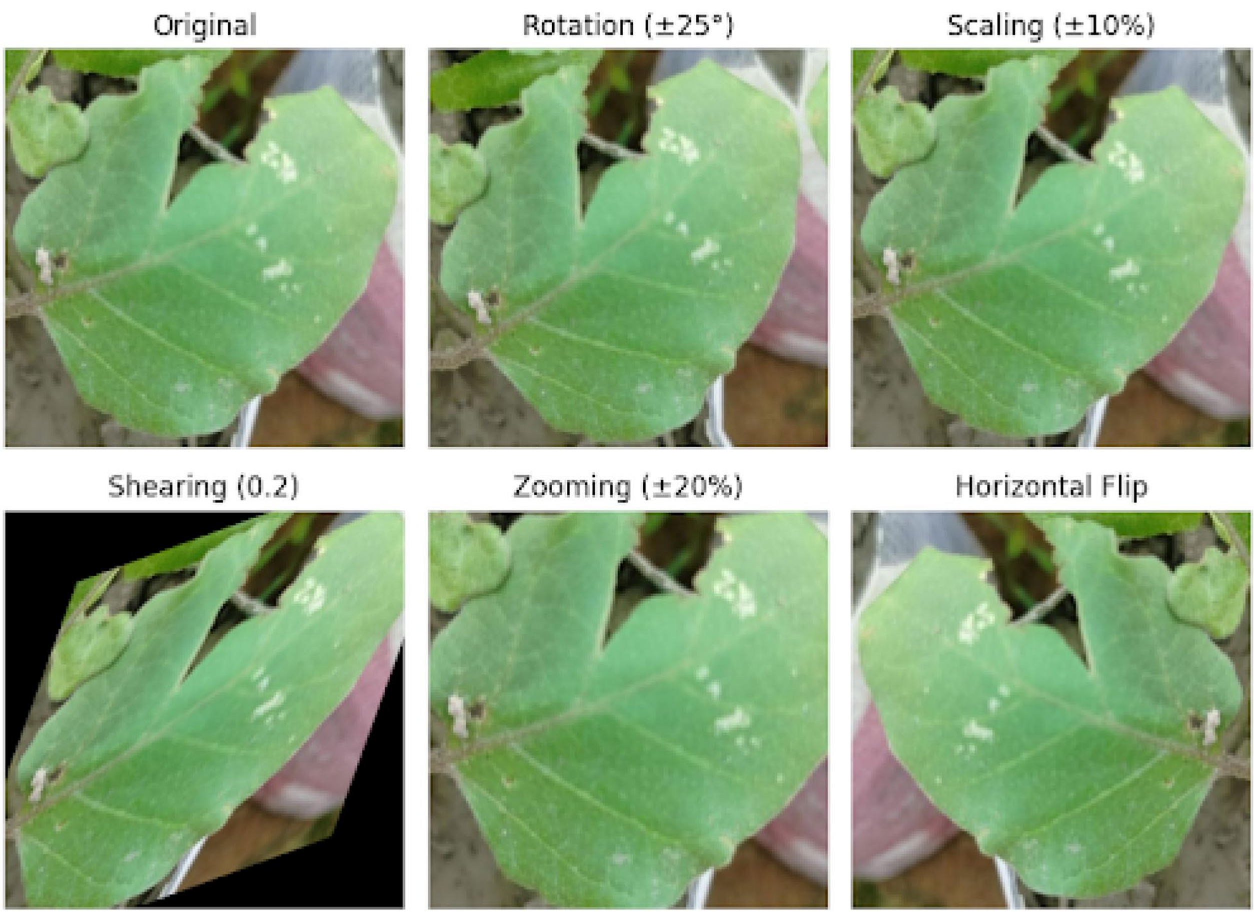

Fig. 4 Data Augmentation

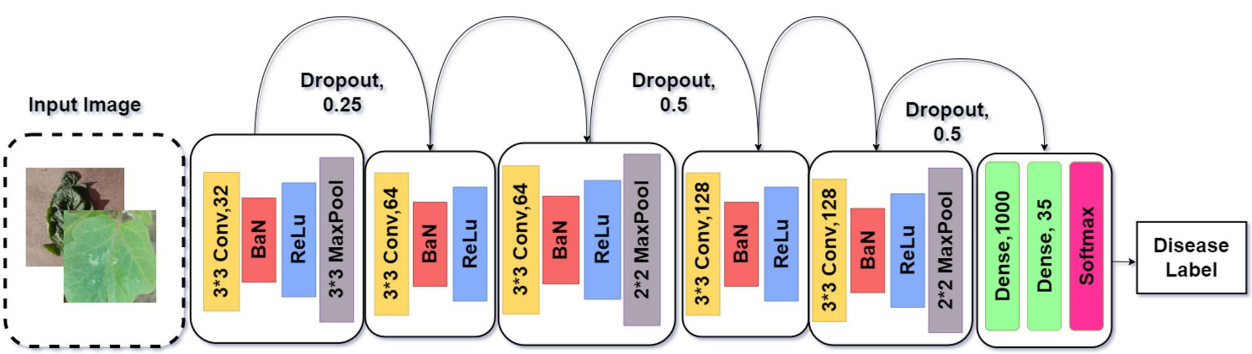

Fig. 5 The proposed PlantCareNet architecture

capture minute differences in plant disease symptoms. By minimizing the computational complexity linked to more intricate methods like layer-wise convolutions, this design decision guaranteed reliable feature extraction. Rather, by combining methods like batch normalization, dropout, and max-pooling, we were able to improve model generalization and stability across a variety of datasets while keeping the structure small and portable. In the end, this strategy allowed PlantCareNet to succeed in providing effective disease detection and high classification accuracy for practical agricultural applications.

The architecture is designed for the highest possible effectiveness, ensuring the model operates in real-time environments, which is crucial for disease detection applications dependent on mobile devices. To be sure of PlantCareNet's effectiveness, we evaluated it against some popular deep learning models along with InceptionV3 and ResNet50, which are both renowned for their superior performance on image classification tasks. We used standard evaluation metrics, including accuracy, precision, recall, and F1-score, to evaluate the model's efficacy. The Results section indicates that PlantCareNet excels in plant disease classification, particularly on resource-constrained mobile devices.

Model training

To maximise the performance and guarantee generalisation over a wide range of disease categories, the model was trained using a set of carefully selected hyperparameters. To promote steady convergence and enable the model to accurately capture the intricate characteristics of plant diseases without overfitting, a learning rate of 0.0001 was used. In order to ensure efficient updates to the model weights and minimise memory use during training, the batch size was chosen at 32 to strike a compromise between computational efficiency and model stability. Categorical cross-entropy was used as the loss function, as it is well-suited for multi-class classification problems, allowing the model to optimize predictions across all disease classes simultaneously.

To ensure consistency and fair comparability across models, all models were trained for 250 epochs. This duration was selected to provide sufficient time for the network to learn complex patterns and generalize effectively across diverse disease categories. By standardizing the number of epochs, we minimized potential discrepancies arising from varying training durations and ensured uniform experimental conditions. Additionally, a checkpointing system was employed to save model states at regular intervals, allowing the selection of the best-performing model based on validation metrics. This approach enhanced model robustness, ensured reproducibility, and facilitated more reliable performance evaluations.

The hyperparameter selections and their justifications for enhancing the model's performance are compiled in Table 2. In order to create an efficient architecture that was suited to the dataset and job requirements, every parameter was meticulously chosen through extensive testing, striking a balance between accuracy and computational economy.

The model was trained and assessed on a Kaggle notebook environment, with two NVIDIA Tesla T4 GPUs (each with 16 GB of RAM) used to accelerate the training process using parallel processing. When combined with the Intel Xeon CPU architecture, the GPUs allowed for effective processing of massive amounts of visual data. The system was set up using CUDA 12.6 to guarantee the best GPU acceleration and performance throughout the training and inference phases, while TensorFlow 2.17 and Keras were utilized for model creation. Consistency in performance evaluation was ensured by measuring inference time on a batch size of 32 with the model deployed in the same hardware configuration. The average inference time per sample was calculated to assess model efficiency, and results were obtained using this environment, providing a reliable and reproducible analysis of the model's real-time performance in plant disease classification tasks.

Model evaluation and visualisation

The suggested model, PlantCareNet, was carefully evaluated to confirm its usefulness in real-world plant disease categorisation. Its performance on the validation set was evaluated using key measures including accuracy, precision, recall, and F1-score, which gave a thorough picture of its categorisation skills as shown in Fig. 6. In order to assess the model's classification accuracy and identify potential misclassifications, a confusion matrix was produced.

