Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 09 Issue 01
2025

Research Article
https://doi.org/10.56979/901/2025

Crop Medic: Intelligent Diagnosis and Treatment Guidance for Crop Diseases using Machine Learning

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Received: April 27, 2025 **Accepted:** May 31, 2025

Abstract: The small and marginal farmers across Pakistan still rely on visual disease diagnosis of the crops which is never 100% accurate since most diseases have similar symptoms. This often leads to an excessive number of agricultural losses as the response is significantly delayed. To tackle this, the research aims to introduce a novel idea which integrates both image processing techniques and machine learning algorithm to build an app for the farmers. Five machine learning models namely Random Forest, Support Vector Machine, Ridge Classifier, Decision Tree, and K-Nearest Neighbor were tested exhaustively on four different crops i.e. cotton, rice, wheat and sugarcane. The analysis results showed the highest testing accuracy for the Random Forest Classifier, indicating its stability during real world applications. A mobile application Crop Medic was also developed to deploy the proposed machine learning model for disease detection, that encourages farmers to rapidly diagnose crops and then in turn cut back their pesticide application thereby encouraging sustainable farming and better crop health. This initiative promotes efficient agricultural systems, productivity growth and reduced environmental impact.

Keywords: Digital Image Processing; Machine Learning; Disease Prediction; Pesticide Recommendation; Mobile App

1. Introduction

Agriculture is one of the backbones of Pakistan, but small farmers struggle heavily on getting proper diagnosis of crop diseases. Farmers currently rely on their experience as well as visual inspection for diagnosis and treatment of crops. These techniques can also cause misdiagnosis, delayed treatment and high rates of crop loss contributing to food insecurity and poverty in rural areas [1]. Meeting those significant challenges calls for novel solutions that arm farmers with highly accurate and timely information. The traditional diagnostic methods need to be replaced by modern machine learning techniques [2].

There are research studies that highlight advancements in plant disease detection and classification using technologies such as image processing, machine learning, and deep learning [3-5]. They explore methods like Support Vector Machines, Convolutional Neural Networks, and Autoencoders for analyzing plant images to detect and classify diseases with high accuracy [6, 7]. Image processing techniques, including noise removal, segmentation, and feature extraction, are emphasized for isolating diseased regions and identifying symptoms [8, 9]. Deep learning architectures are showcased for their robust capabilities in enhancing detection and classification efficiency [10, 11, and 12].

Khalid et al. [13] proposes an AI-driven system using image processing and machine learning techniques like ANN and CNNs, to provide a scalable, real-time solution for cotton leaf disease detection. Abbass et al. [14] used transfer learning and generative adversarial network for the disease detection of tomato plant. They generated image data for tomato plant leaves to improve the classification accuracy. Abinaya et al. [15] proposed an autoencoder-based system with context-aware remedy recommendations to boost early detection and crop productivity. Enkvetchakul et al. [16] proposed a plant leaf disease detection system using multiple CNN architectures. Trivedi et al. [17] proposed a CNN model for early detection of tomato plant diseases. Upadhyay et al. [18] reviewed 278 research articles on plant disease detection and analyzed computer vision approaches, detection stages, methods, and performance on various crops. Despite many advancements in this research field, there are several research gaps left unsolved. First, most existing research focuses on identifying diseases of a single crop. Second, most of them focus on high classification accuracy but ignore practical deployment challenges, such as the requirement of high computational devices which are mostly not available in resource constraint environments. Addressing these gaps could lead to more reliable, scalable, and farmer-friendly AI solutions for sustainable agriculture.

