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Detailed Analysis and Advanced Classification of Bean Leaf Diseases using MobileNetV3

Minakshi C. Satape[1], Namrata A. Jadhav[1], Deelip A. Patil[1], Venkata Naga Siva Kumar Challa[2], Shalini Sharma[3], Saba Tahseen[4]

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ABSTRACT

Background: The timely and precise detection of foliage diseases is essential for the efficient management of bean crops. Conventional techniques for detecting leaf diseases need professionals to physically examine the leaves, which is laborious and subject to human mistakes. Due to advanced machine learning (ML) computations, convolutional neural networks (CNNs) are capable of examining leaf diseases. MobileNetV3 is particularly effective for edge device applications because of its lightweight and efficient design.

Methods: In this study, the effectiveness of MobileNetV3 in distinguishing three disease categories: Angular leaf spot, bacterial blight and healthy, from images of bean leaves is evaluated. The dataset utilized in this study is sourced from Kaggle and comprises a total of 1295 images categorized into three classes. Each image was resized to 224×224 pixels and normalized to a range of [0, 1] to prepare it for input into the MobileNetV3 model. Data augmentation techniques, including rotation, flipping and zooming, were applied to enhance the model's generalization capability. The MobileNetV3 architecture was implemented with a batch size of 32 and trained for 25 epochs using the Adam optimizer with a learning rate of 1e-4. Performance was evaluated based on accuracy, precision, recall and F1-score, using a split dataset consisting of training (80%), validation (10%) and test (10%) subsets.

Result: The MobileNetV3 model demonstrated a high level of performance in classifying bean leaf diseases. The model achieved an overall accuracy of 92.19% with a macro average F1-score of 92.27%. These results indicate that MobileNetV3 is effective for automated classification of bean leaf diseases, with high precision and recall, particularly for angular leaf spot.

Key words: Agricultural technology, Convolutional neural networks, Data augmentation, Image classification, MobileNetV3.

INTRODUCTION

Legumes such as chickpeas, fava beans, lentils and field peas are important components of human diets because of their high protein, dietary fibre, vitamin content and essential nutrients. These legumes are often referred to as "poor man's meat". In addition to their nutritional importance, legumes also provide ecological benefits such as deep root systems, tolerance to environmental stresses and the ability to fix atmospheric nitrogen, which improves soil fertility and sustainability in agricultural systems. Legumes enhance the resilience of agricultural systems to the effects of climate change, reduce emissions of greenhouse gases, reduce the amount of pollution in groundwater and contribute to the storage of carbon (Hazra *et al.*, 2020; Jena *et al.*, 2022). However, despite the fact that the worldwide pulse production had a boom between the years 2000 and 2021, with a sixty percent rise, exceeding the thirty percent growth in the world's population, the continuous demand-supply mismatch, particularly in South Asia, is a serious problem (CGIAR, 2023). Consequently, local prices have increased as a result of this shortage, which indicates that there may be difficulties in satisfying the nutritional requirements of the expanding population. In addition, the rising dependence on pulse imports, in conjunction with the sensitivity of legumes to diseases in situations where they are based on rainfall, raises worries about the integrity of the global supply chain. To ensure that people will continue to have access to this essential source of nourishment, it is

[1]Department of Computer Applications, Kasegaon Education Society's, Rajarambapu Institute of Technology, affiliated to Shivaji University, Sakharale-415 414, Maharashtra, India.
[2]KL Business School, Koneru Lakshmaiah Education Foundation, Guntur-521 180, Andhra Pradesh, India.
[3]Department of Language, Culture and Society, SRM Institute of Science and Technology, Delhi NCR Campus, Modinagar, Ghaziabad-201 204, Uttar Pradesh, India.
[4]Department of Computer Science and Business Systems, Dayananda Sagar College of Engineering, Bangalore-560 111, Karnataka, India.

Corresponding Author: Namrata A. Jadhav, Department of Computer Applications, Kasegaon Education Society's, Rajarambapu Institute of Technology, affiliated to Shivaji University, Sakharale-415 414, Maharashtra, India. Email: namratakoravi09@gmail.com ORCIDs: https://orcid.org/0009-0001-2130-8739, https://orcid.org/0009-0003-9378-3103, https://orcid.org/0000-0002-8302-0888, https://orcid.org/0000-0002-2746-7685, https://orcid.org/0000-0002-9117-6954, https://orcid.org/0000-0001-7185-9312

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essential to find a balance between the spike in production and appropriate disease control techniques.