Table 2 Overview of Hyperparameter Choices

Parameter	Reasons	Trials Done	Best Choice
Conv filters	Capture various features	32,64,128	All in different stage
Activation	Introduce non-linearity	ReLU, Leaky ReLU	RelU
Pooling	Reduce spatial dimensions	2x2,3x3	Both required
Dropout Rate	Prevent overfitting	0.2, 0.25, 0.5	0.25 and 0.5
Batch Norm	Stabilize training, speed up convergence	Before/After Convolution	After
Learning Rate	Control the size of weight updates	0.001, 0.0005, 0.0001, 0.05, 0.01	0.0001
Epochs	Ensure enough training time to learn	50, 100, 150, 250	250

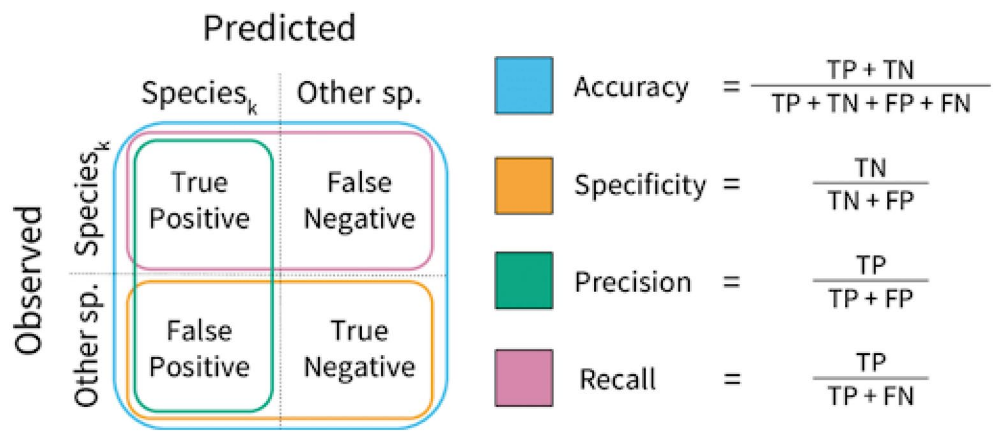

Fig. 6 Performance Metrics for the Classification Model

We visualised training and validation loss and accuracy across epochs to track training progress, exposing convergence tendencies and the effects of methods like batch normalisation and dropout. These revelations were crucial to comprehending the stability and optimisation process of the model. PlantCareNet was further validated by comparing it to cutting-edge architectures like as InceptionV3, ResNet50, and MobileNet. Using the same dataset and assessment methodology, the comparisons revealed that PlantCareNet regularly outperformed or matched these models, indicating its utility for actual agricultural applications.

The model's decision-making process was visually explained using Grad-CAM (Gradient-weighted Class Activation Mapping) in Fig. 7, which was used to further confirm PlantCareNet's predictions. By emphasising the areas of the plant photos that the machine concentrated on during classification, these visualisations improved predictability and increased confidence in the results. Grad-CAM findings demonstrated the model's capacity to make significant and comprehensible judgements by confirming that its predictions match disease-specific characteristics. These evaluations validate PlantCareNet as a reliable, interpretable, and scalable tool for accurate plant disease diagnosis and practical agricultural applications.

Mobile application development

The mobile application for identifying and recommending plant diseases is developed in Kotlin [59] specifically

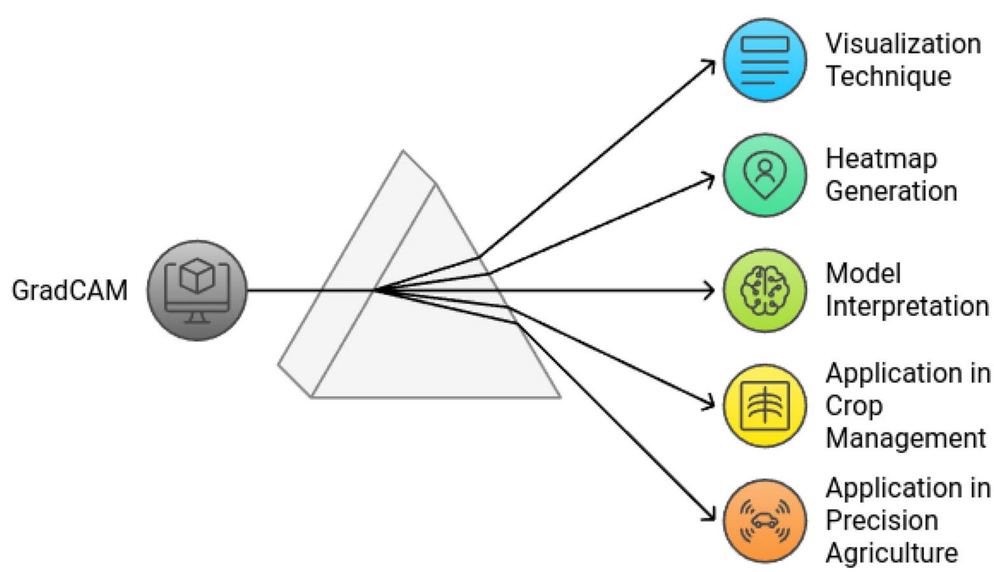

Fig. 7 Exploring the Dimensions of GradCAM

for the Android platform. The objective is to furnish farmers and agricultural specialists with an intuitive interface for real-time disease diagnosis and actionable insights.

The app assists in identifying plant diseases by offering concentrated information on symptoms, prevention, and treatment, therefore empowering users to make educated decisions on crop health management. Upon launching the app, users can select a crop type (e.g., rice, potato, or tomato) from a predefined list and upload an image of a plant directly from their mobile device. A RESTful API [60] accepts this input and utilizes the PlantCareNet model housed on Roboflow to analyze the image. The method yields the disease name, confidence score, and relevant recommendations following the classification of the ailment. In cases where the model's classification confidence is low or when it encounters a disease outside the predefined 35 categories, the app flags the result as "unknown". This feature ensures that users are informed of uncertainties in the classification, maintaining transparency and preventing misclassifications.

The program additionally lets users upload multiple photos of the same plant to increase classification accuracy. With the ability to analyze many photographs and decide the disease diagnosis based on a majority vote across all uploaded images, this function helps lessen the impact of inadequate lighting or poor image quality. The program uses each prediction's confidence score to determine which class has the highest confidence as the outcome if the votes from the classes are tied. By combining data from several sources, this feature makes sure that the system can still produce a diagnosis that is more accurate and trustworthy even if one or more of the photos are of poor quality. Users can easily understand and utilize the results, as the outcomes are presented clearly. The workflow diagram of the developed app, shown in Fig. 8, illustrates the entire process from start to finish.

To guarantee optimum performance, quick reaction times, and accurate analysis, the calculations are now carried out on the cloud. This cloud-based architecture has the capacity to accommodate complicated models like PlantCareNet while still providing a seamless and responsive user experience. The system leverages a diverse training dataset to ensure reliable performance across varying image conditions, minimizing the need for explicit user guidance during image capture. Given that our primary target users are farmers and agricultural professionals in places with varying technical access, the system has been developed to work with a broad range of Android smartphones, including those with limited processing capability. This assures that users can access the system reliably, even on low-end devices, and reduces adoption obstacles.

To ensure broad accessibility and seamless user experience across various devices, the mobile application for plant disease identification and recommendations was designed to support Android versions ranging from Android 7 (Nougat) to Android 15 in order to guarantee wide accessibility and a smooth user experience across multiple devices. This range was selected to guarantee compatibility with both older and more recent smartphones, enabling users with varying device capabilities to make efficient use of the application. Additionally, a OnePlus 7T running Android 12 with 8 GB of RAM was used to test the mobile application's performance. We were able to assess and validate the application's correctness, stability, and responsiveness in real-world use cases thanks to this testing environment. By choosing this gadget, we made sure the system could support smartphones ranging from the mid-range to the high-range, further guaranteeing that a wide variety of users can access the application without performance issues.

The application enables efficient data exchange by integrating an internet backend that allows real-time server connectivity. To provide accessibility for users with varying levels of technical proficiency, it employs a user-friendly design, explicit instructions, and intuitive navigation. The interface serves as a reliable instrument for real agricultural scenarios, designed for simplicity while ensuring rapid response times and accurate outcomes. The program has undergone testing in several agricultural environments to simulate field conditions and confirm its practical applicability. This ensures its durability and adaptability, even in challenging environments. The program is meant to be expandable, allowing it to accommodate new crop varieties and disease classifications in future updates, so maintaining its relevance as agricultural issues evolve.

Recommendation system

Figure 9 shows the recommendation system for disease management, outlining the steps to provide actionable suggestions to users. The capacity to provide farmers and agricultural specialists with actionable advice for efficiently controlling plant diseases is a crucial part of this system. It functions in two separate modes, LLM Mode and Reference Mode (Ref Mode), both of which is designed to accommodate varying degrees of interactivity and information richness. The system provides clear, preconfigured suggestions in Ref Mode, including critical information about illness signs, preventative methods, and treatment alternatives.These guidelines are founded on specialist knowledge, guaranteeing their conformity with generally recognized agricultural methods in Bangladesh.

