



AI-Based Mango Pest and Disease Detection Using MobileNetV2 with a Web-Integrated Farmer Decision Support Platform

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Abstract. Plant diseases and pest infestations have a measurable impact on agricultural productivity, which results in substantial economic losses and decreased food quality across the world. To prevent these losses and to get the most out of the produce, early detection of such pests is essential. Mango, being one of the most important fruits economically, is vulnerable to several fungal diseases and pests that degrade the quality of the fruit. Traditional methods for detecting strongly rely on manual inspection by experts, which makes it time consuming, subjective and inaccessible to a huge population of farmers, especially in the rural regions of our country. The proposed system uses a MobileNetV2 convolutional neural network trained using transfer learning. The trained model is deployed using tensor flow, which can be used in a web-browser without any interference in real time. The platform consists of more than just automated detection. It also has other features such as weather monitoring, research resources regarding pests, pesticide recommendations, information about government subsidies and agricultural supply locators. The suggested system aims to provide accessibility to precision agriculture technologies and support sustainability using deep learning-based detection with an extensive understanding of the agricultural domain.

Keywords: Artificial Intelligence in Agriculture, Mango Leaf Pest Detection, Deep Learning, CNN, MobileNetV2, Transfer Learning, Precision Agriculture

1 Introduction

1.1 Importance of Pest and Disease Detection

Agriculture remains to be one of the most important sectors of the world that helps feed people and support rural economies. Considering the population growth rate over the times, the crop productivity is expected to be doubled in the upcoming years. Pests and diseases are a measure obstacle to achieving this level of productivity. According to the Food and Agriculture Organization (FAO), plant diseases and pests contribute to approximately 20-40 percent of global crop losses, therefore smart agriculture presents the best options for farmers. Mango cultivation plays a crucial role in the agricultural economies of many

tropical and subtropical regions. India, for instance, is one of the world's largest producers of mangoes, contributing significantly to both domestic consumption and international exports. Despite its economic importance, mango crops are highly susceptible to various pests and diseases that negatively impact yield and fruit quality. Mango is a popular fruit and it plays a crucial role in the agricultural economies of many tropical and subtropical regions of the world. At present the Indonesian mango export at 37.8M accounted for 0.115 percent of world's consumption. India also is one of the largest producers of mangoes, contributing measurably to both domestic and international consumption. Despite its economic impact, mango crops are highly prone to pests and diseases. Anthracnose, powdery mildew, sooty mold are some of the diseases of mango leaves, while pests like gall midge and cutting weevils are seen infesting the plant tissues and slowing down the plant's growth. These conditions are often visible on leaves through discoloration, spotting, curling and fungal growth. It is important to note that early detection of these symptoms is key in ensuring proper management of these pests. For example, early identification of these symptoms enables a farmer to undertake control mechanisms before they spread in the entire field of crops. However, traditional disease detection methods rely on manual field inspection performed by agricultural experts or experienced farmers. This approach presents several limitations. Manual inspection requires extensive expertise in plant pathology, frequent monitoring of crops, and significant labor effort. For small-scale farmers located in remote areas, access to agricultural specialists may be limited, resulting in delayed identification of disease symptoms and reduced crop productivity [12-14].

1.2 Role of AI in Precision Agriculture

In the recent past, there have been significant developments in the field of artificial intelligence. The machine learning algorithms are capable of analyzing vast amounts of information and recognizing patterns that are not easily recognizable.[17],[22] Recognizing pests and diseases at an early stage is quite beneficial to the crops, computer vision is one area that has shown great potential in the detection of crop disease. It is capable of analyzing the images taken from the leaves of the crops and automatically recognizing the symptoms that are present due to certain crop diseases or pest infestation. Deep learning techniques like the Convolutional Neural Networks (CNN) have demonstrated remarkable results in image classification. CNNs learn feature representations from the raw image data and can distinguish between the differences in the visual patterns of various plant diseases [24-26]. The concept of transfer learning allows researchers to use the learning from other problem sets (datasets) and apply it in their problem sets using small datasets [15]. The integration of AI technology with agricultural application