Bean crops, such as kidney beans, black beans and chickpeas, are a fundamental source of food for millions of people everywhere. Beans have an important part in ensuring global food security, as stated by the food and agriculture organisation. They provide vital proteins, vitamins and minerals to diets, particularly in underdeveloped nations. The worldwide cultivation of beans covers roughly 33 million hectares, with Brazil, India and China being the primary producers (FAO, 2023). However, bean crops are susceptible to a wide range of diseases, which significantly impacts their output. Common diseases affecting bean plants include bacterial blight, angular leaf spot and rust, which can severely reduce crop yield and quality. These diseases have the potential to cause substantial decreases in agricultural productivity and reduced crop quality, which presents difficulties for farmers and affects food security. Bacterial blight may lead to a significant decrease of up to 30% in crop production. On the other hand, Angular leaf spots can greatly affect bean harvests, particularly when environmental circumstances are favourable (IFPRI, 2022; Lugito *et al.*, 2022).

Abed and Esmaeel (2018) presented an innovative method using image processing to identify two distinct diseases that affect bean leaves: Bacterial brown spot and powdery mildew. The approach comprises many stages: Acquisition, preprocessing, segmentation, feature extraction and classification. The research used images from a publicly accessible database for both training and testing purposes. The findings showed that their created method obtained a detection accuracy of 100% for both forms of plant leaf diseases. The bean has become an essential component in sustainable agriculture because of its significant impact on soil health and crop output. For example, research conducted in Australia by Heuzé *et al.* (2021) highlighted the importance of beans in improving soil quality and mitigating soil-borne threats such as nematodes and crown rot. The use of green manure improves soil quality for different crops, highlighting the need to protect soil health. Yao *et al.* (2023) provide a detailed review of machine learning techniques for leaf disease classification, focusing on data, methodologies and applications. The paper examined publicly available datasets, traditional methods like decision trees and support vector machines and advanced deep learning approaches like convolutional neural networks. It also discusses augmented learning techniques that enhance model performance through data augmentation. The paper concludes by discussing the practical applications of these techniques in smart agriculture, highlighting their role in effectively monitoring and managing leaf diseases.

Gomez *et al.* (2024) developed an AI-driven system for detecting common bean diseases using deep learning and object detection technologies. The system uses a large dataset of images from Africa and Colombia, focusing on five major diseases: Angular Leaf Spot, Common Bacterial Blight, Common Bean Mosaic Virus, Bean Rust and Anthracnose. YOLO architectures, including YOLOv7, YOLOv8 and YOLO-NAS, were used. The system achieved the highest detection accuracy for whole leaf annotations, with a 97.9% mAP and 98.8% recall. Despite challenges with micro annotation, the system achieved 90% classification accuracy on unseen data. Gill *et al.* (2023) have developed a sequential model for classifying and visualizing bean leaf diseases using deep learning techniques. The model, which achieved over 90% classification accuracy, was trained on a dataset of 2,134 images representing three distinct classes of bean leaf diseases. The model's effectiveness in early disease detection and management was assessed through metrics such as loss, accuracy and confusion matrix comparisons. Sharma *et al.* (2024) studied the impact of plant leaf disease detection on crop quality. They used advanced DL models like VGG16, AlexNet, ResNet18 and MobileNetV2 to improve disease classification. They evaluated their performance on a dataset with 39 disease classes across 14 plant species. MobileNetV2 demonstrated the highest accuracy of 94.4%, demonstrating its superior capability for early disease detection and classification. Recently, studies have investigated the use of AI in the management of huge data sets and have highlighted the efficacy of various machine learning techniques (Kim and AlZubi, 2024; Min *et al.*, 2024; Mostafa *et al.*, 2025).

Despite the progress achieved in previous studies, several challenges remain, including the need for efficient deep learning architectures that provide high accuracy with lower computational complexity for practical agricultural applications. Lightweight models are particularly important for real-time disease detection systems that can be deployed in field environments.

Therefore, this study proposes the use of the MobileNetV3 architecture for automated detection of bean leaf diseases using an open-source image dataset. The model performance is evaluated using training and validation accuracy, loss curves, confusion matrix, classification metrics and ROC-AUC analysis. The objective of this work is to develop an efficient and reliable deep learning framework that can support early detection of bean leaf diseases and assist farmers in improving crop monitoring and disease management.