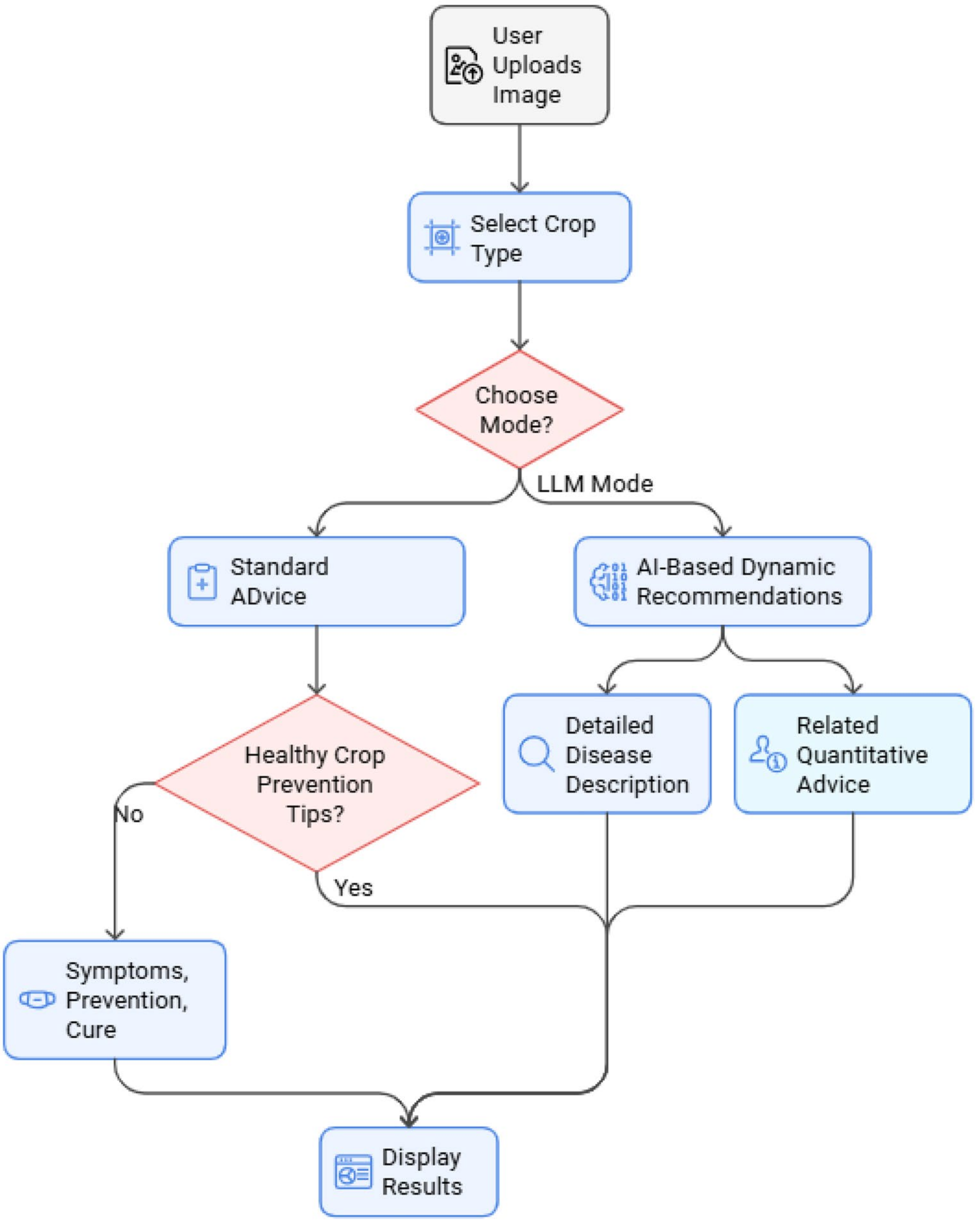

Fig. 8 The workflow diagram of the developed APP

Ref Mode provides customers with trustworthy, context-aware advice without needing further user engagement because the suggestions are based on a well maintained database of ailments that are often observed in the area. When a user uploads an image of a crop and specifies its name, the PlantCareNet model identifies the disease, and the system uses this information to retrieve tailored recommendations. These recommendations center on doable disease management strategies, such as identifying symptoms, prescribing appropriate treatments, and implementing locally-specific prevention measures. Ref Mode's main goal is to provide farmers and agricultural specialists with fast access to expert-based, actionable insights that guarantee efficient disease management with little effort.

LLM Mode utilizes OpenAI's GPT to provide dynamic and thorough suggestions, leveraging its proven accuracy, ease of integration, and robust performance in generating relevant, domain-specific recommendations. Its pre-trained model offered a reliable, computationally efficient solution, ensuring high-quality outputs while adhering to privacy and security standards. Following

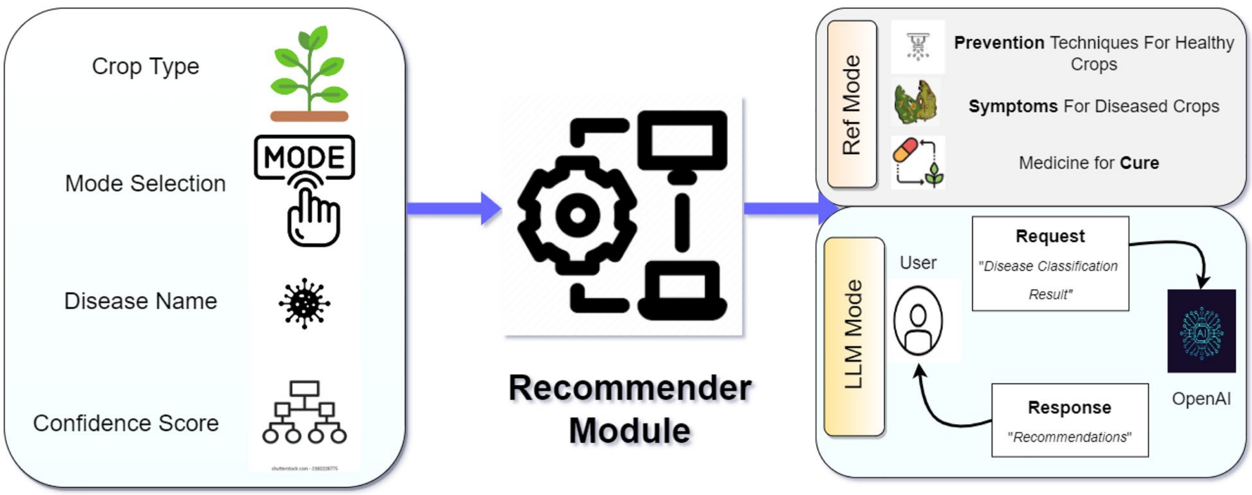

Fig. 9 Recommendation System for Disease Management

disease identification, the PlantCareNet model sends pertinent information to the GPT API, including crop type, disease name, and classification confidence. Following a brief overview of the diseases, the system provides comprehensive, situation-specific advice on symptoms, preventative measures, and available treatments. This mode provides complex and locally appropriate answers for a variety of situations. For example, if the system detects a fungal disease in rice, Ref Mode might suggest general fungicide use and irrigation adjustments, while LLM Mode would provide a more comprehensive description, including specific fungicides, their application methods, and timing recommendations tailored to local conditions. Connecting with people in LLM Mode for quick input will allow the system to dynamically improve its ideas. This technology revolutionizes plant disease management by combining dynamic flexibility with static reliability for precise, accessible, and efficient solutions.

Results

The findings and analysis are conducted on individual datasets first, followed by customized datasets, including a comparative study with the latest models.

Performance on individual datasets

The performance of PlantCareNet in comparison to Inception and ResNet across five datasets is shown in Table 3, indicating its adaptability and dependability in

Table 3 Performance metrics of different models on various datasets

Dataset	Models	Acc.	Loss	Prec.	F1	Recall
Eggplant Disease Recognition Dataset [58]	Inception	0.73	0.17	0.77	0.72	0.68
	Resnet	**0.86**	**0.11**	**0.87**	**0.86**	**0.85**
	PlantCareNet	0.85	0.12	0.86	0.85	0.85
New Bangladeshi Crop Disease Dataset [57]	Inception	0.81	0.09	0.81	0.79	0.78
	Resnet	0.73	0.13	0.72	0.71	0.7
	PlantCareNet	**0.83**	**0.08**	**0.84**	**0.84**	**0.83**
VegNet: A dataset of cauliflower images [56]	Inception	**0.86**	**0.12**	**0.9**	**0.9**	**0.88**
	Resnet	0.8	0.2	0.79	0.78	0.81
	PlantCareNet	0.82	0.18	0.71	0.71	0.7
Plant Village Dataset [55]	Inception	0.88	0.04	0.89	0.88	0.87
	Resnet	0.92	0.03	0.92	0.92	0.92
	PlantCareNet	**0.94**	**0.03**	**0.94**	**0.94**	**0.94**
VegNet: Vegetable Dataset with quality [61]	Inception	0.87	0.12	0.88	0.87	0.87
	Resnet	0.8	0.22	0.8	0.81	0.79
	PlantCareNet	**0.96**	**0.05**	**0.96**	**0.96**	**0.96**

the categorisation of plant diseases. By presenting the highest accuracy (Acc.), precision (Prec.), recall, and F1 score, as well as the lowest loss, the bold values highlight the best outcomes for each dataset and highlight the models' optimal performance in each aspect. With the best accuracy (94%) and F1 Score (0.94) on the renowned PlantVillage dataset, PlantCareNet fared better than both ResNet and Inception. Likewise, it demonstrated its resilience in managing quality-related variability with an outstanding accuracy of 96% on the VegNet Quality dataset, significantly outperforming ResNet (80%) and Inception (87%).

