Journal of Applied Information Science
14 (1) 2026, 07-14
www.publishingindia.com/jais
https://doi.org/10.21863/jais/2026.14.1.002

Submitted: 02 June 2025
Accepted: 03 July 2025

CropCare App

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Abstract: CropCare and farm productivity are paramount to the sustenance of the increasingly large global population. The future of farming is on the verge of revolution through technology, especially through machine learning. CropCare is a revolutionary mobile application on iOS and Android platforms, which aims to help farmers in crop care. CropCare incorporates a wide range of functionalities, from weather prediction and a forum where people can exchange ideas to a sophisticated diagnostic tool for crop diseases as well as exhaustive information on cures and causative organisms. CropCare uses machine learning algorithms to scan crop pictures and recognise the disease correctly. Once the disease is recognised, CropCare gives exact details about the likely causes and treatment. Further, the app provides real-time weather patterns and predictions in relation to the location of the user, allowing farmers to plan intelligently in terms of sowing, irrigation, and harvesting. The collaborative feature invites farmers to interact with agricultural researchers and analysts to exchange innovative solutions alongside best practices.

Keywords: Mobile application, Machine learning, Weather forecasting.

I. Introduction

Agriculture continues to be the backbone of most economies worldwide, and its production and sustainability are important to meeting the growing needs of a global population that is constantly increasing. Traditional farming methods are time-consuming and labour-intensive, and this could lead to reduced yields as well as an increased risk for plant diseases and insect infestations. Adoption of advanced technologies, such as mobile applications and machine learning (ML), has the potential to change the agriculture industry significantly.

CropCare is an innovative mobile application for iOS and Android, aimed at empowering farmers by providing them with the tools and resources to manage their crops effectively. The app provides a comprehensive set of features, such as real-time weather forecasting, a community forum for sharing knowledge among farmers, and an innovative crop disease detection system. By utilising ML algorithms and computer vision techniques, CropCare can diagnose crop diseases using pictures and provide detailed information about the causes and remedies.

Global agricultural production is confronted by an array of challenges that jeopardise both the viability and profitability of farming operations. Technologies that provide timely and accurate detection of plant diseases [1], pest infestations [2], weed pressure [3], and nutrient deficiencies [4] are needed to mitigate the challenges. These challenges must be addressed in a timely manner because farmers must be aware of these problems to mitigate potential impacts on their crops and yield outcomes. In the United States, plant diseases contribute to losses ranging from 20% to 40% of annual crop yields [2] due to either inadequate diagnostics of the problem or lack of future intervention. Farmers have historically diagnosed diseases based on observation of symptoms presented in the plant leaves. The process of identifying the deficiency could prove to be tedious and subjective [5]. Misdiagnosis of plant leaf symptoms poses a further risk of misapplication of fertilisers, which could result in crop damage and cause future nutrient-content problems.

ML and computer vision are currently popular technologies for tackling these problems in precision agriculture [6, 7]. These methods enable farmers to maximise production and minimise resource waste while diagnosing crop disease through remotely sensed imagery [8, 9, 11]. A mobile application/system based on ML and computer vision that would reliably diagnose plant diseases would be a game-changer, particularly in rural/underserved areas. Farmers would be able to receive instant feedback on the diseases afflicting their crops and receive specific fertiliser recommendations to help mitigate the issue, ultimately improving crop health and farm yield outputs.

This study provides a mobile-based method for detecting plant leaf diseases in real time using deep learning (DL) techniques. Specifically, we designed a computation-sharing distributed system consisting of mobile phones and centralised cloud servers. The system is built on a dataset of over 96,000 images covering 38 plant disease categories from 14 crop species, including the most familiar plant diseases such as apple scab, grape leaf blight, and corn rust. At the cloud level, we trained a convolutional neural network (CNN) model that processed images from the farmer's mobile devices. The CNN model conducted object detection and semantic segmentation to provide information on the disease and also classify the result with a confidence score and processing time.