MATERIALS AND METHODS

Dataset and preprocessing phase

The dataset used in the present study, obtained from Kaggle, consists of images of bean leaves that have been classified into three different categories: Angular leaf spot, rust and healthy (Abode, 2022). The dataset has a total of 1295 images, which were partitioned into training, validation and test sets in an 80:10:10 ratio. More precisely, a total of 1035 photos were assigned to the training set, while 130 images were assigned to both the validation set and the test set.

For preprocessing, the images were resized to a resolution of 224×224 pixels to maintain uniform input dimensions since the images were collected from different devices and may contain varying resolutions. In addition, the pixel values were rescaled to a range of 0 to 1 to enhance the efficiency of the model's training process. Data augmentation techniques such as random rotations, flips and shifts were included in the training images to increase the diversity of the dataset. Specifically, random horizontal flipping was applied with a probability of 0.5, rotation was applied within a range of ±20° and width and height shifts were applied up to 0.1 of the total image dimensions. These transformations were applied during training to improve model generalization. By using augmentation methods, the data is replicated under diverse conditions, which enhances the model's capacity to generate predictions beyond the data it was originally trained on. The dataset was imported into TensorFlow using the image_dataset_from_directory function, which effectively arranges and categorises images based on the directory structure. To ensure the robustness of the model performance, the training process was repeated multiple times using different random seeds and the average evaluation metrics were considered during analysis.

MobileNetV3 Model specifications

Model architecture

The model utilized in this work is based on MobileNetV3Small architecture, which is a lightweight and computationally efficient convolutional neural network designed for image classification tasks and pre-trained on ImageNet. The MobileNetV3Small model was initialised using the ImageNet weights (weights='imagenet') and was adjusted with include_top=False to remove the final classification layer. During transfer learning, the convolutional base of MobileNetV3Small was initially frozen to preserve the pre-trained feature representations. After initial training, selected higher layers were unfrozen for fine-tuning to allow the network to adapt more effectively to the bean leaf disease dataset. This configuration allows for the model to be adapted for the particular task of bean leaf classification. The architecture is designed as follows:

Global average pooling 2D Layer

This layer employs spatial dimension reduction by computing the average value of each feature map, resulting in a single value. Mathematically, the output tensor Y for an input tensor X with dimensions Height (H) × Width (W) × Depth (D) is defined as:

$$Y_d = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_{i,j,d}$$

This operation reduces the number of parameters while preserving important feature information extracted by the convolutional layers.

Dense layer

It is added after Global Average Pooling2D Layer with 256 units and rectified linear unit (ReLU) activation algorithm. The ReLU activation function is mathematically defined as:

$$\text{ReLU}(x) = \max(0,x)$$

This function integrates non-linearity by converting negative values to zero and preserving positive values.

Dropout layer

It is included with a dropout rate (p) of 0.5 to reduce the problem of overfitting. During the training process, each neuron has a 50% chance of being given a value of zero. This operation improves the regularisation of the model.

$$\text{Dropout}(x) = \text{Sample}_{\text{dropout}}(x,p)$$

Output layer

It is created by adding a Dense layer with 3 units and a softmax activation function. The softmax function transforms raw scores (logits) into probabilities.

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

The variable z_i represents the raw score for class i and the denominator is the total of the scores for all classes.

Model compilation

The model was trained using the Adam optimiser, with a learning rate (η) of 0.0001. The Adam optimiser modifies weights by using the following formula:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + e} .m_t$$

θ_t= Model parameters at step t.

m_t and ν_t= Estimates of the first and second moments of the gradients. ε Tiny constant used to prevent division by zero.

$$\text{Loss} = -\sum_{i=1}^{n} y_i \log(p_i)$$

The variable y_i represents the true label, which is encoded using one-hot encoding. The variable p_i is the predicted probability for class i. The model performed training with the objective of optimising accuracy, which was evaluated using the following metric.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Training procedure

The training was carried out for a maximum of 25 epochs, with the following callbacks:

- The ModelCheckpoint callback function saves the weights of the model at the epoch when the validation accuracy was the maximum.
- The EarlyStopping callback is designed to stop the training process if the validation accuracy does not increase for 5 consecutive epochs. This is done to avoid overfitting.