Although there is plenty of research done in this field, it lacks practical implementation, especially in developing countries like Pakistan. This research hopes to bridge the gap between traditional agriculture and digital world, changing agricultural landscapes while fostering resilience, innovation, and self-sufficiency among farmers. It aims to promote healthy, efficient and sustainable agricultural practices among farming communities and empower them with the information they need to make appropriate decisions about disease management and treatment choices available in local markets. It promotes sustainable farming through targeted treatment recommendations, thus minimizing pesticide misuse, improving productivity and contributing towards food security. The novel contributions of this research are as follows:

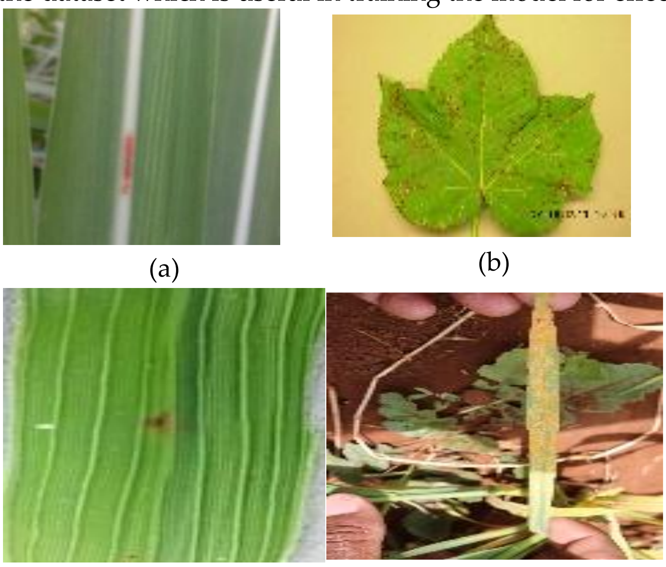
- Improve the precision of diagnosis by using machine learning and image processing methods to quickly and accurately identify plant diseases.
- Create a mobile application with an intuitive user interface that enables farmers with less technological expertise to upload pictures and receive prompt feedback about the health of their crops.

  Provide an offline mode, enabling farmers in remote regions without internet connection to utilize the app and its assistance in disease diagnosis and management.

2. Materials and Methods

2.1. Data Collection

The datasets used in this research are cotton leaf [19], rice leaf [20], wheat leaf [21], and sugarcane leaf [22]. It is important to note that the datasets consist of images of diseased and healthy and unhealthy leaves for the crops including cotton, rice, sugarcane, and wheat as shown in Figure 1. The aim is to achieve diversity and realism in the dataset which is useful in training the model for effective disease diagnosis.



(a) (b)

(c) (d)

Figure 1. Leaves of (a) sugarcane, (b) cotton, (c) rice and (d) wheat.

2.2. Preprocessing

It is important to preprocess the data in such a way that diseases can be diagnosed accurately and can also be applied in the field by the farmers. Preprocessing techniques such as resizing, normalization as well as noise elimination were used to improve the quality of the images while augmentation through rotation, flipping and brightness adjustment enables the dataset to be more diverse and additional resources [18].

Resizing ensures significant disease-related structures are preserved while reducing non-essential details, simplifying model processing [23]. This step minimizes inconsistencies in batch processing, improves model efficiency, and accelerates training convergence for better performance. After that normalization is used, that transforms pixel values to a numerical range from zero to one. Essentially, this is done with the goal in mind of defining standard pixel ranges and limiting variations and distortions in natural surrounding elements such as brightness, contrast, and light. Normalization forces clouds or shadows of images or any other illumination difference to no longer use it as an attribute to detect the images. In such situations, normalization is effective in complementing the effects of data processing methods. Next step is to improve the edges and outlines of diseased parts including the lesions, spots or other body deformities caused by plant diseases. The relevant details are emphasized by sharpening technique so that the model can view the pertinent parts of the image more efficiently.

On the contrary use of smoothing techniques, for instance, Gaussian filtering was used to minimize the amount of noise and unwanted details in the images. Such noise in the images as background, dirt, and other plant parts not related to the model can be a source of confusion leading to wrong predictions by the model. Smoothing helps to get rid of these distractions enabling the model to focus on the key features that represent the plant disease.