To make the system accessible to farmers with limited resources, we created an Android mobile application that allows farmers to capture and submit images of diseased plant leaves for analysis. The mobile application is mapped onto the CNN model running on their phone, with the diagnosis output not only displaying disease information but also percentage confidence and processing time.

This work makes three contributions. First, we introduce a distributed ML-enabled platform that leverages mobile device features and cloud processing for effective disease detection. Second, our platform facilitates the capture, processing, and display of major agricultural datasets. Third, we created a friendly mobile application that gives farmers an easy interface for using the disease detection system.

II. Literature Survey

With growing demand and scarce resources, agriculture needed to look to artificial intelligence (AI) for efficient production and loss minimisation. This project presents a mobile app that identifies 38 plant diseases among 14 crop species based on a CNN model with 96,206 images for training. The app is for instant, field-level utilisation and assists farmers with instant disease identification and prevention of detrimental fertiliser abuse, ensuring healthier crops and soil. The model is accurate and identifies images in less than a second for a quick, trustworthy diagnosis [1].

The iOS app designed to detect cotton disease supports iOS programming and user-interface guidelines, providing smooth navigation and correct offline disease detection. As efficient as it stands, there is room for improvement with the app by moving ML processes to the server, enabling usage with a large variety of algorithms for enhanced accuracy and performance. The upgrade will make it possible to enjoy both online and offline functionality, which will increase the app's versatility. An increase in the dataset will enable the detection of a large variety of cotton diseases, increasing the diagnostic features of the app [2].

A TensorFlow model was converted into a CoreML model and used to develop an iOS app for offline detection of two cotton leaf diseases, that is, boll rot and leaf spot, and for healthy leaves. The app is accurate and complies with iOS programming and design guidelines. Accuracy may be enhanced by increasing the dataset and fine-tuning the parameters. The design is expandable for future developments, for example, for detection of additional diseases or for similar app development in other domains. Incorporating server-side application programming interface (API) functionalities will make model updates easier without changing the app but will be costly based on server requirements [3].

A two-dimensional (2D) CNN model was implemented to identify 12 disease categories and two health categories for both tomato and cotton crops with 97.3% accuracy – higher than heavy and lightweight transfer learning models. It is lightweight with three convolution and max-pooling layers and stores three to four times less than transfer learning models, and hence is best suited for mobile deployment. As part of the Android application 'Plant Disease Classifier', it offers almost live detection (4.84 ms). It is effective, but needs to be high on RAM and CPU/GPU for optimum mobile performance and will have to be periodically updated with new disease data and environmental conditions. Future research will make it faster, include additional crops, and make it smaller [4].

An iOS app was developed in alignment with iOS programming and interface guidelines, offering smooth screen navigation and accurate, offline cotton disease detection. The app performs well and currently identifies common cotton diseases without needing an internet connection.

Server-side integration can be included to handle ML processes. It will enable both offline and online modes for the app and incorporate additional ML algorithms to make the app perform and provide results with higher accuracy. The diagnostic aspects of the app can also be enhanced with an expanded dataset to enable detection of additional cotton diseases [2].

The research tested how CNNs were used to detect plant ailments. The model had high accuracy within the Plant Village dataset, which illustrated that CNNs are efficient for crop disease diagnosis. The researchers opined that CNNs have higher accuracy at disease identification with improved architectures when used for agricultural purposes [5].

Utilisation of ResNet and InceptionV3 models through transfer learning provided some of the highest rates of accuracy for crop disease detection. Transfer learning is noted to significantly improve these models and potentially improve managing agricultural disease in real time [6].

With VGG16 and transfer learning, this research achieved more than 98% accurate results for plant disease classification. Transfer learning assists researchers to develop robust models, which identify plant diseases with accuracy for different crops [7].

