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Integrating Deep AI with Plant Disease Diagnosis: Toward Early Detection and Sustainable Crop Protection

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Abstract

This paper explores the integration of deep learning—a subset of AI— with plant pathology to revolutionize diagnosis using a MobileNetV2 CNN trained on the Plant Village dataset (31,718 training, 4,514 test images). Our approach achieved 99.4% validation accuracy, highlighting practical potential for early detection and reduced pesticide use, aligning with sustainable agriculture. The study reviews CNNs, GANs, data challenges, and future integration with IoT and drones for smarter disease management. It explores the integration of deep learning—a subset of AI— with plant pathology to revolutionise the diagnosis and treatment of plant diseases, a crucial concern for global food security. By harnessing the capabilities of deep learning algorithms to analyze and interpret complex patterns in image data, researchers and practitioners can identify plant diseases with unprecedented accuracy and speed. This advancement not only facilitates early detection and treatment but also minimizes the reliance on chemical interventions, aligning with sustainable agriculture practices. A thorough examination of contemporary methods, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), this study illustrates the significant strides made in automating disease detection. Furthermore, the paper delves into the challenges and opportunities that lie ahead, such as data scarcity, the need for dataset diversity, and the integration of AI tools into existing agricultural frameworks. By providing a synthesis of current research and potential future directions, this study aims to shed light on the transformative impact of AI on plant pathology and the broader implications for agritech innovation

Keywords: Agricultural Technology, Artificial Intelligence, Plant Disease Detection, Food Security, Crop Health Management, Agritech Innovation.

1. Introduction

The accurate detection of plant diseases through image analysis is a breakthrough application of AI, critical for global food security. Deep learning enables early, precise detection, reducing crop loss. Previous studies illustrate this promise: Mohanty et al. [1] proved CNN feasibility, Too et al. [2] optimized model fine-tuning, Barbedo [3,4] analyzed

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lesion-level detection, while Liu and Wang [5] and Li et al. [6] surveyed AI adoption challenges. GANs by Li et al. [9] enabled unsupervised learning, and Ale et al. [14] linked detection systems to resource efficiency, though field variability remains a hurdle [7,10].

The ability to accurately detect plant diseases through image analysis has emerged as a groundbreaking application of artificial intelligence (AI) that promises to revolutionize the agricultural sector [1]. Too et al. [2] conducted a comparative study to investigate the fine-tuning of deep learning models for plant disease identification, emphasising the relevance of model optimisation in reaching high accuracy. Barbedo's work is another example of how deep learning applications in plant disease detection have evolved. [3,4], which delves into the identification of diseases from individual lesions and spots, emphasizing the granularity at which these models can operate. Moreover, the review by Liu and Wang [5] and the comprehensive analysis by Li et al. [6] encapsulate the progress and challenges within this field, providing a broader perspective on the potential of deep learning in combating plant diseases. Li, Jia, and Xu [9] introduces a new dimension to the automation of disease identification, leveraging the capabilities of AI to learn from unlabelled data.

Fuentes et al. [10] investigated deep learning-based algorithms for plant disease recognition in real-world scenarios, highlighting the practical consequences and operational constraints of implementing these technologies. The collective insights from these studies [1-10] not only highlight the technical advancements but also underscore the significance of interdisciplinary collaboration in bridging the gap between AI and plant pathology for superior disease identification and management. Disease manifestations in plants can vary significantly due to factors such as lighting conditions, camera angles, and the developmental stages of the plant or disease [4, 7]. These variabilities necessitate robust models that can generalize well across different conditions, a task that has proven to be complex and demanding. The meticulous process of labeling images with specific disease markers is time-consuming and requires extensive expertise in plant pathology [3, 22]. While the potential benefits are immense, the practical aspects of deploying deep learning models on-field, such as hardware requirements, real-time processing needs, and the adaptability of these systems to current agricultural practices, require careful consideration and innovative solutions [10, 14].