PlantCareNet continuously excelled or nearly equalled its rivals in region-specific datasets. For example, it maintained the lowest loss (0.08) and obtained greater accuracy (83%) on the New Bangladeshi Crop Disease dataset, demonstrating its excellent optimisation for regional agricultural concerns. Its performance (85% accuracy) on the Eggplant Disease dataset outperformed Inception (73%), roughly matching ResNet's 86% performance. On the VegNet Cauliflower dataset, however, PlantCareNet performed mediocrely, falling short of Inception in terms of accuracy and precision, suggesting possible areas for improvement. These findings highlight PlantCareNet's generalisability across a variety of datasets and point out certain areas that require further development in more challenging situations.

Performance on the custom dataset

After undergoing a thorough evaluation on a specially created dataset pertaining to Bangladeshi crops and related diseases, the suggested PlantCareNet model demonstrated remarkable performance metrics, including 97% accuracy, 97% precision, 97% recall, and a 97% F1-score. These outcomes highlight the model's resilience and efficiency in tasks involving the classification of plant diseases. The Fig. 10 presents the model's performance metrics across different training phases on the custom dataset. Figure 10a shows the model's accuracy over epochs, highlighting its learning progress. Figure 10b displays the loss trajectory, showing how the model reduces error as training progresses. Figure 10c illustrates the precision performance, while Fig. 10d shows the recall metrics, both reflecting the model's capability in correctly identifying plant diseases

The model successfully handled changes in image quality, environmental factors, and data heterogeneity, exhibiting high generalization across a variety of input situations. Targeted data augmentation techniques improved its steady performance, even when there was a class imbalance. The confusion matrix, which displays accurate discrimination between disease classes, including those with small visual changes, further demonstrates the model's dependability. This demonstrates how well-suited PlantCareNet is for practical agricultural uses.

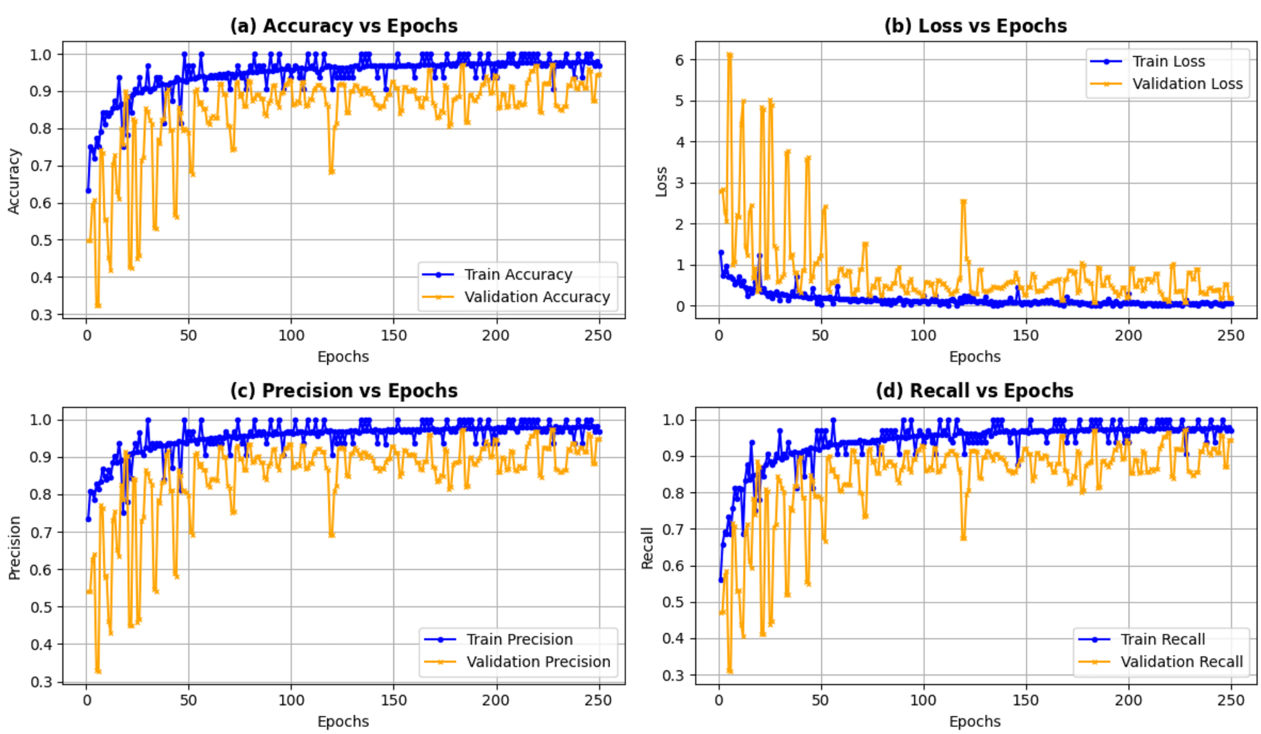

Fig. 10 Performance Evaluation of the Proposed Model on Custom Dataset

Performance evaluation

The performance evaluation of our model, which classifies 35 different plant diseases across various crops, shows its strong capabilities, as highlighted in Table 4. The model achieved outstanding results, with perfect F1-scores and MCC values of 1.00 for key diseases such as Corn Common Rust, Tomato Yellow Leaf Curl Virus,, demonstrating its ability to accurately identify both common and visually diverse diseases. The model also performed well across many other diseases, such as Potato Early Blight (F1 = 1.00) and Tomato Septoria Leaf Spot (F1 = 0.98), showing its strong generalization ability. However, some diseases, like Rice Brown Spot (F1 = 0.67), Rice Leaf Smut (F1 = 0.67), and Eggplant Insect Pest Disease (F1 = 0.77), proved more challenging due to their similarities with other diseases and limited training data. Despite these difficulties, the model's overall performance represents a significant improvement over traditional methods, particularly in handling more complex and visually similar diseases. This evaluation suggests that there is still room for further improvement, especially in boosting accuracy for these more challenging disease categories.

Table 4 Performance metrics for all 35 classes

Crop	Class	Prec.	Rcl.	Spec.	F1-S.	MCC
Cauliflower	Bacterial spot rot	1.00	0.93	0.98	0.96	0.93
	Black Rot	1.00	0.88	0.95	0.93	0.90
	Downy Mildew	0.96	0.92	0.95	0.94	0.91
	Healthy	0.96	1.00	1.00	0.98	0.96
Corn	Cercospora leaf spot	0.96	0.94	0.98	0.95	0.95
	Common rust	0.99	1.00	1.00	1.00	1.00
	Northern Leaf Blight	0.97	0.98	0.99	0.98	0.97
	Healthy	1.00	1.00	1.00	1.00	0.98
EggPlant	Healthy Leaf	0.77	0.84	0.89	0.81	0.76
	Insect Pest Disease	0.68	0.88	0.91	0.77	0.75
	Leaf Spot Disease	0.89	0.68	0.93	0.78	0.74
	Mosaic Virus Disease	0.75	0.83	0.95	0.79	0.72
	Small Leaf Disease	0.95	0.68	0.97	0.79	0.74
	White Mold Disease	0.88	0.88	0.98	0.88	0.79
	Wilt Disease	0.90	0.97	1.00	0.93	0.93
Potato	Early blight	0.99	1.00	1.00	1.00	0.99
	Late blight	0.99	1.00	1.00	1.00	0.97
	Healthy	0.96	1.00	1.00	0.98	0.94
Rice	Bacterial leaf blight	0.71	1.00	0.98	0.83	0.95
	Brown spot	1.00	0.50	0.91	0.67	0.71
	Healthy	1.00	0.97	1.00	0.99	0.99
	Leaf smut	0.50	1.00	0.95	0.67	0.71
Tomato	Bacterial spot	0.99	0.97	0.97	0.98	0.94
	Early blight	0.87	0.96	0.98	0.91	0.96
	Late blight	0.97	0.97	0.99	0.97	0.94
	Leaf Mold	0.99	0.97	1.00	0.98	0.95
	Septoria leaf spot	1.00	0.97	0.96	0.98	0.98
	Spider mites	0.97	0.98	0.99	0.97	0.88
	Target Spot	0.94	0.9	0.99	0.92	0.77
	Yellow Leaf Curl Virus	1.00	1.00	1.00	1.00	1.00
	Healthy	0.94	1.00	0.98	0.97	0.84
	Mosaic virus	1.00	0.98	1.00	0.99	0.97
Wheat	Brown Rust	0.99	0.97	0.98	0.98	0.95
	Healthy	0.99	1.00	1.00	0.99	1.00
	Yellow Rust	0.97	0.99	0.99	0.98	0.98