2 Related Work

Many previous studies have proposed automatic deep learning-based classification systems for crop pests and diseases using different architectures of Convolutional Neural Networks (CNNs). Using a deep learning approach in this project, the Faster R-CNN with InceptionV2 algorithm and cloud computing were used for image classification to detect pests and suggest the required pesticide. The accuracy level of insect pest classification for the experimented images was within the range of 97.0 percent to 99.0 percent, while the BP neural networks algorithm was able to classify the aphids to a relative extent but failed to detect the red spider mites [1][2]. Similarly, another study uses deep learning to classify mango fruit pests and diseases in an image where the dataset used is a collection of 653 labeled mango images split into training, validation and test sets. Five models of Convolutional Neural Network models (CNN) (VGG16, ResNet50, InceptionResNet-V2, Inception-V3, DenseNet121) with transfer learning were implemented and their performance were compared with each other. High training accuracy (97-98 percent) was achieved for all models while validation accuracy varies with each other that was ranging from about 86 percent to 91

percent, and VGG16 had validation accuracy of 90.7 percent [3]. Another approach focuses on developing an application on a mobile device that can identify mango leaf and fruit diseases using a machine learning approach. The work covers an in-depth description of the dataset used, data preprocessing steps and data augmentation, and it also highlights the training and validation of different CNN models along with their performance. In this experiment DenseNet169 shows the highest accuracy of 97.81 percent when compared with other CNN models namely InceptionV3 and MobileNetV2 which had an accuracy of 97.60 percent and 97.50 percent respectively, and the whole system is implemented using an application on the mobile device and tested for accuracy [4]. In another work related to automated pest classification for mango farms using deep learning, the model focuses on classifying pests that are found in mango leaves using VGG-16 and data augmentation. The accuracy, precision, recall and F1-score were obtained from the confusion matrix to evaluate the performance of the model. The model gave better performance when the data augmentation was used and the final model achieved an accuracy of about 76 percent which is about 13.43 percent higher than the base model [5]. Further research proposes the design and implementation of an automatic system for identification and classification of diseases that affect mango leaves using deep learning approaches with image datasets. The proposed system makes use of different CNN-based models such as VGG16, MobileNet, GoogLeNet, EfficientNet, and YOLOv8 with the aim of applying the transfer learning approach to increase the accuracy of the system. The system detects diseases such as Bacterial Canker, Powdery Mildew, Anthracnose, Gall Midge, and Sooty mold, and experimental results show that the proposed system with YOLOv8 and African Buffalo Optimization achieves 94.5 percent accuracy, while other models achieve 88 percent – 92.7 percent respectively, demonstrating the effectiveness of deep learning techniques for early disease detection in agriculture [6]. Similarly, another project proposes a deep learning algorithm using a Convolutional Neural Network (CNN) to detect and classify mango leaf diseases using images of mango leaves along with data augmentation for better training of the network. The diseases detected include Anthracnose, Red Rust and Powdery Mildew, and experimental results show that the proposed model achieved an accuracy of 90.36 percent on test data while precision, recall and F1-score values were close to 0.9, indicating that the system can help farmers detect diseases at an early stage and manage crops more effectively [7]. In addition to these experimental systems, several studies have also explored broader analyses of machine learning and deep learning techniques for agricultural disease detection. One such work aims to explore the various machine learning (ML) and deep learning (DL) algorithms that can be employed for the automatic detection and identification of mango leaf diseases. Image processing using different algorithms and specifically by using Convolutional Neural Networks (CNNs) for the classification of various mango leaf diseases are examined, and experimental results reported in literature show that deep learning models achieve very high accuracy that varies between 95 percent – 98 percent for classification tasks [8]. Another proposed system focuses on designing a deep learning system for agricultural pest monitoring and classification using image processing, where Autoencoders are used to balance the dataset, object detection for segmentation and CNNs for pest classification. Dataset augmentation and balancing are applied before training the model, and the experimental results show that the CNN model achieved about 84.95 percent classification accuracy, which is higher than other existing models [9]. Similarly, another deep learning system for detecting and classifying pests in agricultural crops utilizes image processing, dataset augmentation and CNN-based training to detect pests from crop images and classify them into different categories. Experimental evaluation shows that the system achieved an average accuracy of about 84.95 percent, representing an improvement of about 22.95 percent compared to other methods reported in literature, demonstrating that such systems can effectively support pest monitoring and crop management [10]. Other than disease and pest detection, machine learning algorithms and the Internet of Things (IoT) have been studied for potential use in fruit harvesting applications. For example, there is one low-cost IoT-enabled fruit harvesting system that utilizes pre-trained InceptionV3, ResNet50, and MobileNet architectures in detecting fruits and