It sought to advance classification of plant disease through modifying a CNN model. The improved model increased accuracy, and this is helpful during crop disease inspections and initial intervention steps [8].

A combined DL model incorporating CNN with attention features was built and attempted to identify plant disease with greater accuracy. Experiments indicated that the combined model performed better than regular CNNs, which indicates that integration of various architectures enhances the model's ability to recognise disease signs [9].

The increasing significance of agricultural software is to facilitate data-driven decision making and sustainable agriculture. Such technologies enable enhanced productivity, cost-effectiveness, and resistance to setbacks such as climate change and food insecurity. Through monitoring, analysis, and optimisation features, agricultural software is changing contemporary farming methods and moving agriculture towards long-run environmental and economic sustainability [10].

Crop disease identification can be improved with enhanced numbers and variety of images within the database, specifically with images of different orientations. Since image processing is utilised by the system, high-resolution cameras are necessary. Experiments with three cameras showed that smartphones with cameras higher than 8 MP resolution identified conditions correctly in nine out of 10 instances, while lower-resolution cameras were only accurate in seven out of 10 instances. More features of images to compare can improve precision. For prediction of yield, different input parameters were tried and the system was successful in providing accurate results through database analysis and the Bee Hive algorithm [11].

Wireless Sensor Network (WSN)-based technologies are efficient means of monitoring micro-climatic conditions of apple farms. WSNs provide reusability, adaptability, and scope for supporting an informed decision-making process for farmers. Research supports the importance of time-series collection of data to streamline farm management and fill gaps between time-tested methodologies and newer technologies. Farmers' involvement, through these systems saves manual labour, improves monitoring of an orchard, and allows timely interventions. In addition, advances in technology introduce possibilities to make these types of systems cost-effective, user-friendly, and innovative [12].

Plant leaf disease detection applications represent an important leap forward for technology's application to agriculture and food security. With ML, user-friendly interfaces, and back-end cloud support, these tools provide timely and accurate advice for disease control. Promising results have been achieved, but addressing existing gaps and building functionality will be key to ensuring that they have maximum impact for sustainable agriculture and worldwide food security initiatives [13].

III. Proposed Methodology

The primary purpose of this system is to develop a new, simple-to-use, and reliable smartphone app that implements an ML image inspector to identify and classify crop ailments in a timely manner. The system inspects crop photographs to provide farmers with clear, live information regarding crop well-being. It assists to identify diseases early, enabling farmers to respond timely with appropriate treatments, reducing crop loss while increasing farm yield. The app is designed to be simple, extendable, and efficient to provide numerous farmers, both far and wide, as well as to facilitate sustainable farming with improved food security.

A. Dataset Description

For this study, we employed the Plant Village dataset, which is a very popular dataset of labelled images for plant disease classification. It contains three crops, that is, potato, tomato, and bell pepper, and these three crops are contained within 13,602 images. These images are classified under two principal categories: healthy and unhealthy, where there are 1,630 images of healthy plants and 11,972 images of unhealthy plants. The unhealthy images contain various diseases for the three crops.

The dataset contains high-resolution images, which are above the plant leaf surface and include illumination, background, and environmental variation, and is thus apt for training consistent image classifier models. The disease class contains various heterogeneous diseases such as late blight and early blight of potato, leaf mould, and bacterial spot of tomato, and bacterial spot of bell pepper, among others.

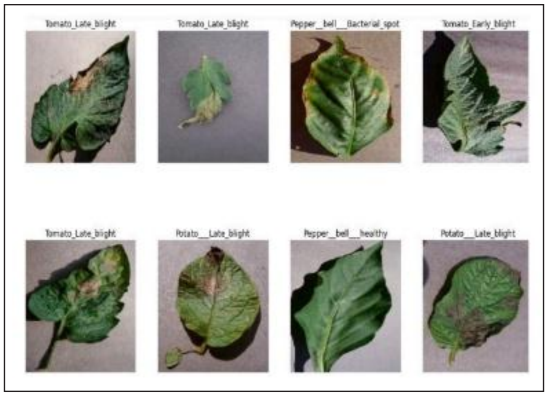

Fig. 1: Examples of Diseased Images [14]

B. Data Preprocessing

- All images are subjected to standardisation in terms of resizing and normalisation to conform to CNN model specifications.
- Some of the data augmentation techniques involved rotating, flipping, and cropping so that additional training images can be fed to enhance model accuracy.