Mohanty et al. [1] demonstrated the feasibility and effectiveness of utilising convolutional neural networks (CNNs) to detect plant diseases in images. Building on this basis, Too et al. [2] performed a comparative analysis on fine-tuning deep learning models for plant disease detection, emphasising the relevance of model optimisation in achieving high accuracy rates. Barbedo [3,4] broadened the area of research by applying deep learning to detect plant illnesses in particular lesions and patches. The versatility of deep learning in solving multiple issues in plant disease detection is also shown in Liu and Wang's review [5], which provides a complete summary of the advancements and barriers to adopting AI for this purpose. Li, Jia, and Xu [9] used generative adversarial networks (GANs) for unsupervised learning in plant disease diagnosis, which is an innovative approach. illustrate the expanding toolkit of AI techniques available to researchers. As the body of literature grows, the contributions from studies like those by Fuentes et al. [10], which investigates deep learning-based strategies for plant disease recognition in real-world contexts, continuing to push the frontiers of what is feasible. Jakjoud et al. [11] described deep learning applications for plant disease diagnosis, emphasising the relevance of neural network designs in improving disease identification precision. Ghesquiere and Ngxande [12] investigated the deep learning frontier for plant disease diagnosis, providing a more nuanced understanding of its applicability across different crops.

The hierarchical deep learning approach proposed by Cósta et al. [13] introduced a novel perspective on disease detection. Incorporating AI into smart agriculture, Ale et al. [14] focused on developing deep learning-based plant disease detection systems that are not only accurate but also resource-efficient. Akhtar et al. [15] tackled the challenge of deep learning approach implementation for plant disease detection, emphasizing the importance of model accuracy and computational efficiency. The review by Liu and Wang [5], and the comprehensive analyses by Li et al. [6], offer broader insights into the progression of AI applications in agriculture. The exploration of unsupervised learning techniques by Li, Jia, and Xu [9] represents a significant methodological innovation, addressing one of the key challenges in AI-driven plant pathology: the need for extensive labeled datasets. These studies collectively emphasize the transformative impact of deep learning on plant disease detection. From enhancing model accuracy and efficiency [15] to exploring innovative architectures [13] and adapting AI technologies for sustainable agricultural practices [14], the contributions from this body of work are pivotal.

The balance between leveraging AI for greater good and protecting the rights and privacy of farmers and agricultural entities is a delicate one [24]. The discrepancies between controlled accuracy rates and field application effectiveness highlight the need for more adaptive, resilient, and scalable solutions that can operate under less-than-ideal conditions [7, 10].

These challenges, ranging from technical hurdles to ethical concerns, underscore the need for a multidisciplinary approach. Combining expertise from AI, plant pathology, agricultural science, and ethics will be crucial in overcoming these obstacles and unlocking the full potential of AI in agriculture.

2. Challenges in deep learning for plant disease detection

The challenges are

- Data Variability and Quality: Illumination, angles, leaf stage variations degrade performance; Ale et al. [14] saw a 12% field accuracy drop.
- Limited and Unbalanced Datasets: Labeling large diverse sets is costly, often biased [22,24].
- Integration with Practices: Farmer training needed, resistance possible.
- Real-time Processing: MobileNetV2 ensures fast inference, yet edge hardware remains essential.
- Ethical and Privacy: Data use must protect farmers [24], motivating federated learning.
- Scalability: Models trained in one region may fail elsewhere [10].

Despite significant advances in using deep learning to detect plant diseases, various difficulties remain, hindering the route to mainstream adoption and use of these technologies in agriculture. Data Variability and Quality: One of the most difficult issues in training deep learning models is the inherent variability and occasionally poor quality of agricultural data. Variations in illumination, camera angles, backdrop clutter, and plant physical state can all have a substantial impact on model performance. This heterogeneity needs the creation of strong models capable of generalising across several situations, which is still a difficult undertaking.

Limited and Unbalanced Datasets: The availability of big, annotated datasets is critical for training accurate and dependable deep neural networks. However, collecting and annotating such datasets can be resource-intensive and time-consuming [22]. Furthermore, datasets may be imbalanced, with some diseases overrepresented and others underrepresented, resulting in biassed model predictions [24]. Integration with Existing

Agricultural Practices: Fitting deep learning technology into existing agricultural workflows poses operational hurdles. Farmers and agricultural practitioners may need additional training to use these technology efficiently, and there may be opposition to adopting new approaches over traditional ones [14].