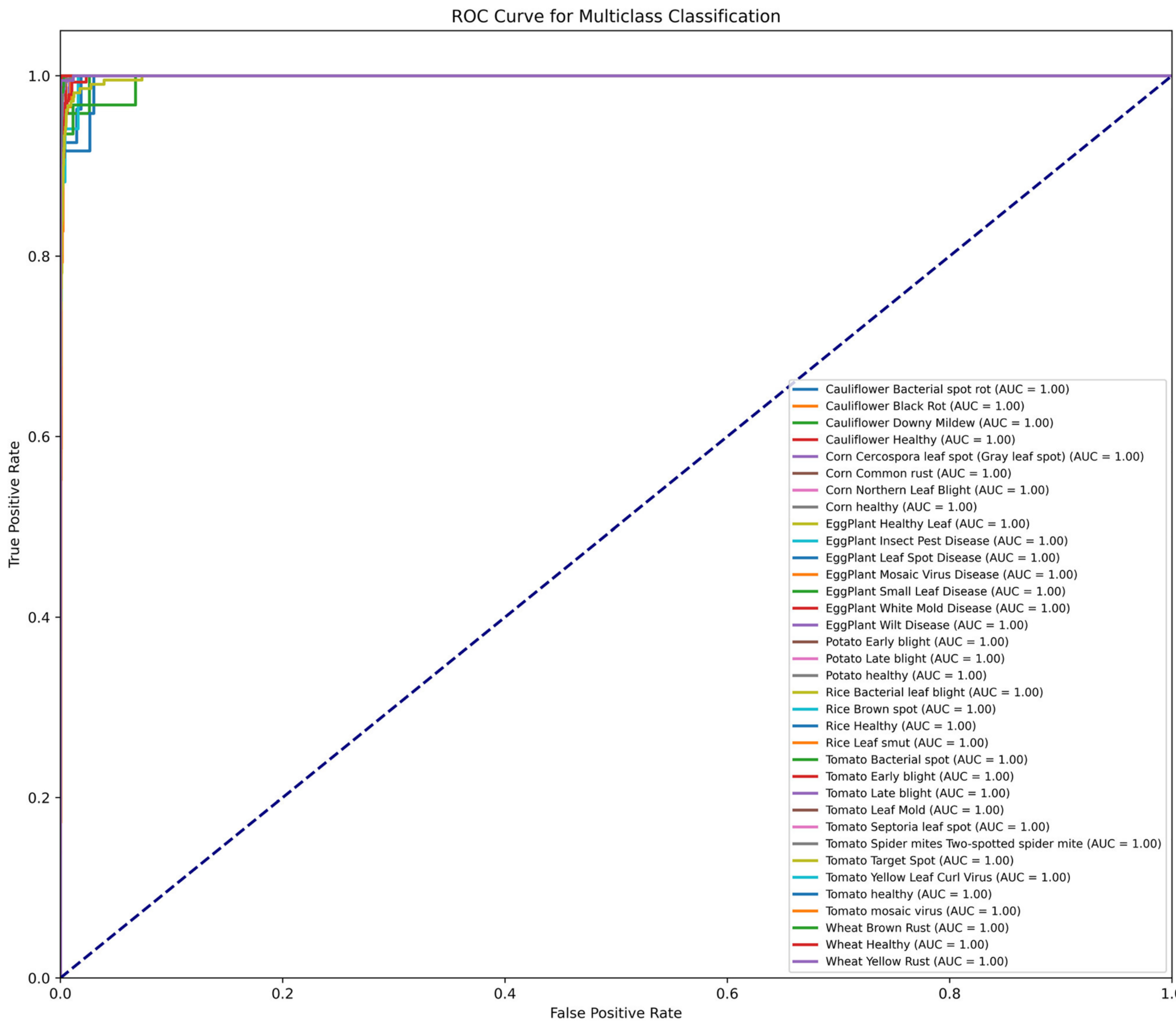

Fig. 11 Receiver operating characteristic (ROC) curve

The model's general superiority in class discrimination is shown by the Receiver Operating Characteristic (ROC) curves, which are displayed in Fig. 11. Most classes had Area Under the Curve (AUC) values more than 0.99, and several, such as important crop diseases, had perfect AUC values of 1.00. This demonstrates the model's exceptional capacity to confidently differentiate between several disease classifications. In conclusion, the method demonstrates high accuracy and reliable classification performance across the frequently occurring plant diseases in commonly cultivated crops in Bangladesh, showcasing its applicability within the defined scope of this study. Notwithstanding modest difficulties in a few low-representation classes, the approach works well for classifying plant diseases on a wide scale, opening the door for useful applications in agriculture.

Handling class imbalance in disease classification

When certain classes contain an excessive amount of samples, this is known as class imbalance and can cause the model to be biassed in favour of the over-represented classes. In addition to over-represented classes like Tomato Bacterial Spot and Corn Common Rust, which contained substantially more samples than other illnesses, we also encountered imbalance in our study from under-represented classes like Rice Leaf Smut and Eggplant Insect Pest Disease. Predictions may become skewed as a result of the model favouring the over-represented classes due to this imbalance.

In order to address this imbalance, we used data augmentation methods including colour jittering, flipping, and rotation to broaden the variety of the minority classes, which improved the model's ability to generalise about these uncommon illnesses. The model's capacity to identify under-represented illnesses was enhanced by these methods, as seen by the confusion matrix, which shows fewer False Negatives for these classes.

The impact of our class imbalance strategies is demonstrated in Fig. 12, where the model performs well for the majority classes, correctly predicting 775 cases of Tomato Yellow Leaf Curl Virus and 188 cases of Corn Common Rust, highlighting the model's ability to detect common diseases by utilizing the large amount of data available for these classes. Crucially, the model also performs better on minority classes with fewer samples, including EggPlant Insect Pest Disease (15 accurate predictions) and Cauliflower Downy Mildew (22 accurate predictions), demonstrating the effectiveness of class weighting and data augmentation techniques in improving the model's capacity to detect under-represented diseases, even with limited data.

The performance shows a notable increase over training without these balancing strategies, even though the prediction accuracy for minority classes is still somewhat worse than that for majority classes. Overall misclassification rates are still low, despite occasional uncertainty for some classes, including Tomato Bacterial Spot. This illustrates the model's improved ability

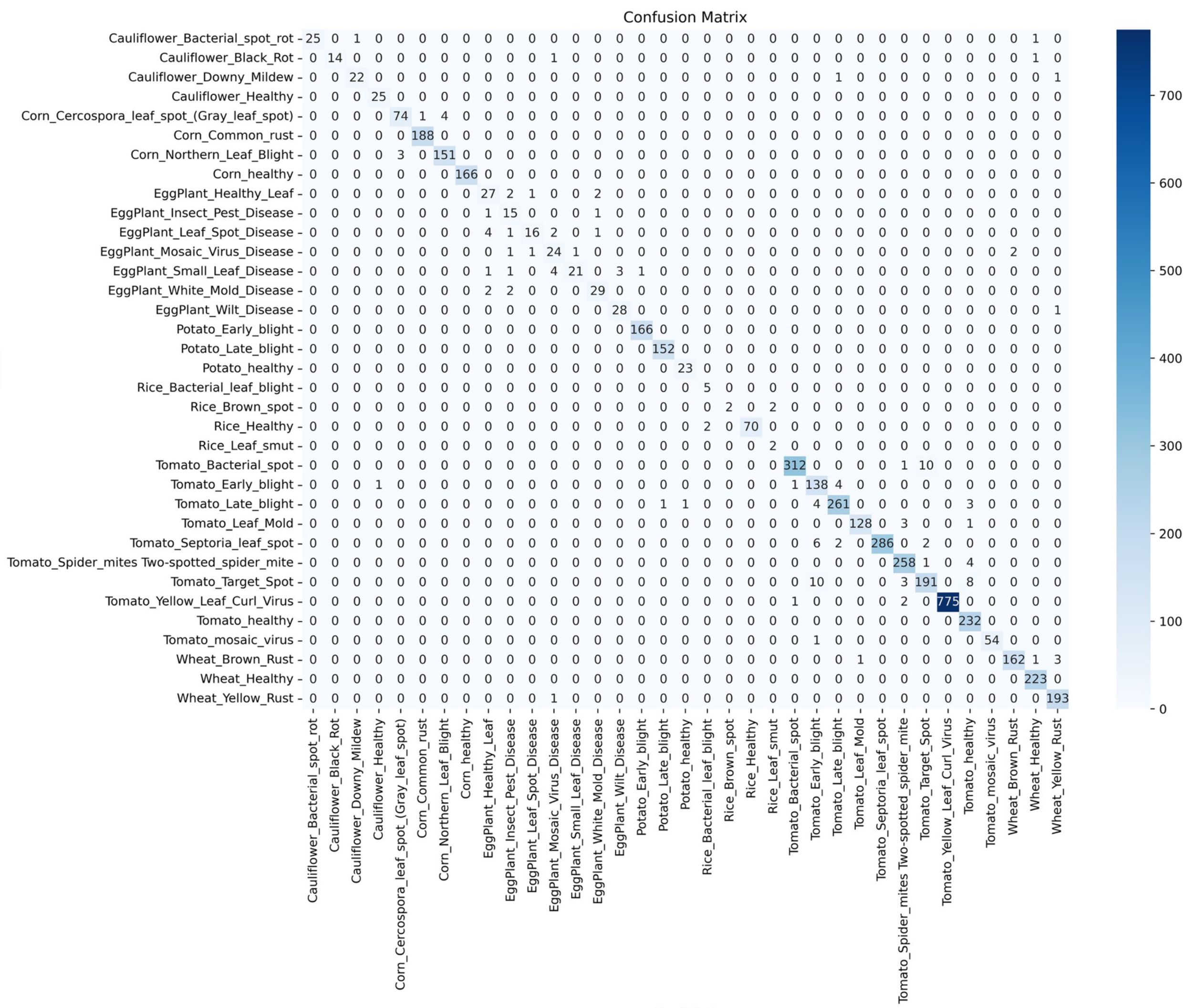

Fig. 12 Confusion Metrices for the Classification Model

to control class imbalance, which allows it to more precisely generalize across both common and uncommon plant disease types.