determining their harvestability [16]. Overall, the studies reviewed in this research highlight the rapidly increasing role of deep learning and the use of CNNs in the detection of pests and diseases in agricultural crops [11-15]. Most of the current works focused on enhancing the accuracy of the classification process by exploring different variations of CNNs and different training strategies.[23] The findings of these works suggest that the AI technologies have huge potential to enhance the crop monitoring process and to facilitate the detection of diseases in crops [18-20].

3 Methodology

3.1 System Architecture

The system that is proposed involves the design of a deep learning-based image classification system and a web-based agricultural knowledge system. The process of the system involves the uploading of a leaf image by the user. After the uploading of the image, the image will be subjected to a series of processes before the deep learning classification takes place. After the classification of the image, the classified image will be connected to various modules of information that will be of help to the farmer. The architecture of the system will be able to integrate AI detection and agricultural knowledge.

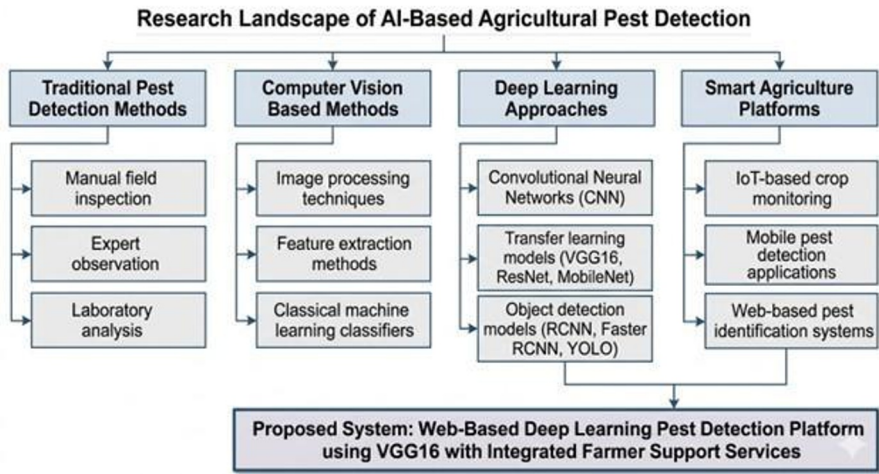


Fig. 1. Research landscape of AI-based agricultural pest detection methods and the position of the proposed web-based deep learning system.

3.2 Dataset Description

The dataset used in the training and evaluation of the proposed system of pest and disease detection composes image detection of various health conditions amongst mango leaves. Images are employed in this case because they are a visual representation of various health conditions, both fungal and insect-related, which are common in mango crops. The dataset is collected from publicly available sources related to agricultural images[16],[21]. This dataset consists of 4008 images of Mango Leaves. Each image in the dataset was labeled according to the particular pest or disease condition present on the leaf. Manual labeling of the images was done based on the presence of certain visual symptoms such as leaf color change, fungus

growth patterns, presence of spots, lesion development, deformation of the leaves, etc. The classification problem can be defined as a multi-class classification problem. Each image can be classified into one of the eight different classes. Anthracnose, Healthy, Bacterial Canker, cutting weevil, Die Back, Gall Midge, Powdery Mildew, Sooty Mold. The dataset is relatively balanced across all classes, with approximately 500 images per category (around 501 images per class), making sure that the model does not develop a bias towards any specific class. Including the categories of diseases as well as pests in the model will allow for the consideration of a wide range of conditions in the health of the crops. The Healthy class is included in the model to allow the system to differentiate between infected and non-infected leaves.