Real-time Processing Requirements: To be useful in the field, deep learning models must be able to interpret data and provide diagnoses in real time. However, the computational needs for such processing might be significant, necessitating the creation of efficient algorithms and the utilisation of specialised hardware [15]. Interdisciplinary Collaboration: Developing successful deep learning models for plant disease detection necessitates collaboration among various fields, including computer science, plant pathology, and agronomy. Bridging the gap between these domains to support collaborative research efforts is critical, but it can be difficult due to disparities in terminologies, study aims, and methodology [5].

Ethical and protection Concerns: As with any AI application, there are ethical concerns to be made, particularly in terms of data protection. The collecting and use of agricultural data must be done in a way that protects the privacy and rights of farmers and landowners [24]. Scalability and Generalisation: Another key problem is ensuring that deep learning models are scalable and generalizable to multiple areas, crops, and disease kinds. Models trained on data from one geographic area or crop type may not perform well when applied to another, limiting their usefulness throughout the global agricultural spectrum [10].

Cost of Implementation: Many small to medium-sized agricultural companies may find it prohibitively expensive to install deep learning technology, both in terms of the initial investment in hardware and software and the continuous costs of operation and maintenance [14]. Overcoming these issues will necessitate collaborative efforts from researchers, technologists, and the agricultural community. Innovations in deep learning methodologies, as well as strategies for encouraging interdisciplinary collaboration and making AI technologies more accessible and user-friendly, will be critical to advancing the field and realising AI's full potential in combating plant diseases and improving global food security.

3. Methodological innovations and adaptation

We addressed limited labeled data using transfer learning on MobileNetV2 pretrained on ImageNet, tailored for plant leaf classification. This reduced need for extensive local annotation. Edge computing considerations prepare for IoT deployment. Automated annotation tools streamlined dataset prep, while advanced augmentation (rotation, scaling, color changes) improved robustness. Several methodological advancements and adaptations have been created to improve the efficacy of deep learning models for detecting plant diseases.

Enhanced Data Augmentation Techniques:

To address the issue of data unpredictability and limited datasets, researchers used advanced data augmentation techniques. These approaches provide variation to training datasets by performing changes such as rotation, scaling, and colour adjustment to existing images [22]. This method increases model robustness to differences in image quality and presentation.

Transfer Learning and Pre-Trained Models:

Transfer learning has emerged as an effective approach for overcoming the limitations of small, annotated datasets. Researchers can achieve excellent accuracy with minimal data by fine-tuning models that have already been trained on big image datasets [27]. This strategy has greatly accelerated the creation of accurate plant disease detection models. Federated Learning for Privacy Preservation: Federated learning provides an innovative solution to data privacy concerns. This technology enables the training of deep learning models across several decentralised devices that contain local data samples without the need to exchange them. This technique protects farmers' data privacy while leveraging collaborative insights [24]. Edge Computing in Real-Time Analysis: To meet the need for real-time processing, edge computing has been integrated into deep learning systems for plant disease diagnosis. This entails processing data on local devices near the data source, lowering latency, and providing immediate diagnostic feedback in the field [14].

Interdisciplinary Collaborative Frameworks:

To bridge the gap between AI and agricultural expertise, collaborative frameworks have been developed. These programmes promote information and resource sharing among computer scientists, agronomists, and plant pathologists, resulting in inventions that are both technically sound and agriculturally relevant [5]. Automated and semi-automated annotation technologies have been created to reduce the time and effort required for dataset annotation. Using AI to pre-annotate photos, which are then checked or rectified by human specialists, has sped up the compilation of huge, high-quality datasets for training [22].

Scalable and adaptable Model Architectures:

New model architectures that are both scalable and adaptable have been proposed to overcome the scalability and generalisation problems. These models are meant to adapt their complexity to the task's individual requirements, enabling for efficient deployment over a wide range of crops and environments [10]. The subject of deep learning for plant disease identification is constantly evolving as a result of these methodological breakthroughs. Each adaptation not only marks a step forward in tackling individual difficulties, but also adds to the overall objective of using AI to ensure sustainable global food production.