Interpretability with grad-CAM

Grad-CAM was used to create visual heatmaps that shed light on the areas that PlantCareNet predicted were most important. These heatmaps employ colour gradients, where areas of greater significance are indicated by warmer tones (orange, red), and those of lesser importance by cooler tones (blue, green). In order to verify the interpretability and robustness of the model, the visualisations correlate the highlighted areas with either healthy or known disease-specific properties.

The heatmap for Cauliflower Downy Mildew in Fig. 13a precisely focusses on disease-specific regions by highlighting distinctive fungal patches in warm tones. Similarly, Cauliflower Bacterial Spot Rot is shown in Fig. 13b, where bacterial lesions are accurately localised by vivid colour zones, demonstrating the model's capacity to properly identify infection patterns. Wheat Brown Rust is shown in Fig. 13c, where the heatmap corresponds with rust pustules, confirming PlantCareNet's ability to identify subtle but physiologically significant disease signals.

On the other hand, Fig. 13d depicts a healthy aubergine leaf with a uniform distribution of cooler tones, indicating that there are no signs of illness. This demonstrates how the model can prevent false positives while still accurately recognising healthy samples. With an emphasis that corresponds with domain expertise, these visualisations demonstrate PlantCareNet's reliability and guarantee precise categorisation of both healthy and sick samples. The method highlights physiologically significant characteristics that are essential for plant health diagnostics, hence enhancing the model's usefulness in practical agricultural applications.

Grad-CAM was used to generate visual heatmaps of the regions that had an impact on the predictions made by the model. This was done in order to validate the central focus of the model and improve its interpretability. These heatmaps revealed that the model is able to correctly find disease-specific spots on plant leaves, as indicated by the domain knowledge. The Grad-CAM visualisations, which are displayed in Fig. 13, provide evidence that PlantCareNet focuses on the ill zones, hence demonstrating its dependability for disease classification. One example is the heatmap shown in Fig. 13a, which highlights the places on the leaf surface that are damaged by mildew. This heatmap demonstrates the thorough attention that was paid to diseased areas. By accurately recognizing the peculiar elongated lesions that are characteristic of Corn Northern Leaf Blight, as shown in Fig. 13b, the model guarantees that interpretation of the forecasts is of the highest possible quality.

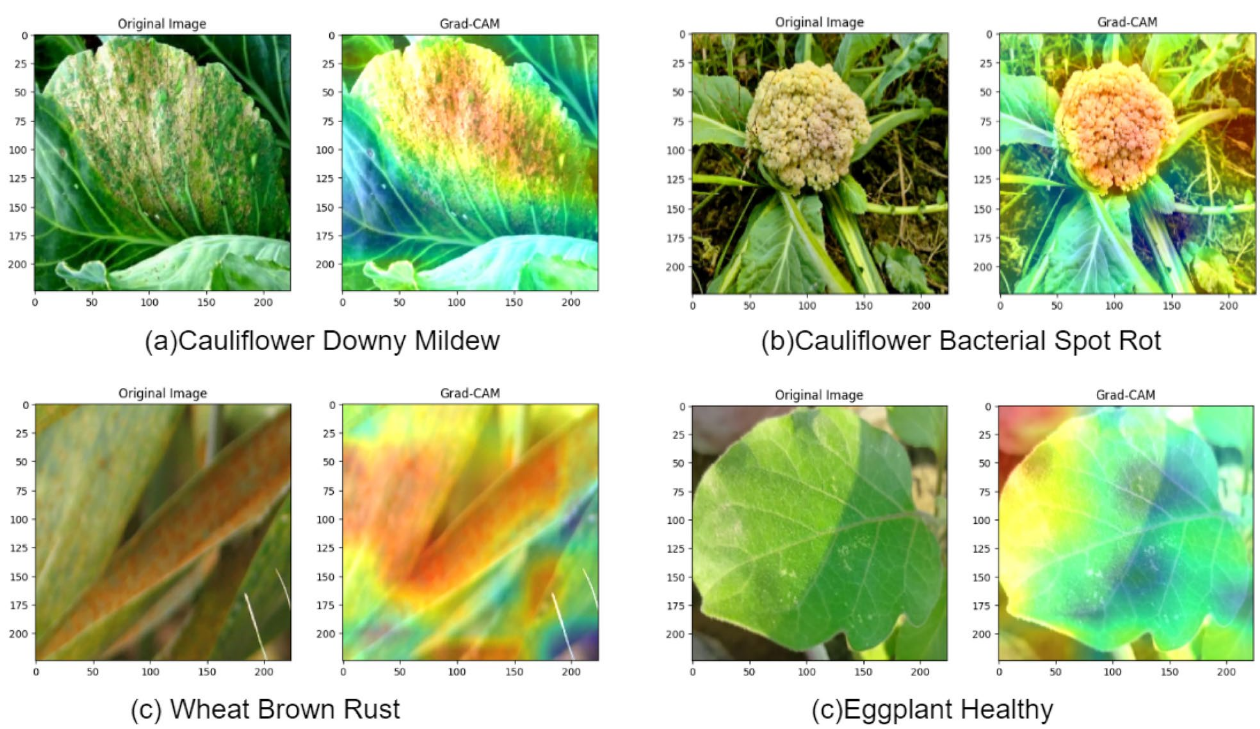

Fig. 13 Attention Heatmaps Generated by Grad-CAM

Comparative analysis

PlantCareNet is a very good option for real-time plant disease detection in resource-constrained contexts because of its higher classification performance and computational economy when compared to top deep learning models. In addition to computational aspects like parameter count and inference-time, which are crucial for on-device deployment, this study included important metrics including accuracy, precision, recall, F1-score, and loss.

As illustrated in Table 5, PlantCareNet outperformed well-known models like ResNet50 (94%) and DenseNet121 (89%), achieving the greatest accuracy of 97%. Additionally, it showed strong precision (97%), recall (97%), and F1-score (97%), guaranteeing accurate plant disease detection across a range of classes. Lastly, models like MobileNetV3Small and MobileNetV3Large struggled with F1-scores below 55% and showed much lower accuracies of 51% and 54%, respectively, suggesting limited application for accurate disease classification in actual agricultural contexts.

This table compares the performance of various deep learning models, with bold values highlighting the best-performing values for each metric. With an average inference time of under 0.0021 s and a parameter count of just 5 M, PlantCareNet is doing well in terms of efficiency, outpacing ResNet50, which has a slower inference time (0.1956s) and a much higher parameter count (24.9M), while maintaining high accuracy. PlantCareNet also has a smaller model size of 19.2 MB compared to ResNet50's 95.05 MB, making it more suitable for devices with limited storage. On the other hand, models with fewer parameters, such as MobileNetV3Small (1.5M parameters) and MobileNetV3Large (3.7M parameters), struggle with accuracy, achieving only 51% and 54% accuracy, respectively, along with low F1-scores. These lightweight models, while fast, significantly compromise accuracy, making them less suitable for real-world applications where precise disease detection is essential. PlantCareNet, with its balance of speed, efficiency, and high accuracy stands out as a very good choice for on-device, real-time plant disease detection.

The ability of PlantCareNet to combine outstanding predictive capability with a lightweight design is what makes it unique. For example, it achieves better classification metrics, such as a 13% higher accuracy and a shorter inference time, while matching MobileNetV2's (5 M) parameter count. For end users in distant agricultural areas, this optimisation guarantees that PlantCareNet is not only accurate but also highly adaptive to mobile and embedded devices, allowing for quick and trustworthy forecasts.

PlantCareNet's capacity to tackle important issues in agricultural technology is demonstrated by its excellent accuracy, computational efficiency, and adaptability to low-resource conditions. It establishes a new standard for using deep learning models in smart agriculture by providing cutting-edge performance while still being lightweight and quick, enabling efficient disease management and boosting output in practical situations.

We compared parameters, model size, and inference time to assess model efficiency in addition to classification accuracy. PlantCareNet is appropriate for implementation on mobile devices with limited resources since it provides excellent accuracy with a reduced model size and faster inference time. Compared to bigger models like ResNet50 and InceptionV3, which are accurate but less suited for on-device inference, this efficiency offers a substantial advantage. The findings highlight how PlantCareNet offers the best possible mix between computing economy and performance, which makes it perfect for detecting plant diseases in agricultural settings with limited resources.

Table 5 Performance Comparison of Various Models

Model Name	Acc.	Prec.	Rcl.	F1 Score	Loss	#Par	Mod. Size (mb)	Avg. Inf. Time
ResNet50 [62]	0.94	0.94	0.94	0.93	**0.015**	24.9M	95.05	0.1956 sec
InceptionV3 [63]	0.79	0.82	0.77	0.79	0.032	23M	88.24	0.2706 sec
MobileNetV2 [64]	0.84	0.86	0.84	0.85	0.024	5M	12.19	0.0130 sec
MobileNetV3Large [65]	0.54	0.63	0.47	0.54	0.064	3.7M	14.4	0.0147 sec
MobileNetV3Small [65]	0.51	0.67	0.41	0.49	0.067	**1.5M**	**5.78**	0.0111 sec
NasNetMobile [66]	0.80	0.85	0.75	0.79	0.614	6.7M	19.4	0.0594 sec
DenseNet121 [67]	0.89	0.86	0.88	0.88	0.019	9M	29.92	0.0382 sec
ResNet152V2 [68]	0.84	0.87	0.81	0.84	0.51	59.6M	227.59	0.05 sec
PlantCareNet	**0.97**	**0.97**	**0.97**	**0.97**	0.09	5M	19.2	**0.0021 sec**

Performance of the recommendation system

The suggestion system was designed using a user-centred approach to improve plant disease control. Two main image input choices are included on the app's homepage: users can upload an existing image from their device storage or use their smartphone's camera to take a real-time picture of a plant. A smooth and accessible experience is guaranteed for all users thanks to user-friendly dropdown menus that also let users select the crop type and operating mode, such as LLM Mode or Ref Mode. With these characteristics, the app should be useful and flexible enough to meet the demands of a wide range of users, including farmers and agricultural professionals.