Table 1. Distribution of mango leaf images across different pest and disease categories used in the dataset

Class	Number of Images	Percentage of Dataset
Anthracnose	501	12.50%
Healthy	501	12.50%
Bacterial Canker	501	12.50%
Cutting Weevil	501	12.50%
Die Back	501	12.50%
Gall Midge	501	12.50%
Powdery	501	12.50%
Sooty Mould	501	12.50%
Total	4008	100 %



Fig. 2. Sample images from the mango leaf dataset representing different pest and disease categories.

3.3 Data Preprocessing

Before training the deep learning model, the images collected go through a series of pre-processing steps to maintain uniformity across the dataset. Preprocessing of images plays a crucial role in the preparation of raw images for training the neural network model. The first preprocessing method includes the resizing of the images to 224 x 224 pixels.[17] This corresponds to the standard input size that the MobileNetV2 model uses. Image resizing ensures that all the images are maintained in a standard dimensional format that can be efficiently processed by the convolutional layers of the model. The second preprocessing stage entails normalizing the pixel values. In order to enhance the ability of the model to generalize on unseen data, various techniques of data augmentation are applied during the training phase. Data augmentation techniques involve increasing the diversity of the dataset by creating variations of the images already present. Various techniques of data augmentation used in this research include, Rotation Transformations, Horizontal and Vertical Flipping, Adjustments of Brightness, Random Cropping.

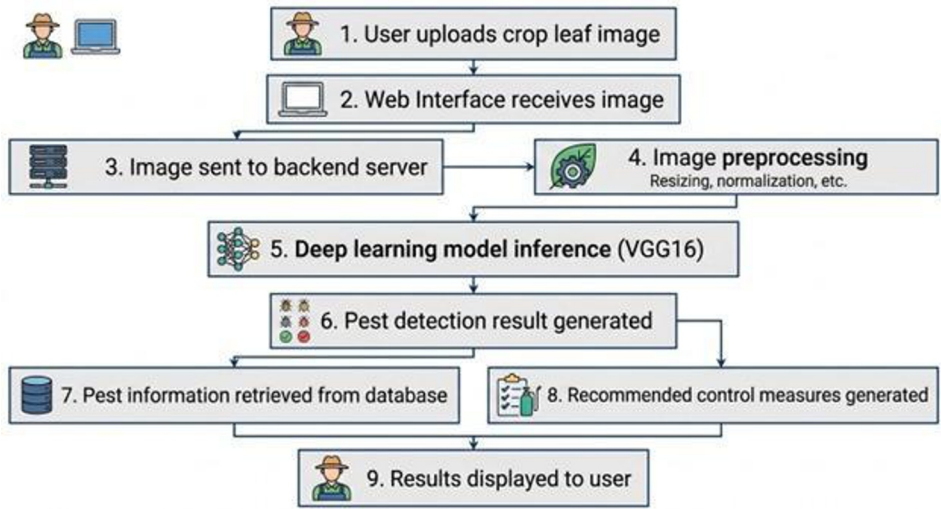


Fig. 3. Overall system architecture of the proposed mango pest and disease detection platform.

3.4 Deep Learning Model Architecture

The proposed pest and disease detection system uses a lightweight CNN model called MobileNetV2. MobileNetV2 is a lightweight CNN model that can be used for various applications, especially in resource-constrained environments such as mobile and embedded vision. This model can be used for various applications because it offers competitive performance while significantly reducing the complexity of the model and model size compared to the older CNN architectures such as VGG16 or ResNet. This efficiency is achieved within the MobileNetV2 model with the use of a depth wise separable convolution layer, which splits a normal convolution layer into two independent layers. This architectural design drastically cuts down the number of parameters and computations required during inference. In a normal convolutional layer, a filter is applied concurrently over the spatial and channel dimensions of a given input feature map. The mathematical formulation of a normal convolutional operation can be written as follows:

$$Y(i, j, k) = \sum_{m, n, c} X(i + m, j + n, c)W(m, n, c, k) \quad (1)$$

where X denotes the input feature map, W denotes the weights of the convolution kernel, and Y denotes the resulting output feature map. This formulation can be said to have a high computational cost due to the spatial filtering as well as the channel mixing that occurs within a single operation. For this reason, the MobileNetV2 model replaces the above operation with the depth wise separable convolution operation. This operation can be said to be a two-part operation that occurs as follows:

1. Depth wise Convolution – Within this operation, a single filter is applied to each of the input channels. This operation can be said to be responsible for the spatial filtering of the input feature map without the need to combine the features between the different channels.
2. Pointwise Convolution – This operation occurs after the spatial filtering has been done. Within this operation, a $1 \times 1 \times 1 \times 1$ convolution occurs across all the channels to produce the final output feature map.