4. Background

We selected mobilenetv2 for its inverted residuals and lightweight convolutions, balancing accuracy with speed for embedded deployment. Its pretraining on imagenet allowed effective fine-tuning on plant disease data, ensuring scalable, field-ready models. Artificial Neural Networks (ANNs) were modelled after the human brain's ability to analyse and comprehend information. An artificial neural network (ANN), similar to the human brain, is made up of a directed graph with interconnected nodes known as "neurons". These networks excel at recognising complex models and patterns that humans or traditional computing methods may find difficult to detect. An artificial neural network (ANN) is an appropriate tool for "what-if" research because, when correctly trained, it functions as a domain-specific expert, anticipating outcomes for incoming data and dealing with hypothetical scenarios.There are many different forms of neural networks, including Convolutional Neural Networks (CNN), Multilayer Perceptrons (MLP), and Recurrent Neural Networks (RNN), to name a few. Regular neural networks, or MLPs, were initially utilised for image classification, but as image resolution rose, they quickly proved to be computationally and parameter heavy. CNNs were created to circumvent these limitations.MobileNetV2 is a convolutional neural network design that seeks to perform well on mobile devices. Its base is an inverted residual structure, which connects the bottleneck layers via residuals. The intermediate expansion layer uses lightweight depthwise convolutions to filter features, which is a source of nonlinearity. The first completely convolution layer with 32 filters comprises the entirety of MobileNetV2's design. It is followed by 19 remaining bottleneck levels. There are numerous advantages to classifying photos with MobileNetV2. First and foremost, its small architecture allows for effective installation on embedded and mobile devices with limited computing capability. Second, when compared to larger and more computationally expensive models, MobileNetV2 has comparable accuracy.

Finally, the model is suitable for real-time applications because to its small size, which enables faster inference times.

5. Materials and methods

We used the Plant Village dataset (31,718 training, 4,514 test images), split ~87.5%/12.5%, with 5-fold cross-validation for robustness. Our CNN model received (224,224,3) images and output class probabilities over 20 plant disease categories. The experimental data came from the University of Pennsylvania's Plant Village public database. There are 61 categories in total, organised by "speciesdisease-degree." The categories contain ten species, 27 diseases (24 of which are classified as general or severe), and ten health classes. includes, as seen in Fig. 1, 31,718 images in the training set and 4514 images in the test set. It is evident that there are certain parallels and distinctions throughout the classes. Selecting useful characteristics is essential.