As shown in Table 6, the mobile application performs effectively across a number of important parameters. The application guarantees seamless operation even on devices with limited resources thanks to its optimized memory consumption (38–40 MB in the background and 89–92 MB when active) and launch time of roughly 1.5 s. Extended use is made possible by the battery's 0.6 mAh per minute use, and its low data usage (about 0.35 MB per response) makes it ideal for locations with spotty network coverage. The average reaction time from app launch to obtaining results is 23 s for LLM mode and 14 s for Ref mode, allowing for quicker decision-making. This performance guarantees that farmers get fast, crop-specific insights that can be put to use. In Ref mode, the app provides tailored solutions for diseased crops and pertinent, crop-specific information on symptoms, preventative actions, and remedies for healthy crops. These figures show that the app is not only effective but also very responsive, which makes it a useful resource for farmers looking for trustworthy, up-to-date advice on managing diseases.

Ref Mode and LLM Mode in the application have diverse functions in providing recommendations for managing plant diseases, each of which is customised to meet the demands of a particular user. Ref Mode uses a static methodology in which predetermined data is retrieved from a reliable database after the illness class has been determined through image classification. Each disease's standard set of data is included in this database, giving users information on symptoms, ways to prevent them, and basic treatment recommendations. This mode is appropriate for people looking for rapid, generalised insights because it is simple and provides dependable, consistent information based on the diagnosed condition. Whereas, LLM Mode uses GPT-powered features to provide more individualised, real-time recommendations by introducing a dynamic, context-aware layer. Following the diagnosis of the disease, the mode adjusts according to the crop's state, which is briefly explained at the start of the mode. LLM Mode offers proactive, preventative guidance for healthy crops with the goal of maintaining crop health. On the other hand, the system provides a thorough analysis of crops displaying illness symptoms, complete with symptom descriptions, customised preventative plans, and more focused treatment choices. The adaptability of this mode guarantees that the recommendations are not only pertinent but also sensitive to the particular circumstances of the user's crop, providing a more thorough and dynamic approach to plant disease control. The two modes work together to create a complementary framework that meets both immediate and in-depth user needs in plant disease management. Ref Mode provides reliable, predetermined information, whereas LLM Mode expands the system's capabilities with clever, context-aware recommendations. A comprehensive overview of the key features and functionality of the mobile app for plant disease detection and management in Fig. 14.

Ref Mode offers standard symptoms, preventative, and treatment guidelines along with static, programmed suggestions based on disease classification. On the other hand, LLM Mode incorporates the most recent treatment possibilities and provides dynamic, real-time, context-specific recommendations. Consequently, compared to Ref Mode, LLM Mode provides more up-to-date and customised guidance, making it better suited for changing plant disease situations. This two-mode technology, which offers both highly customised suggestions and quick reference insights, ensures the platform's adaptability. The software's user-friendly interface makes it a valuable tool for farmers and agricultural specialists to effectively control crop health.

Table 6 Performance Metrics of the Mobile Application

Category	Metric	Details
Performance	Load Time	~1.5 seconds
Memory Usage	Background State	38–40 MB
	Active State	89–92 MB
	App Size	63 MB
Battery	Consumption	0.6 mAh (per minute)
Data	Consumption	~0.35 Mb (per response)
Upload Time	Average Upload Time	~5 seconds
Capture Time	Average Capture Time	~9 seconds
Response Time	LLM Mode	23 seconds
	Ref Mode	14 seconds

Mobile application performance analysis

To assess PlantCareNet's overall efficiency and user experience, a rigorous performance comparison was carried out against three existing plant disease detection systems.

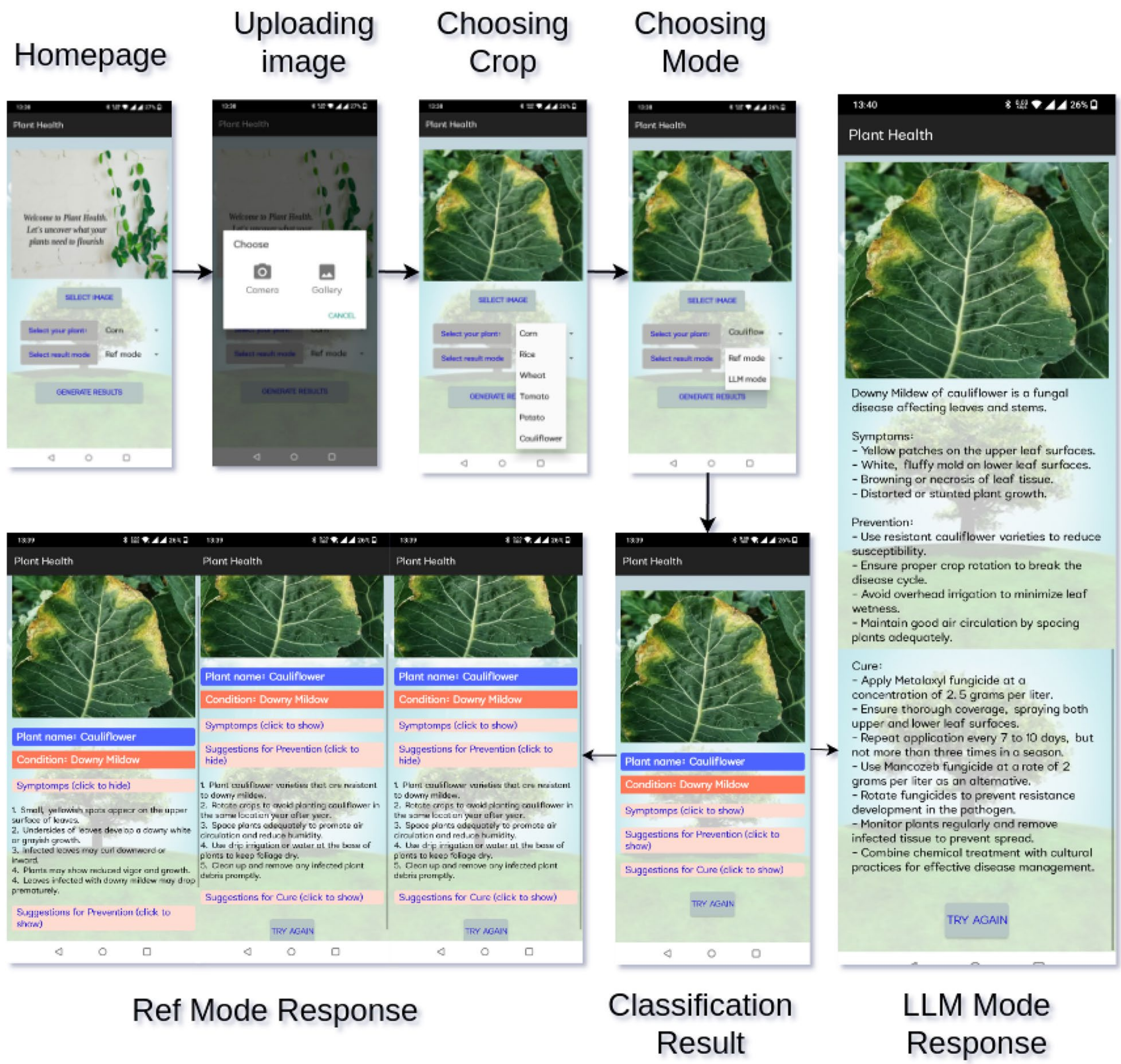

Fig. 14 Demonstration of the Recommendation System Outputs

Table 7 App Performance Comparison

Apps	Cache Resumption	App Size	Avg. Load Time	Network Usage (Mb/Min)	RAM Usage(MB) (Est.)	CPU Usage (%) (Est.)
Agrio	243mb	109 mb	2.64	26.07	300–500	15–30
Plantix	103mb	63.4 mb	1.66	0.81	250–400	10–25
Plant Parent	213mb	258 mb	3.8s	5.07	350–600	20–35
PlantCareNet	129mb	70.4 mb	1.45s	0.65	180–350	8–20

In order to shed light on how PlantCareNet stacks up against other industry-leading programs, this research focuses on important parameters including app size, load time, network usage, memory consumption, and CPU utilization. These critical performance metrics are summarized in the Table 7.