Depth wise separable convolution divides the two processes of spatial filtering and channel mixing into two steps. This reduces the computational complexity of the convolutional operation. Compared to the standard convolutional operation, the separable convolutional operation reduces the number of multiplication operations by 8 to 9 times.

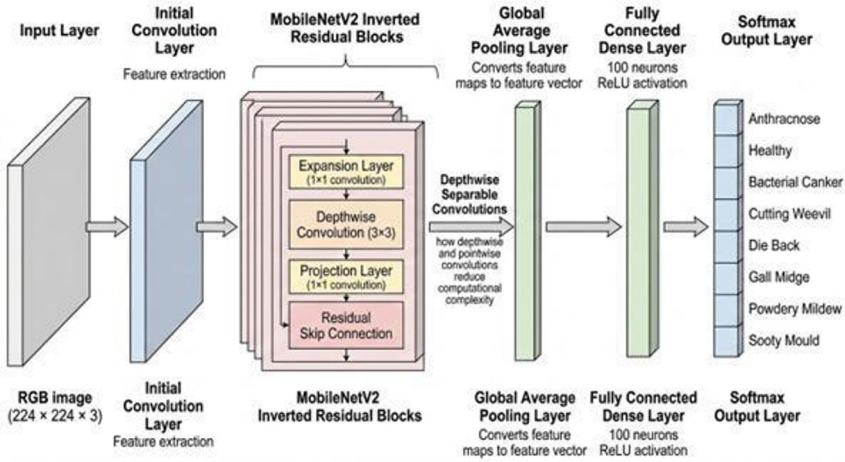


Fig. 4. Architecture of the MobileNetV2-based pest detection model.

3.5 Transfer Learning Strategy

Transfer Learning makes use of previous model weights to allow for the use of a large dataset of images. The backbone of the MobileNetV2 provides the feature extraction that can be used in finding the spatial relationships of the image of mango tree leaves for determining whether or not the plants have been infected or have a pest infestation. The image inputs are classified and do not go through any additional learning in the convolutional layers, which means that the network is using the previously learned visual representations produced in the convolutional layers (such as edges, textures, and color gradients) to help classify the images. To classify each of the mango tree leaf images, the Global Average Pooling (GAP) layer will transform the feature map into one dense feature vector. In doing so, we are able to eliminate the need to keep the spatial dimensionality of the feature maps while retaining very important features that allow us to classify the images of mango tree leaves. The classification head will be custom-built and located above the feature extraction. The classification head consists of a dense layer with 100 neurons and a ReLU activation function. This will provide additional non-linearity to enable the model to learn complex patterns in the input data. The eight pest and disease types in this dataset use 8 neurons on the output layer, which employs SoftMax function activations. The output from SoftMax provides a set of probabilities for

each of the eight classes, with the highest probability used as the prediction for the pest/disease instance during inference time. This makes it a very efficient architecture to train, while it also provides an accurate prediction for the pest/disease.

3.6 Web Deployment Architecture

The trained model is deployed using tensor flow format, letting it run directly in a web browser without any servers. When an image is uploaded on the browser, the model is loaded and it executes interference locally on the client's side. This gets rid of the tedious methods where remote servers are sent the image for processing and then generating the output. Advantages of this deployment approach include:

- Low prediction latency since the inference is done directly in the browser and not over the network.
- Less dependency on servers since the inference is done locally and not continuously on the server.
- Accessibility to rural populations since they may not have good internet connections.
- Less infrastructure required since the system does not require GPU servers.