Along with preprocessing, data augmentation seeks to increase the dataset diversity and its population in a synthetic way without the need of acquiring new pictures. This entails utilizing image transformations to augment existing images to mimic possible real-world variations that can be encountered in deployment. This ensures that the model's generalization capabilities are enhanced since the model is trained under a broad range of conditions. The augmentation techniques used include rotation, flipping, cropping, zooming, and image perturbation. The four datasets Cotton, Rice, Sugarcane, and Wheat comprised of 1711, 6982, 2486, and 707 images. The five augmentation techniques were applied to each image generating 5x total number of images. In case of class imbalance problem, the oversampling of minority class can help. As each dataset was trained separately and there were minor differences in number of samples of each disease class, no oversampling was done.

2.3. Model Training

After preparing the dataset, five machine learning algorithms have been trained and validated under various hyperparameters. The tuning of hyperparameters to refine the model's capabilities was carried out iteratively. The final models came from a set of models that were consistent and reliable according to multiple other evaluation metrics i.e. accuracy, f1-score, precision, and recall. The hyperparameters listed in Table 1 were selected using trial-and-error method. Several combinations of parameters were manually tested, and the best performing values were chosen for training the model. While not exhausted like grid search, this method allows to iteratively test multiple parameters and choose the best performing hyperparameters. The models and the hyperparameters that have been selected for this research are given in Table 1.

Table 1. Hyperparameters of the ML models for each dataset (Cotton, Rice, Sugarcane, Wheat).

Models	Hyperparameter	value for each dataset			
		Cotton	Rice	Sugarcane	Wheat
Random Forest	random_state	42	42	42	42
	n_estimators	200	200	200	60
	max_depth	4	4	4	3

Models	Hyperparameter	value for each dataset			
		Cotton	Rice	Sugarcane	Wheat
	min_samples_split	2	3	3	5
SVM	random_state	42	42	42	42
	kernel	'rbf'	'rbf'	'rbf'	'rbf'
	gamma	'scale'	'scale'	'scale'	'scale'
	C	1.0	1.0	1.0	1.0
Ridge Classifier	random_state	42	42	42	42
	alpha	10.0	10.0	10.0	10.0
	Solver	'cholesky'	'cholesky'	'cholesky'	'saga'
Decision Tree	random_state	42	42	42	42
	max_depth	5	5	5	2
	min_samples_split	2	2	2	4
	criterion	'entropy'	'entropy'	'entropy'	'entropy'
KNN	n_neighbors	3	3	3	7
	weights	'uniform'	'uniform'	'uniform'	'uniform'
	algorithm	'kd_tree'	'kd_tree'	'kd_tree'	'kd_tree'

2.4. Performance Evaluation

The overall performance of the Random Forest, Support Vector Machine, Ridge Classifier, Decision Tree, and K-Nearest Neighbor were tested exhaustively on four different crop datasets. The results for each dataset are given in Tables 2-5. The analysis results showed the highest accuracy for the Random Forest Classifier, indicating its stability during real world applications. Meanwhile, the remaining tested models also performed differently, which shows how significant it is to choose the best classifier for use in practical agricultural disease management. This step was key to confirming the validity of the models and their capability to assist farmers in the early identification of disease.

Table 2. Evaluation Metrics of Cotton

Metric	Random Forest Classifier	Support Vector Classifier	Ridge Classifier	Decision Tree	K-Nearest Neighbor
Accuracy	86%	92%	75%	84%	65%
Precision	82%	77%	79%	72%	58%
Recall	81%	76%	76%	73%	41%
F1-Score	80%	75%	80%	35%	35%

Table 3. Evaluation Metrics for Sugarcane dataset

Metric	Random Forest Classifier	Support Vector Classifier	Ridge Classifier	Decision Tree	K-Nearest Neighbour
Accuracy	73%	80%	88%	67%	69%
Precision	62%	53%	46%	51%	53%
Recall	59%	50%	42%	50%	50%
F1-Score	60%	51%	43%	50%	48%

Table 4. Evaluation Metrics for Wheat dataset

Metric	Random Forest Classifier	Support Vector Classifier	Ridge Classifier	Decision Tree	K-Nearest Neighbor
Accuracy	92%	87%	99%	81%	74%
Precision	98%	88%	92%	78%	76%
Recall	97%	83%	93%	77%	56%
F1-Score	97%	82%	93%	77%	54%