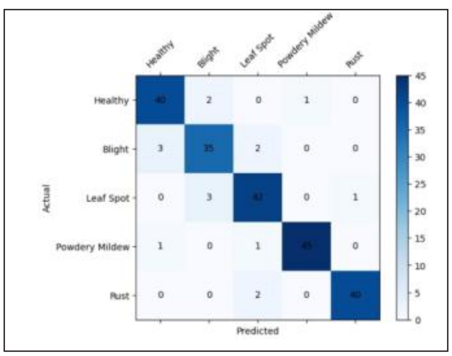

Fig. 2: Heatmap of Different Diseases

C. Image Classifier Model

An image classifier model is an ML-based system that is able to detect and assign labels within images based upon a provided dataset. When given an image, the model processes its content and selects the most suitable label from the available categories, such as 'healthy' or 'disease' for the various classifications of plant health.

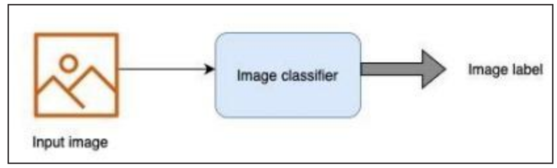

Fig. 3: Flow of Image Classifier Model

i) Training the Model: It is trained from an immense database of labelled images. Data consists of images captured under numerous conditions, including climatic, lighting, and view angles. It is all these factors that make this model robust and effective enough to handle real-world environments. It is extremely critical for successful training that there are equal quantities of images for every class in the data.

ii) Labelling and Organising Data: The images in the dataset are annotated with keywords such as 'healthy' or with exact disease names such as 'Early Blight' or 'Late Blight'. With proper organisation of the dataset, maximum training is possible.

iii) Training Session: The tagged dataset is split among three sets: training data, validation data, and testing data.

- These training data are then used by the model to identify patterns and traits. Validation data are also used to fine-tune and improve model accuracy over training, with testing data measuring its overall performance.
- Data augmentation techniques such as rotating, flipping, or adding noise to images are performed in an attempt to improve model accuracy.

iv) Model Creation: After training, the performance of the model is measured by metrics such as training, validation, and testing accuracy. The trained model is then deployed in programs, such as mobile apps or software programs, to use.

v) Deployment in Applications: The model is applied in apps where it runs over fresh images posted by users. If a user uploads a photo of a plant on an app, the image classifier model will detect disease present (if any) and respond with an appropriate label in return.

IV. Result

The proposed system, which was based on an Image Classifier Model for the detection of disease in crops, was 85% accurate in testing. This is an indicator of the reliability of the model to detect disease from images from the dataset. The model was trained upon the Plant Village dataset consisting of 13,602 images, which included 1,630 images of healthy plants and 11,972 images of disease-infected plants of various types of potato, tomato, and bell pepper crops.

The result is in favour of the model's capability to detect both healthy and unhealthy plants under different conditions such as light, direction, and environmental changes. The accuracy attained here demonstrates that such ML-based image classification models could be implemented in practical agricultural environments, with the provision of disease detection and regulation at an early stage being an efficient approach for farms. However, there could be some further enhancements, such as increasing the dataset size or employing advanced preprocessing or data augmentation techniques, that could possibly improve model performance in subsequent releases.