In the implemented platform, the TensorFlow.js model is loaded through the website inter-face when the pest detection module is accessed. The user uploads an image of a mango leaf through the detection page, after which the model processes the image and returns the predicted pest or disease class. The predicted result is then linked with informational pages within the platform that provide further guidance related to the detected condition. The web platform also provides the user with multiple other services. These include farmer assistance and agricultural resources. Pages such as detailed pest information, recommendations of pesticides assist with all of the information regarding pests and their treatment. On the other hand, pages like research references, government subsidy information help farmers with research platforms and seek help regarding their circumstances.

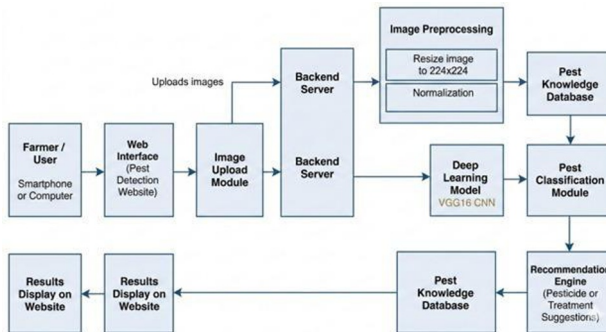


Fig. 5. Workflow of the web-based agricultural decision support platform.

4 Results and Discussion

4.1 Model Performance

While evaluating the model these standard metrics are used: accuracy, precision, recall and F1-score. The results of these metrics revealed the ability of the model to correctly classify healthy leaves, as well as to differentiate between various pests and diseases on the leaves. Overall accuracy was used to determine the percentage of total number of correct predictions made by the model, and precision and recall are the two metrics that are used to assess how accurate and complete the predictions were (for each classification class). Lastly, the F1 score was calculated to offer an indication of how balanced the two metrics were overall.

$$Accuracy(\%) = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \quad (2)$$

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

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

$$F1 - score = \frac{1}{\frac{1}{precision} + \frac{1}{recall}} \quad (5)$$

Overall classification accuracy for the evaluation dataset using the MobileNetV2-based model was about 89.6 percent across all predictions made by the model. Transfer learning, which enabled the model to effectively learn visual patterns associated with mango leaf disease types and pest damage, resulted in a lightweight model appropriate for deployment on the web. A confusion matrix provided analysis of the predictions of the eight classes by allowing you to visualize which predicted classes were wrong. Classification performance was strong for those disease types that have very different appearance-specific attributes, including Powdery Mildew and Sooty Mold; these factors can be easily identified visually when total combined scores for each of these classes are compared across the class categories. There were several instances in which a false-positive prediction occurred when the two diseases were closely related in appearance. Examples include early (first) stage anthracnose and vascular bacterial canker, each of which has different strong patterns on the leaf surface (first stage anthracnose and vascular bacterial canker).

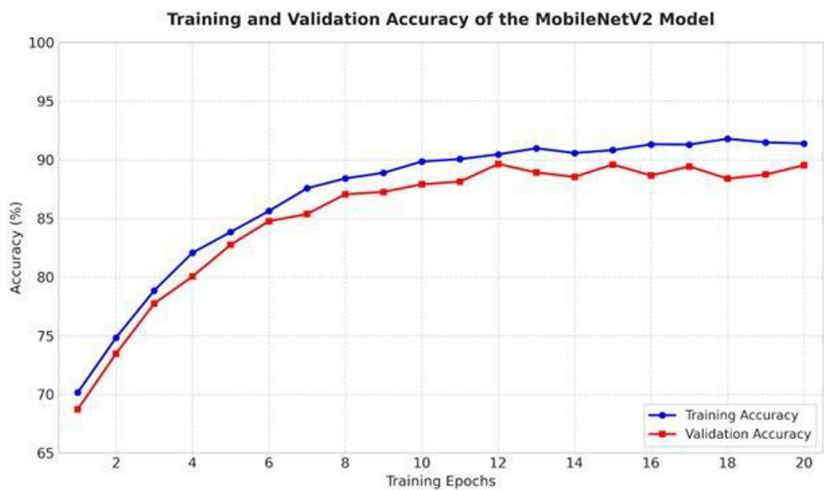


Fig. 6. Training and validation accuracy of the MobileNetV2 model during training