- To improve the reliability of the results, the training process was repeated multiple times with different random initializations and the final performance metrics were averaged across runs.

A flow chart of the procedure is plotted in Fig 1.

Evaluation matrices

After training, the model was evaluated on the test set using output matrices.

Classification report

The precision, recall and F1-score for each class were computed. Precision, recall and F1-score are given by expressions (TP = true positives, FP = false positives and FN = false negatives).

$$\text{Precision (P)} = \frac{TP}{TP+FP}$$

$$\text{Recall (R)} = \frac{TP}{FN+TP}$$

$$\text{F1-score} = 2 \times \frac{P*R}{P+R}$$

Confusion matrix

It provides a thorough assessment of the classification model's performance by presenting the number of true positives, false positives, true negatives and false negatives.

		Predicted class		
		A	B	C
Actual class	A	TP	FN	FN
	B	FP	TP	FN
	C	FP	FP	TP

ROC Curves

The receiver operating characteristic (ROC) curves were created for each class to visually represent the balance between the true positive rate (sensitivity) and the false positive rate (1-specificity). The receiver operating characteristic (ROC) curve is computed by employing the following methodology.

$$\text{ROC curve} = \frac{\text{True positive rate}}{\text{False positive rate}}$$

The area under the curve (AUC) was calculated to evaluate the overall classification capability of the model. Higher AUC values indicate better discrimination ability of the classifier.

RESULTS AND DISCUSSION

The evaluation of the bean leaf disease detection model using MobileNetV3 showed good results in terms of performance indicators after epoch 25 (Fig 2).

The training loss was measured to be 0.2428, indicating a small error in the model's predictions on the training dataset. The training process resulted in an accuracy of 90.91%, meaning that the model accurately diagnosed bean leaf diseases in about 91% of cases. The validation dataset, which evaluates the model's capacity to apply its skills to new data, yielded a reduced validation loss of 0.2121. The decrease in loss indicates successful generalisation and less overfitting. Furthermore, the validation accuracy achieved a remarkable rate of 94.74%, demonstrating the model's strong and dependable capacity to effectively detect diseases in unknown data. The validation accuracy being slightly higher than the training accuracy can be attributed to the application of data augmentation and dropout regularisation during training. Data augmentation introduces variability in the training samples, making the learning task more challenging, whereas the validation dataset contains unaltered images. Consequently, the model may exhibit slightly higher performance on the validation data compared to the augmented training samples. The findings emphasise the effectiveness of MobileNetV3 in achieving accurate disease identification while maintaining a balanced compromise between training and validation metrics.

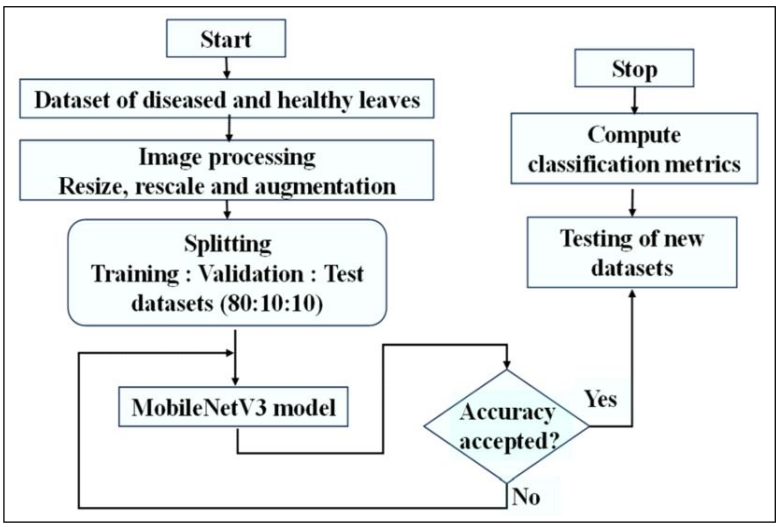


Fig 1: Flowchart of working principle of MobileNetv3 algorithm.

The confusion matrix of the bean leaf disease detection model utilising MobileNetV3 provides a clear representation of the model's performance in classifying angular leaf spot, rust and healthy categories (Fig 3). The model accurately detected 41 instances of angular leaf spot, with only 2 cases mistakenly categorised as Rust and no incorrect positive identifications. The rust detection performance was good, successfully identifying 38 cases. However, there were 5 misclassifications as angular leaf spot and 3 instances that were mistakenly labelled as healthy. The model demonstrated good performance in accurately detecting healthy leaves, correctly recognising 39 cases without any misclassifications. These results indicate that the model performs particularly well in distinguishing healthy leaves from diseased ones, while some confusion occurs between angular leaf spot and rust due to their similar visual characteristics such as lesion colour and texture patterns.

Overall, the confusion matrix indicates that the model is quite efficient, achieving a high level of accuracy in differentiating between healthy leaves and diseases. In addition, it shows low misunderstanding when discriminating between angular leaf spot and rust. The performance of the model highlights its reliable and effective capacity to identify diseases.

The performance metrics of the bean leaf disease detection model using MobileNetV3 are summarised in Table 1. The model achieved a precision of 89.13% for angular leaf spot, indicating that 89.13% of the cases predicted as angular leaf spot were accurate. The recall rate was 95.35%, indicating that the model correctly detected 95.35% of the actual instances of angular leaf spot. The F1-score, a metric that combines precision and recall, achieved a value of 92.13%, indicating a high level of accuracy in disease detection. Based on the dataset, which includes 43 confirmed instances, these measures provide good detection ability for angular leaf spot. The model achieved an accuracy of 88.37% for rust, indicating that 88.37% of the predicted instances of rust were properly categorised. The recall rate was 88.37%, indicating that the model accurately detected 88.37% of the actual instances of rust. The F1-score, which is 88.37%, indicates an optimal equilibrium between accuracy and recall in rust identification. The dataset had 43 verified instances of rust and these metrics demonstrate the efficacy of rust detection. The precision rate of healthy leaves is 100% which indicates all events predicted as healthy were really healthy. The recall rate was 92.86%, indicating that the model correctly identified 92.86% of all real healthy events. The F1-score of 96.30% demonstrates a strong equilibrium between accuracy and recall for healthy leaves, using a dataset of 42 real instances.

The model had an overall accuracy rate of 92.19% across all classes. The macro average measures, which include an accuracy of 92.50%, recall of 92.19% and F1-score of 92.27%, represent the overall performance across all classes, with equal consideration given to each class. The weighted average metrics, including an accuracy of 92.44%, recall of 92.19% and F1-score of 92.24%, take into consideration the number of true instances for each class. These metrics provide a performance assessment that accurately represents the effectiveness of the model across different class frequencies.

The ROC (Receiver Operating Characteristic) curve study of the bean leaf disease detection model using MobileNetV3 offers useful insights into its classification performance across several classes (Fig 4). The ROC curve for angular leaf spots demonstrates a remarkable performance in discriminating angular leaf spots from other classes, as shown by an area under the curve (AUC) of 0.95. The high area under the curve (AUC) indicates that the model has a significant capability to properly detect instances of angular leaf spots with low uncertainty. The ROC curve for rust has an AUC of 0.91, indicating an impressive capacity to distinguish rust from other leaf diseases. Although the AUC for rust is significantly lower than that of angular leaf spot, the result of 0.91 still indicates a high level of performance. This suggests that the model is skilled at identifying rust, even though there may be some

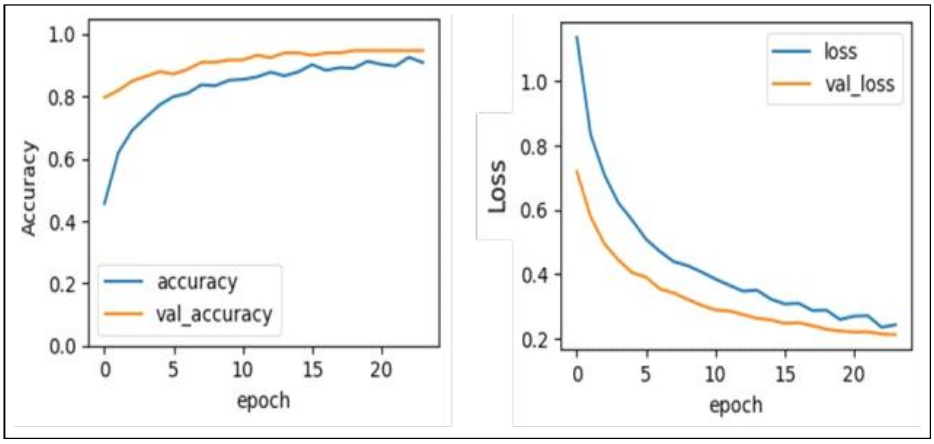


Fig 2: Accuracy and loss measurements as a function of epoch.

similarities with other classes. The ROC curve for healthy leaves has a remarkable area under the curve (AUC) value of 0.96, highlighting the model's remarkable ability to accurately identify healthy leaves. The high area under the curve (AUC) value suggests that the model exhibits outstanding performance in accurately differentiating healthy leaves from both angular leaf spot and rust. This implies a minimal rate of misclassification and highlights the model's reliability in recognising healthy samples. The findings demonstrate the model's efficacy in effectively differentiating between various leaf states, especially in precisely detecting healthy leaves and angular leaf spots with a high level of accuracy.

A comparison of the presented work is done with existing literature in Fig 5. Elfatimi *et al.* (2022) examined the use of MobileNet models in the classification of bean leaf diseases. The research conducted a comparison of several MobileNet topologies, such as MobileNetV2. The model was trained and tested using a total of 1296 images. The findings indicated that the MobileNet model attained a notable classification accuracy, with an accuracy of ~92%. Kumar *et al.* (2022) investigated the use of MobileNet models for accurately detecting and categorising diseases affecting bean leaves. The MobileNetV2 model obtained an accuracy of 93.54% when tested on a publicly available bean leaf dataset. Abed *et al.* (2021) introduced a DL architecture designed to automatically identify bean leaf diseases. The framework comprises two primary stages: identification of bean leaves and diagnosis of diseases. To identify leaves, a U-Net architecture was used, using a pre-trained ResNet34 encoder. The research assessed the efficacy of five DL models: Densenet121, ResNet34, ResNet50, VGG-16 and VGG-19, during the classification phase. The framework underwent testing using a dataset consisting of 1295 images, which were classified into three categories: Healthy, angular leaf spot and bean rust. The findings showed that Densenet121 had better results in both binary and multi-class classification tests. Densenet121 earned a classification accuracy rate (CAR) of 98.31% for binary classification. It also achieved a Sensitivity of 99.03%, Specificity of 96.82%, Precision of 98.45%, F1-Score of 98.74% and an Area Under the Curve (AUC) of 100%. The model obtained a classification accuracy rate (CAR) of 91.01% in the multi-class classification challenge, with image processing durations of under 2 seconds per image. Sahu *et al.* (2021) explored DL models for classifying bean crop diseases. The study utilized a dataset of 1296 images of bean leaves, categorized into three classes: Angular leaf spot, bean rust and healthy. Two deep learning models, GoogleNet and VGG16, were employed for feature extraction from these images. The results indicated that GoogleNet outperformed VGG16, achieving an accuracy of 95.31%. The study also incorporated several visualization techniques, including

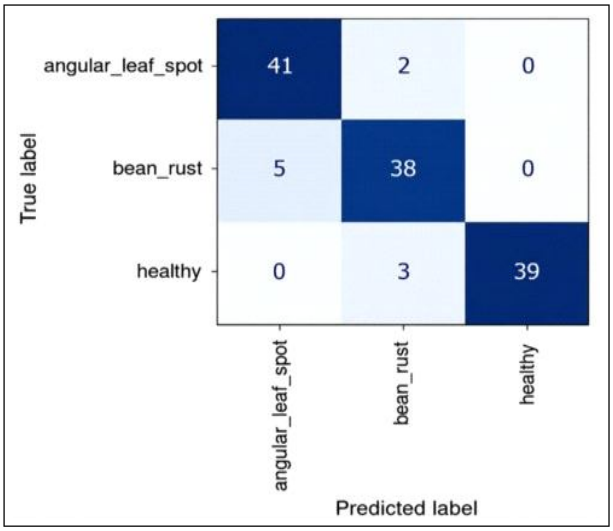


Fig 3: Confusion matrix.

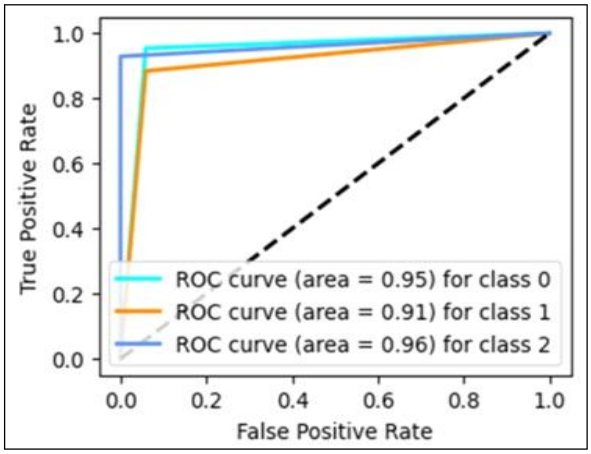


Fig 4: ROC (AUC) curve.

Table 1: Classification report.

	Precision	Recall	F1-score	Support
Angular leaf spot	89.13	95.35	92.13	43
Rust	88.37	88.37	88.37	43
Healthy	100.00	92.86	96.30	42
Accuracy			92.19	
Macro avg	92.50	92.19	92.27	128
Weighted avg	92.44	92.19	92.24	128

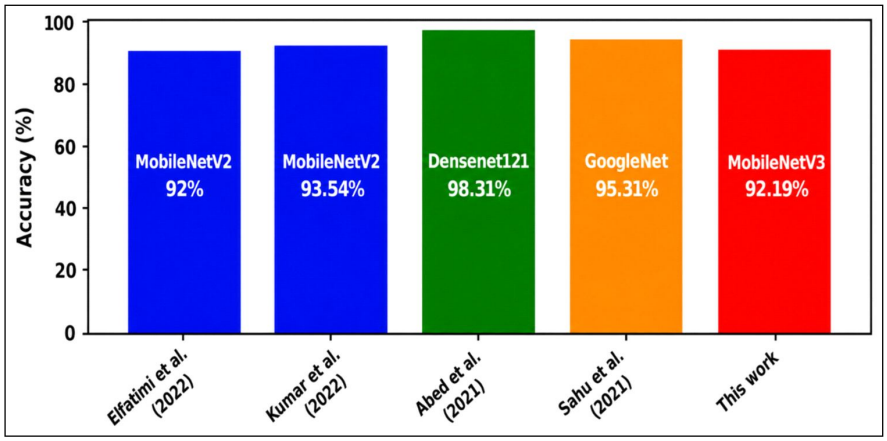


Fig 5: Comparison of existing research with presented study.

Intermediate Layer Activations, CNN Filter Visualization and Heat Maps.

Compared with these studies, the proposed MobileNetV3-based approach achieved a competitive classification accuracy of 92.19%. Although certain architectures such as GoogleNet and DenseNet reported slightly higher accuracy values, these models typically involve larger network structures and higher computational requirements. In contrast, MobileNetV3 is specifically designed as a lightweight architecture that balances accuracy and computational efficiency. This characteristic makes it particularly suitable for real-time plant disease detection applications where computational resources may be limited. Furthermore, the performance achieved in this study demonstrates that lightweight deep learning architectures can provide reliable classification results even when trained on relatively small datasets. This highlights the potential of MobileNetV3 as an efficient model for agricultural disease detection systems that require fast inference and low computational cost.

From a practical perspective, the proposed model can be integrated into mobile or edge-based agricultural monitoring systems, allowing farmers to capture leaf images using smartphones and obtain rapid disease diagnosis. Such systems could support early disease detection, reduce crop losses and improve decision-making in precision agriculture practices. However, further validation using larger field datasets and real-world environmental conditions would be necessary before large-scale deployment.

CONCLUSION

This study demonstrated the effective use of the MobileNetV3 architecture for the automatic categorisation of bean leaf diseases. By using a thorough dataset consisting of 1295 images, obtained from Kaggle and subjected to scaling and normalisation. The MobileNetV3 model demonstrated a remarkable overall accuracy of 92.19%, indicating its strong ability to differentiate between angular leaf spot, bacterial blight and healthy leaf states. MobileNetV3's results highlight its potential as a powerful tool for automated disease categorisation in agricultural environments. The model's remarkable precision not only confirms its efficacy in disease detection but also highlights its potential for practical implementation, offering a significant tool for improving crop management and disease monitoring. The present study has limitations in terms of the variable efficiency of legumes (beans) in various areas and climatic circumstances. Additionally, the provided datasets have limitations and may not include all important environmental or health outcomes. Future research will focus on the expansion of longitudinal studies to get a deeper understanding of the long-term impact of legumes on both health and ecosystems. Additionally, efforts should be made to create more extensive databases that include a wide range of geographical and climatic conditions.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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