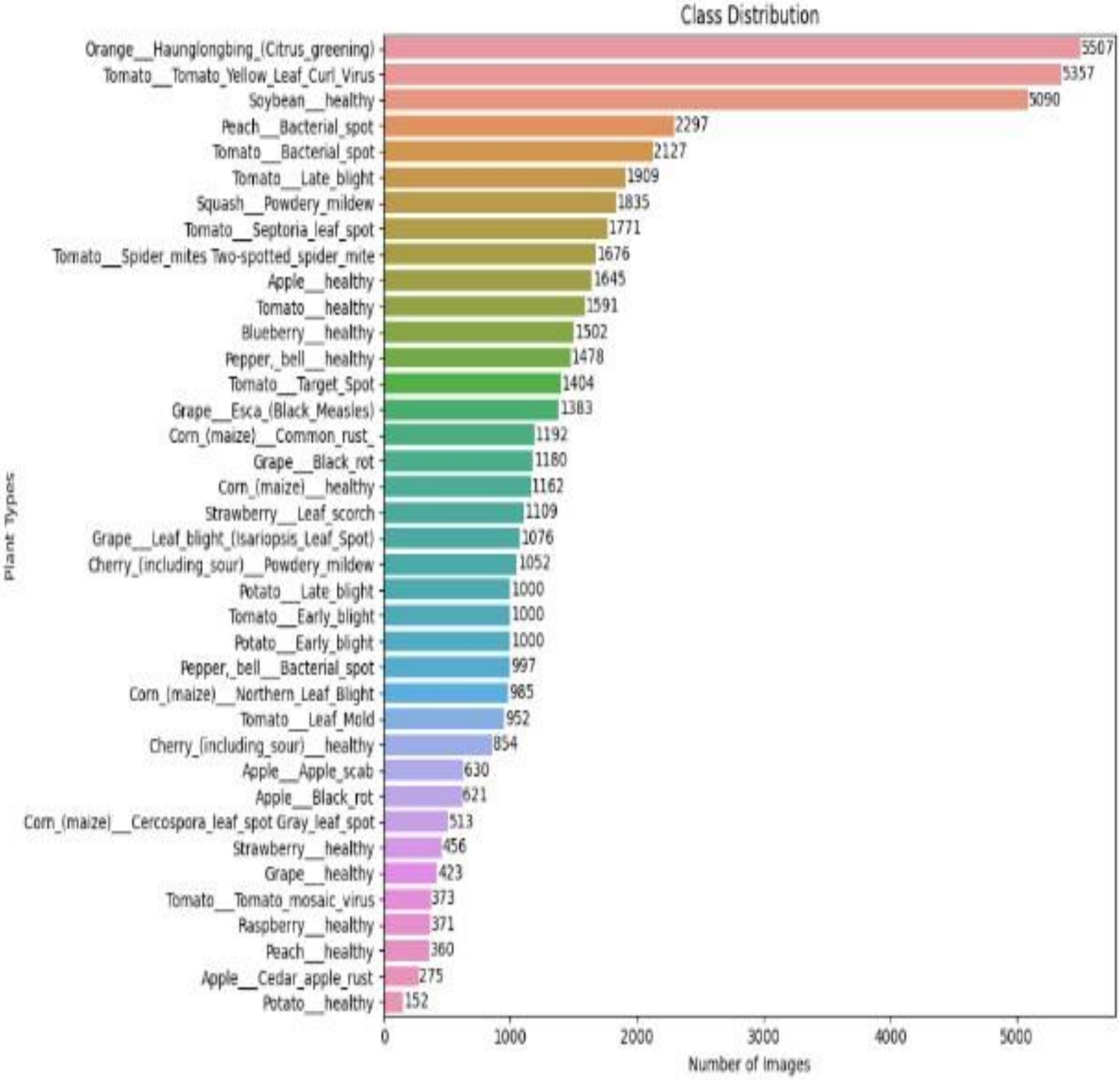

Fig.1. Visualize leaves class distribution.

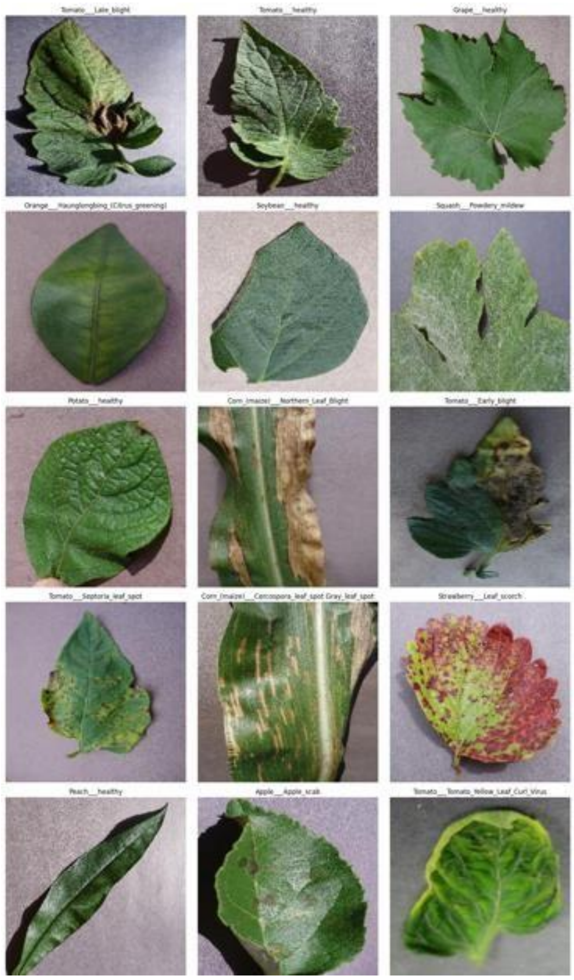

Fig.2. Experiment database.