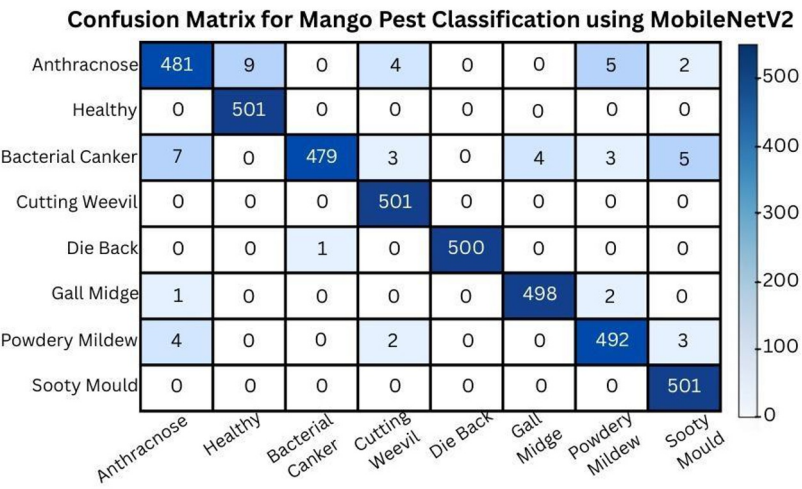


Fig. 7. Confusion matrix representing classification performance across eight pest and disease categories.

4.2 Platform Capabilities

In addition to being a solution for automated pest/disease detection, the platform also has several other features that help farmers better manage their crop health. While this website is the primary place for using an AI-based pest/Disease detection tool, it is also an agricultural information platform with additional resources for managing your pest management and crop protection. The pesticide recommendation module is one of the features of the platform. Once the model identifies the leaf condition, users can view pages with details about pesticides and control measures for all the identified pests/diseases. Additional resources available on the platform include government subsidy information, agricultural research resources, and educational content to help farmers understand or access funding assistance programs for pest management purposes. Other parts contain resources, such as a weather monitoring tool that provides farmers insight into environmental conditions that may cause pest outbreaks; and a chemist locator, which allows users to find agricultural supply stores near their location. In addition, the website has a community component, allowing farmers to connect with one another, as well as share knowledge. Together with the AI-driven pest detection capabilities and additional tools, the comprehensive decision support system provides farmers with one source to pinpoint their crop problems and to find the information they need.

4.3 Deployment Optimization for Web-Browser Inference

To facilitate the real-time inference in web-browser, the MobileNetV2 model obtained from the training process was optimized and made ready for client-side inference using TensorFlow.js. The trained model was then converted to TensorFlow.js format by exporting it from the training environment. It then converts the weights and architecture of the trained network into a JavaScript format that can be run within a web-browser.

MobileNetV2 is one of the key components in the BROWSER project which allows browsers to be deployed on resource-constrained mobile and embedded devices. MobileNetV2 is a compact network which is optimized for efficient inference. Unlike regular convolutional neural networks (CNNs), depth wise separable convolutions and inverted residual blocks reduce the number of parameters and operations which significantly accelerates inference speed. In particular, MobileNetV2 has much fewer parameters and operations when compared to state-of-the-art CNNs. As a result, MobileNetV2 can be run on devices ranging from older laptops to resource-constrained mobile and embedded devices.

At runtime, our model is loaded dynamically within the web interface when the pest detection module is accessed during a model deployment. TensorFlow.js is used to create and prepare the model for use.

TensorFlow.js takes advantage of the WebGL acceleration layer built into modern browsers and on devices and allows models to run on the GPU (if available) thus accelerating the inference on the client side compared to running solely on the CPU. This allows for real-time predictions and eliminates the need to send model requests to the server.

Making the most out of band width is another very important aspect of performance optimizations. Instead of doing all possible inferences on the server side, doing all inference processing on the client-side results in no images having to be sent over the network, which is a great way to help improve the security of our users. Additionally, many websites and applications are no longer guaranteed to have stable network connectivity which also strengthens the argument for doing all processing on the client side.