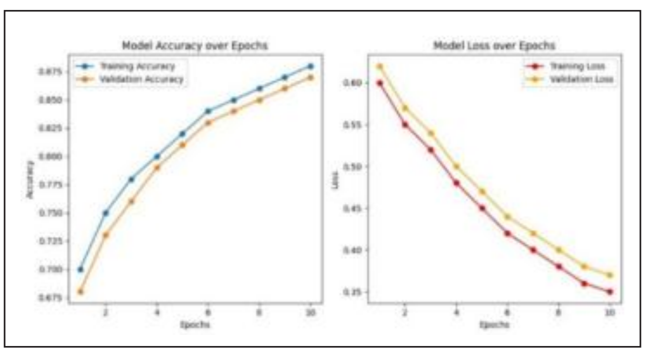

Fig. 4: Model Accuracy and Loss

V. Conclusion

CropCare represents a significant advancement in precision agriculture, harnessing ML and computer vision to provide timely and accurate crop disease diagnoses. Using the Plant Village dataset and a CNN-based image classification model, the app achieves 85% accuracy, showcasing AI's potential in improving crop health monitoring. In addition to disease detection, the app offers real-time weather updates, treatment suggestions, and a community forum, creating a comprehensive tool for modern farmers.

The mobile and cloud-based architecture ensures scalability and accessibility, particularly for farmers in rural areas with limited resources. While the current implementation shows promising results, future enhancements such as expanding the dataset, improving image preprocessing, and integrating more advanced ML models could further enhance the app's performance. In addition, future features such as real-time weather integration, multilanguage support, AI-powered chatbots for farming queries, a crop suggestion system, disease cure recommendations, cross-platform support, and marketplace integration will significantly increase its utility. Ultimately, CropCare empowers farmers to adopt more efficient, sustainable farming practices, demonstrating the transformative impact of technology on agriculture.

VI. Future Scope

The CropCare app has future potential for exponential growth and innovation. One of the primary areas of future growth is that the application can be made to handle more crop and disease types. Although it is now used on potato, tomato, and bell pepper only, it is possible to retrain or fine-tune the model using more location-specific and diverse data to assist farmers in multiple agricultural regions.

Yet another thrilling domain is using satellite data and remote sensing technology to track crop health across large tracts of land. With image-based diagnosis and geospatial information, CropCare would be able to offer early-warning systems for pest attacks, drought, or lack of nutrients.

For enhancing the app's usability, support of multiple languages to serve farmers with diverse linguistic profiles can be leveraged. In addition, chatbot-based interfaces employing natural language processing can assist users in getting personalised guidance and recommendations based on the type of queries in their own languages.

In addition, the integration of a crop record system using blockchain can enable safe, secure recording of crop treatments, weather occurrences, and yield results. This will provide easier access to microloans or insurance programmes, thereby economically empowering farmers.

Lastly, engagement of agri-research centres and government institutions can authenticate the suggestions of the app to position CropCare not only as a technology-based intervention but also as a credible farmer's adviser grounded on scientific truth.

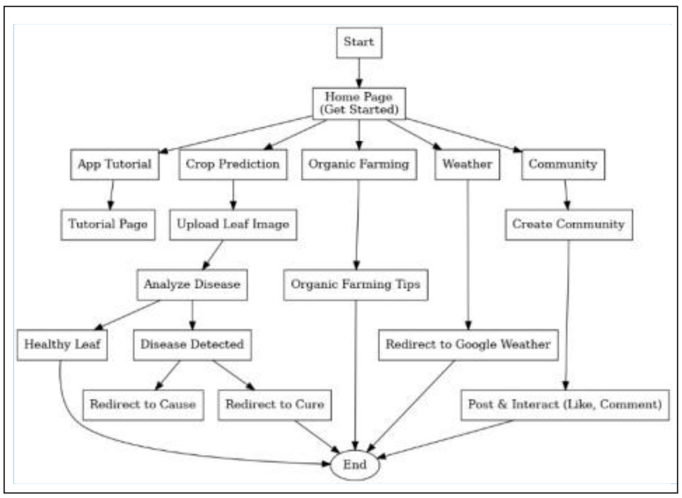

Fig. 5: Flow Diagram of the App

References

[1] A. A. Ahmed, and G. H. Reddy, "A mobile-based system for detecting plant leaf diseases using deep learning," *AgriEngineering*, vol. 3, no. 3, pp. 478–493, 2021.