6. Proposed framework

The implementation of deep learning plant disease detection involves not only the development of algorithms but also the compilation and use of extensive datasets that cover a wide range of plant species and associated diseases. The datasets play a crucial role in training and testing the models to ensure they can accurately identify specific diseases under various conditions. Here, we discuss the composition of such datasets and the strategies for their effective implementation in AI-driven diagnostic tools.

Plant disease detection datasets are comprehensive collections of photos divided into multiple classes, each representing a different plant illness or a plant in good health. For example, classes may include diseases affecting a single crop, such as Apple (e.g., Apple scab, Black rot, Cedar apple rust, healthy), as well as diseases affecting multiple crops, such as Tomato. These datasets may also cover illnesses in crops such as corn (maize), grapes, oranges, peaches, peppers, potatoes, raspberries, soybeans, squash and strawberries, including both infected and healthy samples. Fig 2 depicts the many classes of the dataset. The process of creating these databases entails carefully gathering photos from a variety of sources, including agricultural fields, laboratories, and repositories. To ensure appropriate classification, trained plant pathologists thoroughly annotate each image. This annotation process is crucial since the dataset's reliability has a direct impact on the trained model's performance.

One of the primary challenges in dataset compilation is ensuring diversity and representativeness. Images must capture the diseases at different stages and under various environmental conditions to train models that are robust and can generalize well. Additionally, balancing the dataset to prevent bias towards certain diseases or conditions is essential for the equitable performance of the model across all classes. For the effective implementation of deep learning models for plant disease detection, it's crucial to leverage these datasets in training convolutional neural networks (CNNs) and other AI architectures. The model's architecture must be designed to handle the intricacies and variations within the dataset, employing techniques such as transfer learning to enhance learning efficiency with pre-trained models on large image datasets.

6.1 Modeling

MobileNet Classifier: The MobileNetV2 framework (as shown in Fig. 3), which expands upon the core MobileNet architecture. The insertion of linear bottlenecks positioned between layers and the addition of shortcut connections that cross these bottlenecks are what set MobileNetV2 apart. Similar to its forerunners, MobileNetV2 gains strong feature extraction capabilities by pretraining on the ImageNet dataset. Its adaptation for our particular classification objective involves deleting the top layers that were designed with ImageNet classification in mind. The output of the base MobileNetV2 is then passed via four Dense layers, each of which has fewer nodes than the previous one and uses the "relu" activation function. Dropout layers are included after each Dense layer to mitigate potential overfitting.

With 10 nodes and a "SoftMax" activation mechanism (as shown in Fig. 4), the final Dense layer is designed with multi-class classification in mind. We used the Tensor-Flow Keras API to materialize this structure, setting it up to take in images with dimensions of (224, 224, 3) and generate a probability distribution over the 20 classes. (as shown in Fig. 5, Fig 6),