The comparison demonstrates PlantCareNet's advantages in terms of effectiveness and resource usage. It is a great option for those with limited storage because of its modest size (70.4MB), which is much less than PlantParent (258MB) and Agrio (109MB). PlantCareNet strikes a mix between compactness and higher performance in other areas, despite Plantix having the lowest size at 63.4MB. With an average load time of 1.45 s, PlantCareNet outperforms both PlantParent (3.8 s) and Agrio (2.64 s) in terms of speed, improving the user experience by detecting diseases more quickly. It also has outstanding network efficiency, using only 0.65MB per minute, which makes it the most data-efficient of the apps under comparison. Users in areas with expensive or restricted data plans will especially benefit from this.

PlantCareNet is built for improved resource management in addition to storage and data economy, guaranteeing consistent performance across a range of devices. It works more efficiently than PlantParent (350–600MB) and Agrio (300–500MB), with an estimated RAM utilization of 180MB to 350MB, which makes it appropriate for smartphones with low memory. Its CPU utilization stays low (between 8–20%), which lessens the burden on the device as a whole and improves battery efficiency. Furthermore, the application's cache resumption function minimizes needless data reloads by enabling smooth work continuation. PlantCareNet provides a more balanced and user-friendly experience than Agrio, which has a much greater network usage (26.07MB/minute). As a result, it is a sensible option for a larger spectrum of customers.

Evaluation of similarity between expert and LLM-generated outputs

In order to assess the degree of similarity between the system-generated outputs and expert-curated recommendations-which were regarded as the reference mode-a comparison study was carried out using two significant dimensions: Terminology Similarity and Content Similarity. The system-generated outputs were evaluated against the ideal circumstance, which was the expert recommendations. In order to measure the semantic alignment between the reference and system-generated texts, content similarity was measured using Cosine Similarity and Jaccard Similarity. On the other hand, the Terminology Similarity analysis focused on specialized vocabulary consistency, utilizing Overlap Coefficient and Term Frequency Analysis.

Content similarity

When evaluating the overall semantic congruence between system-generated outputs and expert-curated suggestions, content similarity is essential. It calculates the degree to which the content of the two texts is similar. This makes it possible to assess the overall thematic resemblance despite the texts' differing phrasing. Cosine Similarity and Jaccard Similarity, two popular techniques for determining Content Similarity, offer different but complimentary perspectives on how well the expert and LLM-generated texts agree.

Finding the cosine of the angle between two vectors, each of which represents a text, is how Cosine Similarity operates. This method creates vectors based on the term frequency of each word in the document, where each word represents a dimension in a high-dimensional space. The following formula is used to calculate the cosine similarity:

$$\text{Cosine Similarity} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

where A_i and B_i represent the term frequencies of the words in the texts. The result of this calculation yields a value between -1 and 1, with a value closer to 1 indicating a high degree of semantic similarity. This method allows for a precise measure of how similar the overall context is between the two texts.

On the other hand, Jaccard Similarity calculates the percentage of phrases that are common between the two texts in relation to the total number of terms that are unique in both papers. The intersection of the term sets from the two texts and their union are compared using this approach. The following is the formula for Jaccard Similarity:

$$\text{Jaccard Similarity} = \frac{|A \cap B|}{|A \cup B|}$$

where A and B are the sets of unique terms in each document. The Jaccard Similarity score goes from 0 to 1. By highlighting the similarities, this approach sheds light on how much language and concepts are shared. When combined, these two measures provide a thorough assessment of content similarity, encompassing both word use alignment and the texts' overall thematic alignment.

Terminology similarity

For Terminology Similarity, two additional metrics were employed: Overlap Coefficient and Term Frequency Analysis. This is essential for assessing the system's ability to provide precise and reliable technical language, which is particularly critical when talking about specialist topics like plant diseases and their management techniques.

Taking the smaller of the two sets as the set size, the overlap coefficient calculates the percentage of words that are shared by the two sets. When evaluating the direct overlap in the usage of domain-specific vocabulary, this approach is especially helpful when the emphasis is on precise matches of technical words, such as illness names, infections, or therapies. The following formula may be used to get the Overlap Coefficient:

$$\text{Overlap Coefficient} = \frac{|A \cap B|}{\min(|A|, |B|)}$$

where $|A|$ and $|B|$ are the sizes of the sets of domain-specific terms in the expert and LLM-generated texts. This computation yields a number between 0 and 1, where a higher number denotes a larger percentage of common phrases. This statistic gives a clear indication of how comparable the two texts' specialized language is.

Term Frequency Analysis assesses how frequently particular technical words occur in the documents produced by experts and LLMs. Key domain-specific words, such illness names, infections, and pharmacological therapies, are taken into account in this method; a higher frequency of matching terms indicates a higher degree of similarity. When evaluating the LLM's ability to reproduce the expert's regular use of technical terminology, this approach is very crucial. A higher overlap suggests a more accurate usage of specialist terminology. The Term Frequency score measures how frequently specific key phrases occur in both sets of text.

Together, these two metrics- Overlap Coefficient and Term Frequency Analysis-provide a thorough evaluation of how well the output produced by the LLM complies with the expert-curated technical vocabulary guidelines. To guarantee the correctness and dependability of the created material, they stress the need of using domain-specific keywords correctly and consistently.

Similarity scores comparison

For a comprehensive evaluation, one disease from each crop group was selected to assess the similarity between expert-curated recommendations and system-generated outputs. The diseases chosen for this study include Cauliflower Downy Mildew, Corn Northern Leaf Blight, Rice Bacterial Leaf Blight, Wheat Brown Rust, Tomato Early Blight, Potato Early Blight, and Eggplant Mosaic Virus Disease. Table 8 presents the computed similarity scores for these disease classes based on both content and terminology metrics. The table summarizes the Content Similarity and Terminology Similarity scores for each disease class, providing insights into the alignment between expert and LLM-generated outputs. The content similarity is evaluated based on the general meaning and structure of the recommendations, while terminology similarity focuses on the consistency of domain-specific terms used.

Table 8 Similarity Scores for Content and Terminology across Disease Classes

Classes	Content Similarity (%)	Terminology Similarity (%)
Cauliflower Downy Mildew	88	85
Corn Northern Leaf Blight	80	79
Rice Bacterial Leaf Blight	84	81
Wheat Brown Rust	87	86
Tomato Early Blight	83	80
Potato Early Blight	81	77
Eggplant Mosaic Virus Disease	89	86
Mean	84.57	82.00

The findings from this evaluation show that the system-generated outputs, based on ChatGPT, exhibit a high degree of similarity with expert recommendations, with an average Content Similarity score of 84.57% and an average Terminology Similarity score of 82.00%. This indicates that while LLMs can generate agricultural disease management advice that is semantically similar to expert knowledge, there is room for improvement, particularly in the consistency of technical terminology. These results highlight the need for post-processing mechanisms to refine the domain-specific language used by LLMs, ensuring greater reliability and precision in automated recommendations for agriculture.

With a mean of 84.57%, the table shows that the Content Similarity scores vary from 80% to 89%, indicating a high degree of content alignment between the system-generated outputs and the expert-curated suggestions. Although the system is proficient at employing domain-specific language, there is still significant diversity in the precise vocabulary, especially when it comes to illness treatments and preventative strategies, according to the language Similarity ratings, which range from 77% to 86% (mean of 82.00%). These findings demonstrate the LLM's strong capability in capturing both the overall content and technical terminology of agricultural disease management. While some variation in terminology exists, it suggests exciting opportunities for further enhancement, aiming for even greater consistency and precision in the use of domain-specific language across various platforms.

Conclusions

This study addresses the essential issue of plant disease detection, which is a key barrier to attaining sustainable agriculture and global food security. Particularly in areas with limited resources, current solutions sometimes lack the accuracy, scalability, and pragmatism needed for real-world deployment. In order to close this gap, we created a cutting-edge plant disease detection system that outperforms current algorithms in terms of accuracy and usefulness. The suggested method offers practical insights for illness identification and mitigation tactics by combining a cutting-edge recommendation mechanism with an effective, lightweight AI model. This strategy makes cutting-edge technology accessible to farming communities with limited resources, allowing it to be adopted in a variety of agricultural contexts. In addition to improving detection skills, our technology acts as a link between AI advancements and their implementation in environmentally friendly farming methods. In order to improve the recommendation framework and further optimize model parameters for increased computing efficiency, future research will concentrate on expanding the system's capabilities through the integration of vision-language models, as well as exploring image quality assessment mechanisms to address low-quality inputs. Additionally, the system will be further optimized for deployment on edge devices, allowing for on-device computations, faster response times, and reduced reliance on cloud-based infrastructure. By doing this, we want to improve the system's usability and suitability for use in changing agricultural settings. By providing farmers with accurate, scalable, and easily available technology, our work advances the larger objective of sustainable agriculture and builds resilience in global food systems.

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Author contributions
MMH was responsible for research program conceptualization and experimental design. The image data collection and curation were performed by MI. MI and SEA were responsible for implementing and executing the deep learning analysis. MI and MMH prepared the figures and wrote the first draft of the manuscript. AA, SEA and SAA revised the manuscript. All authors contributed equally to the final editing of the manuscript. All authors read and approved the final manuscript.

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Data availability
The custom dataset, source code for model training and evaluation, and the developed mobile application for plant disease identification and recommendation are available in online repositories. The repository names and access links are provided here: https://github.com/Muhaimin008/Plant-disease-classification-and-recommendations.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Conmpeting interests
The authors declare no Conflict of interest. The funding sponsors had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

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