Table 5. Evaluation Metrics for Rice dataset

Metrics	Random Forest Classifier	Support Vector Classifier	Ridge Classifier	Decision Tree	K-Nearest Neighbor
Accuracy	86%	96%	95%	82%	82%
Precision	85%	89%	85%	84%	81%
Recall	85%	88%	84%	82%	80%
F1-Score	85%	88%	84%	82%	80%

From these results, it is evident that the RF model outperforms other models. It is also more computationally efficient than deep learning models. Model training is faster in RF as it builds multiple decision trees in parallel whereas CNN requires iterative gradient descent. The performance of KNN model was low in almost all the datasets, the reason can be it highly depends on dimensionality reduction and hand-crafted feature extraction methods. Another reason can be that as it is a lazy learner it relies on raw pixel values rather than extracting features. These models can be improved further by hyperparameter tuning.

2.5. Functional diagram of the Mobile Application

After evaluating the results of machine learning models, the next step is to design the mobile application, we named it Crop Medic. This application helps farmers to detect the crops diseases easily. The activity diagram of the mobile application is shown in Figure 2.

2.6. Functional Design of Application

The main screen of the Plant Disease Recognition App presents four plant categories that are Rice, Wheat, Cotton, and Sugarcane, each displayed as a card with an image and brief description for easy navigation. A language toggle supports both English and Urdu, enhancing accessibility. Users can upload images from their gallery or capture live photos using the device camera, with clear instructions and a smooth process suitable for users with minimal technical skills. Once an image is submitted, the app quickly analyzes it and displays the result screen showing the diagnosed disease, its symptoms, causes, recommended treatments, and pesticides. The design is clean and intuitive, ensuring that even nonprofessional users can easily understand and act on the insights provided. This streamlined approach helps farmers detect plant diseases early and take timely action to protect their crops.