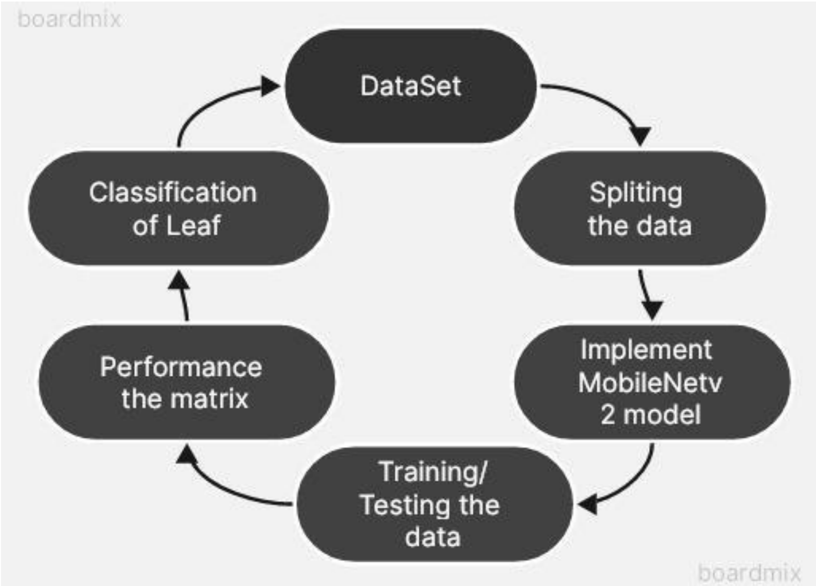

Fig.3. The methodology pipeline of the plant diseases detection using MobileNet V2