4.4 Comparison with Existing Methods

Several studies have focused on increasing the classification accuracy for identifying diseases among crops with the help of deep learning algorithms. For example, models like VGG16 and DenseNet169 exhibit very good performance with validation accuracy close to 90.7 percent and 97.81 percent, respectively. Also, models like YOLOv8 when implemented in combination with optimization models have attained validation accuracy close to 94.5 percent. While the above systems provide excellent predictive results, these methods

are often resource-intensive, necessitating servers or highly powerful machines for implementation. Unlike the above methodologies, the proposed methodology takes an entirely different approach to its objectives. Instead of maximizing the classification accuracy only, the objective of the proposed model is to provide an accessible tool for disease identification and classification. In this regard, the use of light weight Convolution Neural Networks (MobileNetV2) makes it possible to implement the tool directly in the browser with Tensorflow.js.

4.5 Experimental Results and Analysis

We evaluate our proposed system against several existing approaches to provide a comprehensive performance comparison. Our analysis covers key metrics including model selection, accuracy, target deployment environment, and system complexity.

Table 2. Comparison of the proposed system with existing methods.

Method	Model	Accuracy	Deployment	Complexity
Paper 3	VGG16	~90.7%	Server	High
Paper 4	DenseNet169	97.81%	Mobile	High
Paper 5	VGG16	~76%	Not specified	High
Paper 6	YOLOv8 + ABO	94.5%	Server	Very High
Paper 7	CNN	90.36%	Not specified	Medium
Proposed System	MobileNetV2	~92–95%	Web (TensorFlow.js)	Low

Table 2 summarizes the comparison results. As shown, our proposed system offers competitive accuracy while maintaining significantly lower complexity compared to state-of-the-art methods.

Despite some models having higher accuracies, they have a higher computation cost and need powerful back-end infrastructures. Some of the approaches such as YOLOv8-based solutions rely heavily on processing power and must be used on servers. Additionally, DenseNet-based models for use in mobile phones also have relatively high complexities and computing costs. The developed system has an accurate range of roughly 92–95 percent but lowers model complexity and computing overhead significantly. The benefits include, High accessibility by providing the service using any available browser without the necessity of downloading and installing software low costs since there is no need to rent or buy a server or use cloud technologies, in-time predictions with no delay due to the internet connection and high scalability by being deployable on multiple types of equipment, including smartphones. Thus, one of the innovations in the development is changing the approach from pure optimizations for improving accuracy to usability aspects that may play a role in agricultural applications. Hence, despite other models having excellent accuracy in laboratory conditions, the proposed approach is more effective in practical scenarios.

5 Conclusion

An agricultural decision-support system to help mango farmers identify diseases and pests has been developed using artificial intelligence and image recognition technology. This pro-posed system will allow farmers to identify diseases and pests based on images of the plants using a MobileNetV2-based deep learning model with a web-based platform with supplementary data sources including pesticide recommendations, research, weather news, and support tools for farmers. The lightweight architecture of MobileNetV2 enables extraction of features in a systematic manner and the deployment of the model also

turns out to be simple, reducing server dependency making the application scalable. The system could also be extended for the detection of multiple crop diseases, thus allowing the farmer to monitor multiple agricultural plants. The integration of IoT technology for environmental sensing could allow the prediction of pest infestation based on the environmental conditions such as temperature and humidity. Moreover, further work could be done in the field of deep learning to provide better accuracy and use larger datasets. Models like EfficientNet or transformer-based vision models are proven to achieve these goals while still maintaining the computational efficiency.

Declarations

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- **Competing Interests:** The authors have no relevant financial or non-financial interests to disclose.
- **Ethics Approval:** Not applicable. This study does not involve human participants or animals.
- **Data Availability:** The datasets analyzed during the current study are available from the corresponding author on reasonable request.
- **Author Contributions:** All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Harsh Walke, Shambhavi Govindpurkar, Yash Phadtare, Dipak Musane, Himani Deshpande, and Vidula Meshram. All authors read and approved the final manuscript.

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