[2] S. Kumar, R. Ratan, and J. Desai, "Development and simulation of IOS app to detect cotton plant diseases using machine learning techniques," 2022.

[3] S. Kumar, R. Ratan, and J. V. Desai, "Cotton disease detection using tensorflow machine learning technique," *Advances in Multimedia*, vol. 2022, no. 1, p. 1812025, 2022.

[4] H. I. Peyal, M. Nahiduzzaman, M. A. H. Pramanik, M. K. Syfullah, S. M. Shahriar, A. Sultana, ... and M. E. Chowdhury, "Plant disease classifier: Detection of dual-crop diseases using lightweight 2D CNN architecture," *IEEE Access,* 2023.

[5] M. M. Islam, M. A. A. Adil, M. A. Talukder, M. K. U. Ahamed, M. A. Uddin, M. K. Hasan, ... and S. K. Debnath, "DeepCrop: Deep learning-based crop disease prediction with web application," *Journal of Agriculture and Food Research*, vol. 14, p. 100764, 2023.

[6] Z. Li, C. Li, L. Deng, Y. Fan, X. Xiao, H. Ma, ... and L. Zhu, "Improved AlexNet with inception-V4 for plant disease diagnosis," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, p. 5862600, 2022.

[7] P. K. Das, "Leaf disease classification in bell pepper plant using VGGNet," *Journal of Innovative Image Processing*, vol. 5, no. 1, p. 46, 2023.

[8] D. Oppenheim, G. Shani, O. Erlich, and L. Tsror, "Using deep learning for image-based potato tuber disease detection," *Phytopathology*, vol. 109, no. 6, pp. 1083–1087, 2019.

[9] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: Tomato leaf disease detection using convolution neural network," *Procedia Computer Science*, *167*, 293–301, 2020.

[10] H. H. Sarma, B. C. Das, T. Deka, S. Rahman, M. Medhi, and M. Kakoti, "Data-driven agriculture: Software innovations for enhanced soil health, crop nutrients, disease detection, weather forecasting, and fertilizer optimization in agriculture," *Journal of Advances in Biology and Biotechnology*, vol. 27, no. 8, pp. 878–896, 2024.

[11] M. Deodhar, R. Bhave, K. Bhalodia, and M. Rathod, "Android application for crop yield prediction and crop disease detection," Department of Information Technology, KJ Somaiya Institute of Engineering & IT, Sion, Mumbai, India, 2018.

[12] F. Nabi, S. Jamwal, and K. Padmanbh, "Wireless sensor network in precision farming

for forecasting and monitoring of apple disease: A survey," *International Journal of Information Technology,* vol. 14, no. 2, pp. 769–780*,* 2022.

[13] T. A. Seyam, and A. Pathak, "AgriScan: Next. is powered cross-platform solution for automated plant disease diagnosis and crop health management," *Journal of Electrical Systems and Information Technology,* vol. 11, no. 1, p. 45, 2024.

[14] M. M. Islam, M. A. A. Adil, M. A. Talukder, M. K. U. Ahamed, M. A. Uddin, M. K. Hasan, ... and S. K. Debnath, "DeepCrop: Deep learning-based crop disease prediction with web application," *Journal of Agriculture and Food Research*, vol. 14, p. 100764, 2023.

[15] H. Bagwaiya, V. Sharma, and S., Sharma, "Enhanced ReP-ETD anti-spamming technique," *International Journal of Computer Applications,* vol. 975, p. 8887, 2016.

[16] https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset