MobileNetV2-Based Approaches for Plant Disease Detection: A Systematic Review

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Abstract. Control and early intervention with crop diseases is a serious issue in contemporary agriculture, which directly affects food security in the world and livelihoods of farmers. This paper will encapsulate developments in the field of detecting plant diseases and will show that MobileNetV2 is decisively better than ResNet50 (99.41) and InceptionResNetV2 (99.09) when using the same datasets [5], also being much faster, so it will be the most desirable framework to implement these applications that rely on a small footprint and are of top quality. The review confirms MobileNetV2 has a maximum accuracy of 100 per cent and is 6.1 times faster in inference than EfficientNetV2S in [10] and ensemble models that use it and ResNet50 support 99.91 percent accuracy [11], making it a highly suitable model to deploy in resource-constrained hardware in real-time mode. The evaluation combines popular improvement methods, such as the ubiquitous application of transfer learning and data augmentation, and specialized ones, such as ensemble and specialized hybrid models. But the paper also lists two enduring obstacles to a general adoption of the technology, namely the domain gap between the laboratory-trained models and the field conditions and the Black Box Problem, which restricts the trust of farmers. We conclude the paper by suggesting a future-ready system with MobileNetV2 architecture and Explainable AI (XAI) and IoT sensor data, which has been the required next step to achieve the sustainable, intelligent, and data-driven future of crop health management.

Keywords: MobileNetV2, crop disease detection, Plant Village dataset, convolutional neural network (CNN).

1 Introduction

The developing countries, including India, have most of the population who rely on agriculture, whether directly or indirectly. It forms the backbone of the Indian economy. Over 75 percent [19] of the Indian population relies on agriculture. About 51-55 percent is under agricultural production [19]. Nonetheless, there exists a big challenge in this

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sector that jeopardises its productivity and its means of livelihood for farmers. Plant diseases are one of such challenges, and this is one of the most significant and sustained threats to the production of major crops (45%) [19]. These are diseases induced by different fungi, bacteria and viruses that cause huge economic losses and considerable decline in the quality and production of food. In a country that depends directly on its agricultural industry, such loss of productivity is a direct economic and food security threat, and so early and correct identification is necessary [4]. Historically, farmers' or agricultural experts' technical diagnosis has depended on manual, visual observation to diagnose these diseases [5]. This is a flawed approach to do. It is slow, tedious, time-consuming and expensive, and it is also liable to errors [3] and [2]. More to the point, this is a subjective method of the manual that is entirely reliant on the experience of the person [1]. This lack of efficiency usually results in the disease not being diagnosed early enough, resulting in poor diagnosis efficiencies and missing optimal treatment periods [5].

To mitigate the situation, more scholars are currently called upon to turn to automated systems that work with the assistance of artificial intelligence (AI) and computer vision [6], which have altered agricultural diagnostics to allow automated disease detection more precise than a human expert can detect. In this area, the most promising approach is now deep learning. Specifically, the image classification is found to be especially effective with the Convolutional Neural Networks (CNNs), with several studies [5, 11] reporting that models based on MobileNetV2 could classify plant diseases with over 95 percent accuracy in the plant disease classification tasks. CNNs are capable of automatically processing leaf images (color, texture, or shape changes) which could be a sign of a disease, which CNNs are capable of learning complex features and patterns with high accuracy and often much greater than humans [7].

Such strong architectures as ResNet50, VGG, DenseNet, and Inception have been extensively tried [8, 9]. Nevertheless, they are deep, large and computationally intensive [10]. They are intensive in computing and memory, which makes them slow and inapplicable to the real-time operation on mobile and embedded devices [6]. This is a very essential gap, as the most viable guide to a farmer in the field is a smartphone [1].

This gap has been filled by the creation of lightweight architectures, although the most notable one is MobileNetV2 [6, 10, 11]. MobileNetV2 is a CNN model that features depthwise separable convolutions, inverted residual blocks with bottlenecks that are linear and has a 224x224x3 input size (nearly 9x more lightweight than VGG16) [10]. This renders it very efficient and quick to execute in resource-constrained machines [1]. It has a good trade-off between cost of computation and accuracy – depthwise separable convolutions of MobileNetV2 share computation at 89 times that of conventional convolutions and have just 3.4 million parameters, making it possible to run on the mobile CPU in real time. This qualifies it to be the best choice for a practical and field-deployable mobile application capable of providing real-time diagnoses to farmers [1, 11]. The capstone paper is a detailed literature review of how the MobileNetV2 architecture can be used in detecting plant diseases. The review will examine and synthesise the most popular methodologies adopted by researchers to obtain high-accuracy results. These approaches involve the general use of transfer learning as a way of building on the existing models [4, 7] and data augmentation as a way of enhancing the robustness of the model [4, 7]. Also, this review will consider ways researchers build on the base MobileNetV2 model, including by building an ensemble model that combines it with more hefty models like ResNet50 [9], by orchestrating it with object-detection models like YOLOv3 [10], or by building hybrid models with more custom dense layers [1, 6, 11]. In the end, the paper will find out the most effective strategies and unresolved issues (like generalising controlled lab results to the field conditions) [5] and offer a basis to create a future-ready and highly accurate mobile application for farmers.

2. Systematic Review Methodology

This paper follows a structured systematic review methodology to maintain a transparent and reproducible selection of literature that is of interest. The processes involved in the review were identification, screening, eligibility assessment, and ultimate inclusion.
Data Sources: Major academic databases, such as IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, and PeerJ, were searched to retrieve relevant research papers. These databases were identified to have full coverage of peer-reviewed journal articles and conference publications in the field of deep learning and agricultural technology.
Search Keywords: The search in the literature was done with the following combinations of the following keywords: MobileNetV2 plant disease detection, lightweight CNN in agriculture, deep learning in crop disease classification, and MobileNetV2 in agriculture transfer learning. Search results were refined and filtered with the help of Boolean operators like AND and OR.
Time Range: The inclusion criteria were publications published between 2019 and 2025 because most applications based on MobileNetV2 became known during this time.
Inclusion Criteria: The criteria used to select the studies comprised (1) peer-reviewed journal or conference articles, (2) the use of MobileNetV2 to detect plant diseases, (3) the performance measures were the reported quantitative measures of performance, such as accuracy, precision, recall, and F1-score used in classification tasks [8], and (4) the article must be published in English.
Exclusion Criteria: The studies were filtered out based on the following criteria: (1) not using MobileNetV2, (2) not carried out on non-agricultural disease detection, (3) not experimentally validated, (4) duplicate entries.
Selection of Study and Data Extraction: The initial search produced 120 records. Upon the elimination of duplication and the elimination of non-relevant titles and abstracts, 42 studies were shortlisted to be assessed in terms of the full text. After thorough eligibility screening, 18 good-quality studies were chosen to be eventually synthesized. Common preprocessing steps across reviewed papers involved image resizing to 224x224 pixels (the input size that MobileNetV2 requires), pixel normalization to the range [0, 1], and data augmentation steps including horizontal/vertical flipping, 40-degree rotation, zoom, and shearing (enhanced generalization and reduced overfitting) [7]. The most frequently used dataset in the reviewed papers is PlantVillage [6], which had a collection of 54,306 images of 38 disease classes. Crop-specific datasets such as the Robusta coffee leaf dataset (approximately 1,200 images) [3], tomato datasets [8,

11] and large unified multi-source datasets of up to 64 classes have also been reviewed [1]. The analyzed data were extracted and compared to determine the trends of performance, methodological trends and gaps in the research.
The standard set of studied parameters was widely used to review studies, which used Adam optimizer, 32 batch sizes, and 50-100 epochs. Most studies typically divided data as 80 percent training, 10 percent validation, and 10 per cent testing, and ImageNet pre trained weights were used in transfer learning in almost all studies [4, 7, 11].

3. Literature Review

The use of MobileNetV2 in plant disease detection has a long history of investigation that includes tomato, coffee, apple, paddy, and orange, as examples of the crops covered by it [1, 11, 14, 13, 2], making it the most popular lightweight architecture in the field. The literature may be divided into several overall themes: (1) the basic methodologies, which can be used as the baseline of most studies; (2) the creation of hybrid or modified architectures that enhance the performance; and (3) the comparative studies that may be used to benchmark MobileNetV2 to the other trending models. A detailed literature review is given in Table 1. Two fundamental methods are used as the most common baseline of modern research: transfer learning and data augmentation. Transfer learning is a practice that is underlying in nearly all the examined literature. Rather than creating and training a new, complex neural network on its own, which is both data-intensive and computationally intense and requires huge computing resources, researchers utilize an existing MobileNetV2 model. This model has previously been trained on a general-purpose dataset, such as ImageNet, which has millions of images. It is hence already skilled at recognizing simple visual objects such as edges, shapes, and textures [11]. The last layers of the model are then fine-tuned on new specific data, e.g., plant leaf images [4]. This strategy has a tremendous impact on time saved in training, the minimization of the cost of computing, and has retained high-accuracy performance even when using smaller and focused datasets [7].
Data augmentation is a method to counterbalance small or non-diverse data. Big datasets such as PlantVillage are commonly large, but they are usually captured in laboratory conditions, which are not applicable to a realistic field due to the background, changing lights, and angles [5, 6]. As a remedy to this, researchers increase their training data by transforming them through a combination of random geometric and color alterations. These are horizontal and vertical flipping, random rotations, shearing and zooming [6, 7]. This is an artificial method that enlarges the training set and makes it stronger, thereby avoiding the overfitting of the model and enabling it to have a better generalization to the new images, which it has never encountered before [1, 6]. Despite the already high-performing default variant of MobileNetV2, researchers suggested three broad enhancement plans: (1) hybrid networks with custom dense networks [1, 9, 15], (2) ensemble networks with MobileNetV2 and ResNet50 [11] and (3) object detection system integration with MobileNetV2 and YOLOv3 [8], each of which demonstrates state-of-the-art performance under specific conditions.

One popular approach is to make modifications to the foundational MobileNetV2 architecture to make it a hybrid. This may include the introduction of new layers or the introduction of new mechanisms. As an example, [1] came up with an extended version of MobileNetV2 by introducing a few new dense layers, which were optimized with the help of Keras Tuner. This enabled them to use their model to deal with a very complex unified dataset of 64 distinct classes with 95.94% accuracy [3]. On the same note, a modified MobileNetV2 that is a customization of the final layers was also developed by [9], who used the modified version in a binary classifier to identify a healthy and unhealthy tomato leaf [9]. The other changes are more complicated. [15] suggested a better system of lightweight MobileNetV2 that included a channel-attention mechanism. This addition enhanced the model to 99.53 percent accuracy, and the overall number of parameters was reduced, thus making the model even lighter than the original one [15]. Other scholars have used MobileNetV2 as a feature extractor with some other forms of classifiers, including an Extreme Learning Machine (ELM), to produce a new hybrid model [16].

The other widely used advanced method is the "ensemble model" that combines two or more disparate architectures so as to use their respective strengths together. A good example of this is given by [11], who make an ensemble of the lightweight yet effective MobileNetV2 with the deep and powerful ResNet50. Their approach combines the features of both the models and inputs them into a final classification layer. Such a combined method had an impressive test accuracy of 99.91, which is better than that of both models individually [2]. This shows that it is possible to develop a system that is highly accurate and robust by combining a fast model and a heavy model. The latest research is not concerned with mere classification (e.g., this image is diseased) but with object detection (e.g., this part of the leaf is diseased). Authors in [8] were able to do that by using MobileNetV2 as the feature-extraction backbone in the YOLOv3 object detection model. Their resulting MobileNetv2-YOLOv3 was not just immensely accurate (91.32 per cent average precision) but also a lightweight network that could run real-time detection on a mobile terminal.

It is a vital theme to pay attention to this emphasis on practical and real-world deployment. The ultimate product of the study is usually a mobile app that can be deployed to farmers. Authors in [3] have managed to develop such a system, implementing their improved version of MobileNetV2 to a cloud-computing server. It runs their Android app, "Plantscape", that lets a farmer take a picture and be recommended a cure, a diagnosis and a fertilizer calculator. Quite a considerable part of the literature is devoted to comparing MobileNetV2 with other popular CNNs to support its choice.
This performance is also high in individual crops. In the case of apple leaf diseases, it was demonstrated that MobileNetV2 was a method of high precision that could be optimally utilised instead of ResNet152 or Inception V3 [14]. It is efficient and thus can be implemented on low- power edge devices.

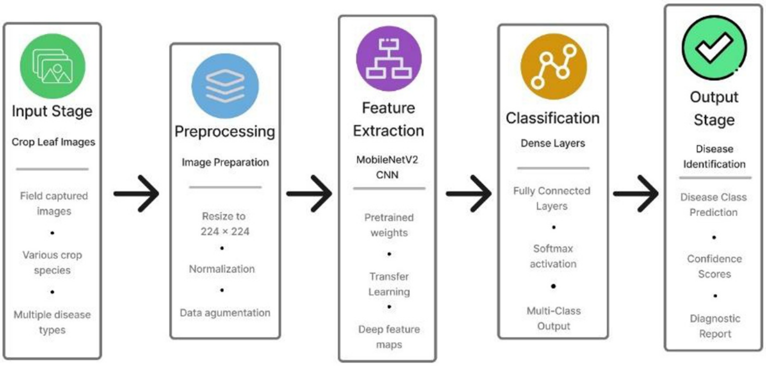

Fig. 1. Overall workflow of the crop disease detection system.

As an example, a study conducted by Tanksale and Mane in 2024 [12] explicitly compared models on Raspberry Pi 5 and proved the appropriateness of MobileNet to this type of hardware. According to other researchers, although models such as ResNet50 have been effective, MobileNetV2 is always chosen due to its high accuracy and computing performance, which make it a better choice when it comes to detecting diseases at an early stage [13]. Fig. 1 shows the workflow followed in our crop disease detection system. It starts with collecting leaf images of different crops, which may contain visible disease symptoms. These images are first preprocessed by resizing them to 224×224 and applying normalization so that they are in a consistent format for the model. After preprocessing, the images are passed into the MobileNetV2 network, which extracts important visual features from the leaf patterns. These extracted features are then sent to the classification layer, where the model identifies which disease category the leaf belongs to. The final output simply displays the predicted disease label. Overall, the diagram represents the step-by-step process of converting raw leaf images into an automated disease detection result.

4. Analysis of Datasets

The performance of a model is essentially correlated with its training data, and the literature reviewed indicates a significant gap between laboratory and real-life data. The most widespread example of benchmarks is the PlantVillage dataset [6, 10], which is popular due to its large size, proper layout, and thousands of high-quality images. Nevertheless, this dataset has its main limitation, according to various researchers, that its images have been taken in controlled laboratory conditions with the same background [5, 6]. This causes a big domain gap; that is, a model that is trained on this clean data might not extend to an actual field, which consists of variable lighting, shadows, and complicated backgrounds [5, 6, 8].

Table 1. Summary of the Existing Literature Review

Ref. No.	Journal / Conference & Volume	Abstract/Key Findings
[7]	Frontiers in Plant Science, vol. 10	Demonstrated the potential of CNNs using the PlantVillage dataset, achieving over 99% accuracy in controlled conditions.
[10]	PeerJ Computer Science, vol. 95	Enhanced MobileNetV2 for crop disease identification, reporting improved inference speed and accuracy suitable for mobile devices.
[11]	Webology, vol. 18, no. 4	Applied MobileNetV2 for detecting tomato and potato leaf diseases, achieving over 95% classification accuracy with reduced latency.
[12]	IJARIIE, vol. 11, no. 2	Proposed a scalable, multi-crop MobileNetV2 framework. proved effective in real-world agricultural scenarios.
[13]	Journal of Smart Computing and Processing, vol. 6, no. 3 11	Compared MobileNetV2 with ResNet50 and EfficientNet for paddy disease, finding similar accuracy with lower computational cost.
[14]	Computers and Electronics in Agriculture, vol. 214	Identified challenges in real-field plant disease detection, emphasizing the need for larger, diverse datasets to improve generalization.
[15]	Computers and Electronics in Agriculture, vol. 210	Integrated MobileNetV2 with YOLOv5 for multi-disease detection, enabling simultaneous classification.
[16]	IEEE Access, vol. 11	Reviewed transfer learning techniques for plant disease detection, highlighting MobileNetV2's efficiency and adaptability.
[17]	Sensors, vol. 24, no. 5	Proposed an IoT-based smart agriculture system combining MobileNetV2 with environmental data for real-time disease prediction.

To address this, most of the more sophisticated research develops its own bespoke databases. These span the spectrum of extremely focused, crop-specific datasets, such as the Robusta coffee leaf dataset [3] or orange leaf dataset [2], to massive complex "unified datasets" that consolidate a number of different sources into up to 64 different classes [1]. The strongest models, like the MobileNetv2-YOLOv3 system, are trained on data that are specifically observed in the natural environment with the purpose to deal with the so-called sophisticated backgrounds [8]. This tendency proves that PlantVillage is an excellent reference point, practical, field-deployable applications need to be trained on more varied, in-the-field data.

Table 2. Comparative Performance of Mobilenetv2-Based Models for Plant Disease Detection.

Ref. No.	Model	Dataset	Accuracy	Special Contribution
[3]	Modified MobileNetV2	Unified 64-class dataset	95.94%	Custom dense layers
[5]	MobileNetV2	Robusta Coffee Dataset	99.93%	Field evaluation
[8]	MobileNetV2-YOLOv3	Tomato Dataset	91.32% AP	Object detection
[11]	Ensemble (MobileNetV2 + ResNet50)	Tomato Dataset	99.91%	Ensemble learning
[10]	MobileNetV2	Multi-crop dataset	100%	6.1× faster inference

5. Research Findings & Discussion

The literature review proves that MobileNetV2 is a good and economically friendly architecture for plant disease detection, as shown in Table 2. Authors in [5] indicated that MobileNetV2 is 99.93 per cent accuracy-wise versus the ResNet50 (99.41) and InceptionResNetV2 (99.09), whereas [10] demonstrated it is 6.1x faster than EfficientNetV2S with 100 percent of accuracy using multi-crop data and is found to be the best option in mobile applications. The most effective implementations improve the original model with transfer learning [4, 7], add hybrid models with custom dense layers [1, 9, 15], use it as a base model in ensemble models with other architectures such as ResNet50 [11], or in object detection models such as YOLOv3 [8, 6]. It is a bad replacement of the in-the-wild pictures in a real farm that have complicated backgrounds, shadows, and changing lighting. These domain gaps are still a significant barrier to generating reliable and field-deployable systems – [17] and [5] in particular note the discrepancy between clean PlantVillage images and real-field conditions to be the major obstacle to generalization, and this is an unaddressed problem across the literature reviewed. These findings are applicable to three different deployment situations studied in the literature: (1) laboratory-controlled settings during the use of PlantVillage [6], (2) in-the-field settings with naturalistic backgrounds and changing illumination [5, 8], and (3) Raspberry Pi 5 edge device deployment because of resource constraints [12].

Deep learning models have become so widespread that they have been called a black box, which cannot answer the question of why they made a given diagnosis [16, 18]. This non-transparency makes farmers distrustful so that Explainable AI (XAI) is required: results here are consistent with the literature on lightweight architecture effects in resource-bound scenarios with heavy networks winning and lightweight networks losing [10, 13], and XAI is the key ingredient that must be added to a deep learning solution to ensure its application in the real world [18]. Proposed Framework. On the basis of these findings, this paper suggests an overall framework (Fig. 1) that integrates the best practices found in the literature and provides solutions to cover the gaps that have been identified as necessary to have a future-ready, deployable system. This framework uses a five-stage pipeline to support a strong realistic mobile application:

Input: This step approaches the domain gap with the help of field-captured images [17], so that the model will be trained on diverse and real-world data [5, 8]. The step normalizes and resizes the images. It should also use heavy data augmentation [6, 7] (e.g., rotations, flips) so that the model is trained to be able to withstand real-world variability and avoid overfitting.

Feature Extraction: It is the heart of the system, which entails MobileNetV2 with Transfer Learning [4, 7]. The model is able to be fine-tuned on the plant diseases with pre-trained weights without having to learn the basic shapes. It is made up of custom dense (fully connected) layers and is used to do the final prediction. It is a hybrid model approach that enables the system to be specialized to the number of disease classes that are specific [1, 9, 15]. The output is a solution to the black box trust problem. The result is not a label but a complete diagnostic report. As demonstrated in the "Plantscape" application, this has the prediction, confidence score and action guidance. Explainable AI (XAI) should also be incorporated in this step to present the farmer with a visual representation of why the model has reached its decision [18].

6. Conclusion And Future Scope

The global food supply is the major goal of modern agriculture that is aimed at diagnosing diseases on a timely basis. This review positions MobileNetV2 as the strong foundation for any future progress in the detection of lightweight plant diseases. Its design is always very accurate, low-latency, and low-computation needs, and hence it is well-suited for farming applications that rely on mobile and Internet-of-Things devices and facilitate the real-time detection in the resource-deprived rural regions. Two primary paths of success discovered in the literature demonstrate the versatility of the model. First, data augmentation and transfer learning are the basis of ensuring a solid performance. Second, the researchers have not only improved the model past the baseline, but they have also applied a variety of strategies: For maximum accuracy, they have developed ensemble models with architecture like the ResNet50; to perform specific tasks, they have used hybrid models with custom dense layers; and to be the efficient backbone to object detection systems like the YOLOv3. This review has been useful in three tangible ways: (1) synthesising and retrieving 18 peer-reviewed articles about MobileNetV2 applications in plant disease detection; (2) introducing the domain gap and explainability deficit as the two essential impediments to deployable systems in the future; and (3) suggesting a five-stage framework that unites MobileNetV2, XAI, and IoT sensing to work effectively in the future. Although the model choice is clear, future directions should be aimed at making the model universal and should overcome the real-life challenges. The next step to undertake is research on enhancing the strength of MobileNetV2 architecture in the real-field environment by foregoing clean lab data and the assembly of various high-quality datasets that were collected in the working farms. Moreover, predictive accuracy should be improved with the incorporation of visual information and additional data by the IoT sensor networks (temperature, soil moisture, and humidity). Importantly, the ultimate system should integrate the Explainable AI (XAI) methods to establish trust in the farmer to make the model predictions understandable and clear. Scalability of such an approach is justified by [12], who proved the successful deployment of MobileNetV2 on Raspberry Pi 5, and by [10], who proved the efficient inference to be 6.1x faster than EfficientNetV2S, so the development of a scalable, sustainable, intelligent, and data-driven solution to global communities engaged in farming became a reality.

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