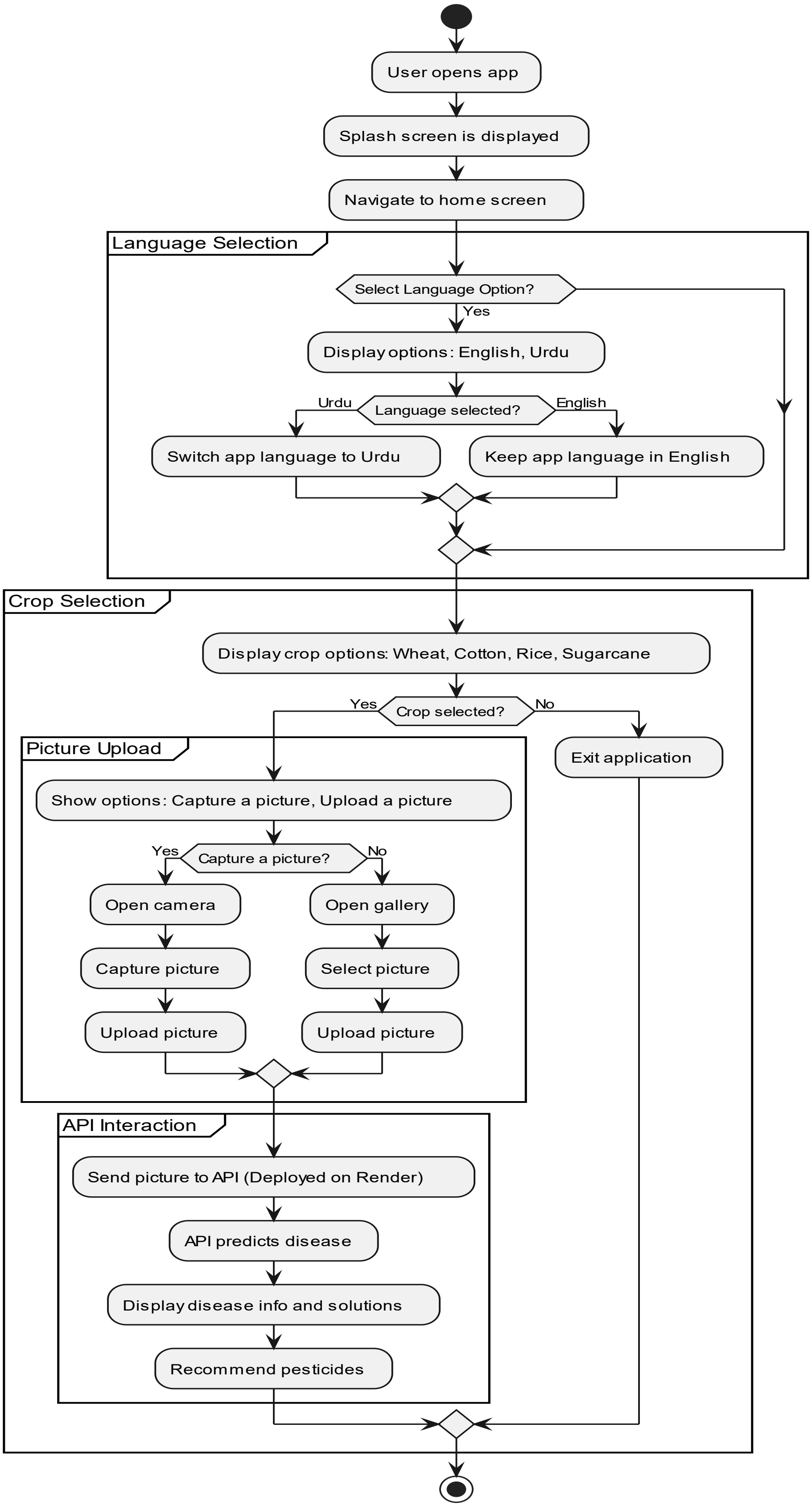
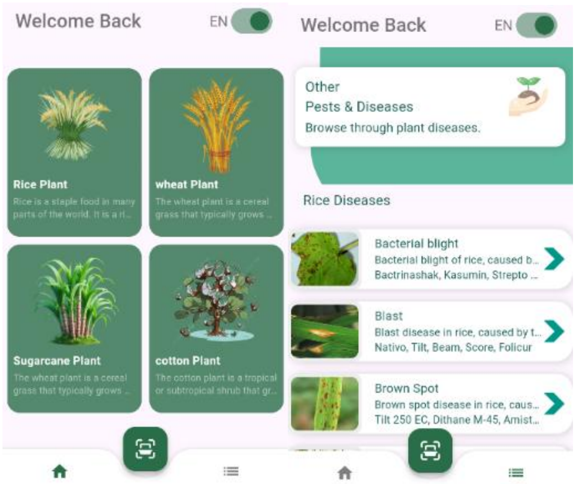


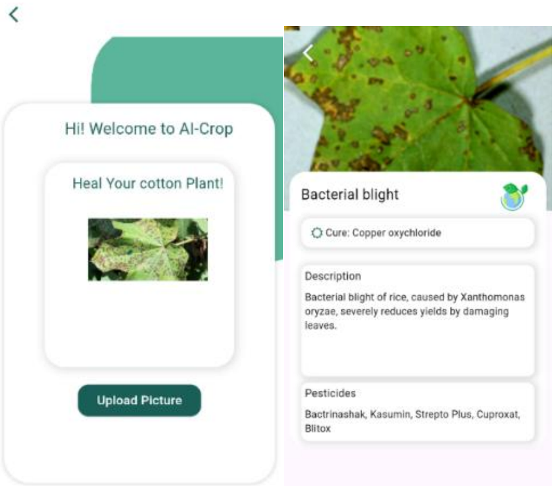
Figure 2. Activity Diagram of the Crop Medic Mobile Application Workflow illustrating the step-by-step process.

Figure 3. Illustrates the user interface screens of the Crop Medic mobile application developed for plant disease identification and management. The crop selection screen allows users to choose from four

crop types, including rice, wheat, sugarcane, and cotton. The disease browsing interface categorizes diseases based on the selected crop and provides a list of common diseases along with brief identifiers. The image upload interface enables users to submit images of infected plant parts for disease diagnosis. The disease diagnosis screen displays the identified disease (e.g., bacterial blight), along with a short description and a list of recommended chemical treatments or pesticides.



(a) (b)



(b) (d)

Figure 3. The Crop Medic Mobile Application User Interface Screens (a) crop selection screen (b) disease browsing interface (c) image upload interface (d) disease diagnosis screen

3. Results

The survey questions were carefully designed to avoid ambiguous and leading questions. A dichotomous scale was used to record responses. The surveys were taken from 25 participants including 10 farmers and 15 common people. The details of each survey is presented in the following sections.

3.1. User Testing and Feedback

During the user-testing phase, the goal was to test the user interface (UI) design to make sure it is intuitive and engaging across different devices and user demographics. The focus was on measuring how easy it is to navigate, find the features, and overall, their thoughts on the layout of the user interface. Mock tasks were simulated on the study tablet, such as uploading images of the crops, viewing recommendations, and switching between languages. With this, surveys and observation sessions were conducted for testing design clarity, button placement, visuals and responsiveness.

The result of the survey is summarized in Table 6. Tests have shown a good response; 88% of users found the interface to be eye-pleasing and intuitive. The app's simple navigation structure and relatively clear labeling of buttons were especially nice, as they allowed for easy access to core features. The bilingual support feature was particularly appreciated, rated positively by 92% of users, which further improved accessibility for those who may not speak English. Small critiques were made, such as the issues of users who are elderly needing to scale the text up and some users were sometimes mis clicking, missing the button they were trying to get examining a roughly organized menu. Concluding remarks on design vs functionality, feedback collectively suggested the design strike the balance between simplicity and functioning to achieve the smoothest user experience possible while also identifying areas in which to iterate for the future.

Table 6. User feedback on Crop Medic App

Feedback Category	Positive Response (%)	Negative Response (%)	Key Comments
Ease of Use	88%	12%	Users found the interface intuitive.
Navigation	85%	15%	The menu structure was clear, making it easy to access features.
Language Accessibility	92%	8%	Bilingual support was highly appreciated.
User Feedback on Recommendations	87%	13%	Suggestions for improvements in care recommendations were noted.

3.2. Behavior Testing

Behavior testing was conducted on multiple devices and operating systems for compatibility, response, and uniform ability. The result is shown in Table 7.

Table 7. Crop Medic Application Behavior Testing.

Aspects	Test Case	Expected User Behaviour	Application Response	Observed Outcomes	Success Rate(%)
Ease of use	User takes a photo of diseased crop and uploads it to the app.	User easily navigates to camera or gallery function.	Image is uploaded and processed without delay.	High success rate of user understanding and navigation.	95%
Accuracy	App identifies plant disease from an uploaded image.	User submits clear and relevant crop images.	Disease detection algorithm provides accurate results.	Accurate diagnosis for most clear input images.	88%
Response Time	User submits an image for processing.	User expects a quick response (under 5 seconds).	App delivers results promptly with recommended actions.	Average response time meets user expectations.	92%
Error Handling	User uploads a blurry or	User retries after error	App provides error message or	Users improve input after	85%

Aspects	Test Case	Expected User Behaviour	Application Response	Observed Outcomes	Success Rate(%)
Scalability	incomplete image of a crop. Multiple users test the app simultaneously across diverse crops.	notification or guidance. Users from different regions use the app concurrently.	prompts for better image. The app maintains performance and consistency.	initial errors or prompts. Consistent performance underload.	87%

3.3. Application and Model Integration Testing

Model and App Integration Testing was performed to check the seamless integration of the disease detection model with the integrated application in the Plant Disease Recognition and Cure Prediction app, the result is summarized in Table 8. Uploaded images could be processed with high accuracy in real time and disease diagnosis was produced along with treatment recommendations relevant to the output of the model. The images were preprocessed in a standard way, involving techniques like scaling down or standardization to give consistent & accurate results. It also diagnosed on time, processing images in the estimated delay interval in the app, ensuring a pleasant experience through its functionality.

Table 8. Crop Medic Application and ML model integration testing.

Test Case	Expected Functionality	Test Results	Pass/Fail	Remarks	Success Rate (%)
Model Integration with App	The disease detection model is successfully integrated into the app and processes images uploaded by users.	Model processes images and provides accurate diagnosis within the app.	Pass	Integration works as expected, providing real-time disease diagnosis.	94%
Real-Time Diagnosis	After uploading an image, the app returns a disease diagnosis based on the model within 5 seconds.	Disease is diagnosed accurately in real-time.	Pass	Diagnosis results are quick and accurate for clear images.	93%
Model-Driven Recommendati ons	After detecting a disease, the app provides treatment recommendations based on model output.	Relevant and accurate recommendati ons are displayed.	Pass	The model triggers actionable recommendations .	90%

Test Case	Expected Functionality	Test Results	Pass/Fail	Remarks	Success Rate (%)
Image Preprocessing Integration	Preprocessing techniques (resizing, normalization) are applied before the model processes the image.	Images are preprocessed and then analyzed for disease detection.	Pass	Image preprocessing is seamless, leading to accurate diagnosis.	91%

4. Discussion

This plant disease recognition mobile app is internally evaluated, and the results are remarkable. It is indeed able to completely change the way in which crops are managed, especially for smallholder farmers. The app improves the accuracy of plant disease diagnosis at an early stage by utilizing machine learning and image processing technologies which minimizes the adverse effects of subjective visual inspection and the risk of misdiagnosis. It promises to enhance agriculture productivity, reduce costs and contribute towards sustainable farming practices. One of the most significant advantages of using the app is its offline functionality; it can still be used in extremely rural areas of the region where people are far from reliable internet services, and this goes a long way in addressing one of the major reliance issues on technology faced by farmers in remote agricultural regions of the country.

But challenges for scalability and usability persist. Although the app has demonstrated encouraging results in controlled experiments using specific crop datasets, trials under real-world scenarios where environments, crop types and disease presentations vary are needed for further validation. For the app to be widely applicable across different agricultural contexts, it should be extended to incorporate a wider range of crops and diseases within its database. The app's dependence on clear, high-quality images could limit its effectiveness in low-light or difficult field conditions. A more focused description of picture-taking or better preprocessing on the part of the app are some things that could really help usability and accuracy.

The final factor that plays a significant role in an app's success is end-user adoption. Smartphone-based diagnostic tools are a rather new concept for many farmers, especially those in rural areas, which may be problematic. Strategies to mitigate this will involve making focused training sessions available to all users along with user-friendly guides and intuitive interfaces in the app. Gathering feedback from early users, and continuously tuning the app according to their feedback will further increase the relevance and accessibility of the app and ensure that it builds towards the practical needs of farmers. By solving such problems, the app can play a prominent role in sustainable agriculture and to the farm communities.

5. Conclusions

The proposed mobile app for detecting plant diseases presents an innovative approach in the field of agriculture to help farmers easily and affordably detect diseases at early detection time. Using machine learning and image processing technologies, the app helps in timely action, minimizing crop loss, improving efficiency in resource utilization, and encouraging sustainable farming practices. This app can be used by smallholder farmers with limited access to technology, especially in rural and remote areas, that makes it a promising solution. However, several problems need to be worked out for the app to achieve mass adoption and long-term viability. To be applicable across a wide range of different agricultural contexts, its database needs to be expanded to include more crops, diseases, and environmental conditions. Some usability improvements, including guidance towards quality-image acquisition and more robust preprocessing capabilities, are also required to overcome issues including low-resolution images and adverse weather conditions. This innovation not only aids individual farmers, but also aligns broader goals of food security, environmental sustainability and economic resilience in farming communities, making it a crucial tool for the future of agriculture.

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