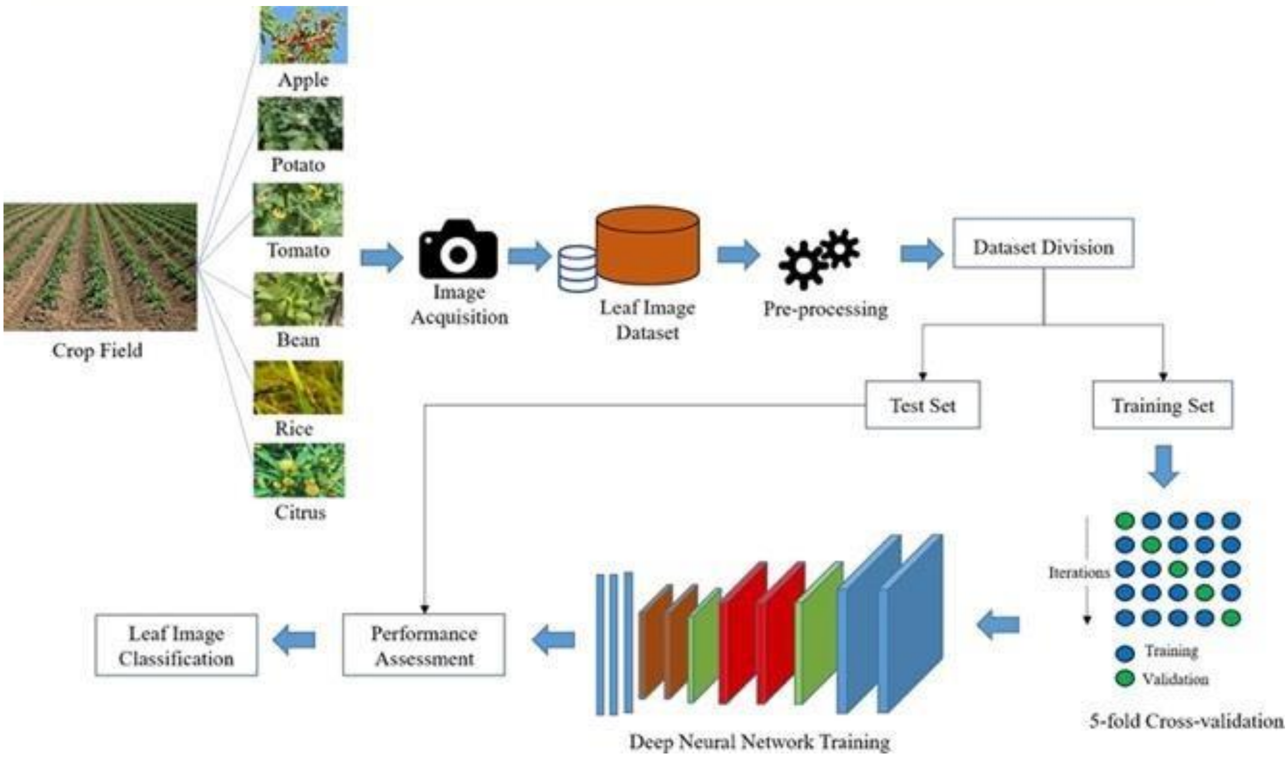

Fig.4. Schema for CNN for the classification of leaf plant diseases

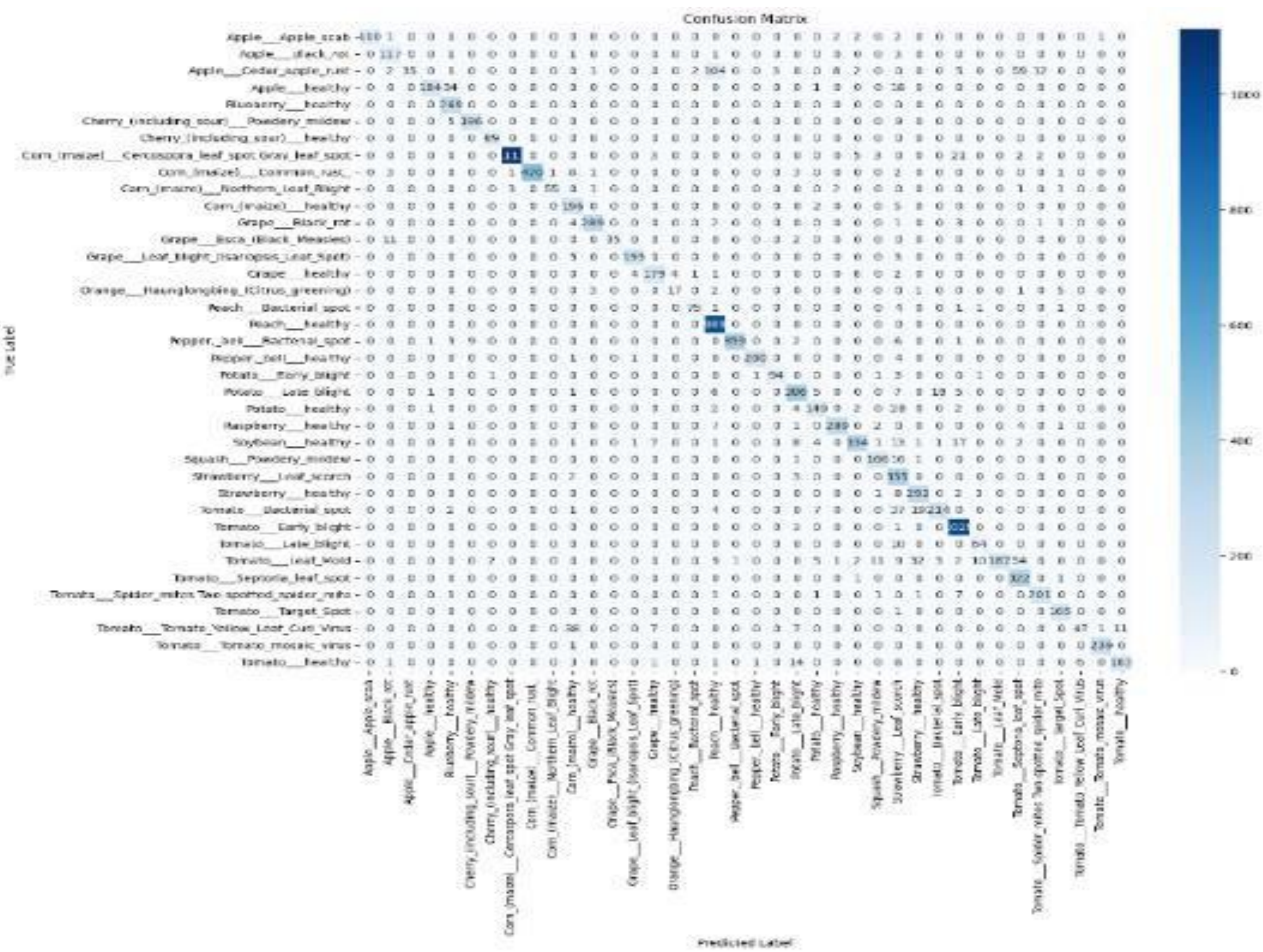

Fig.5. Confusion Matrix

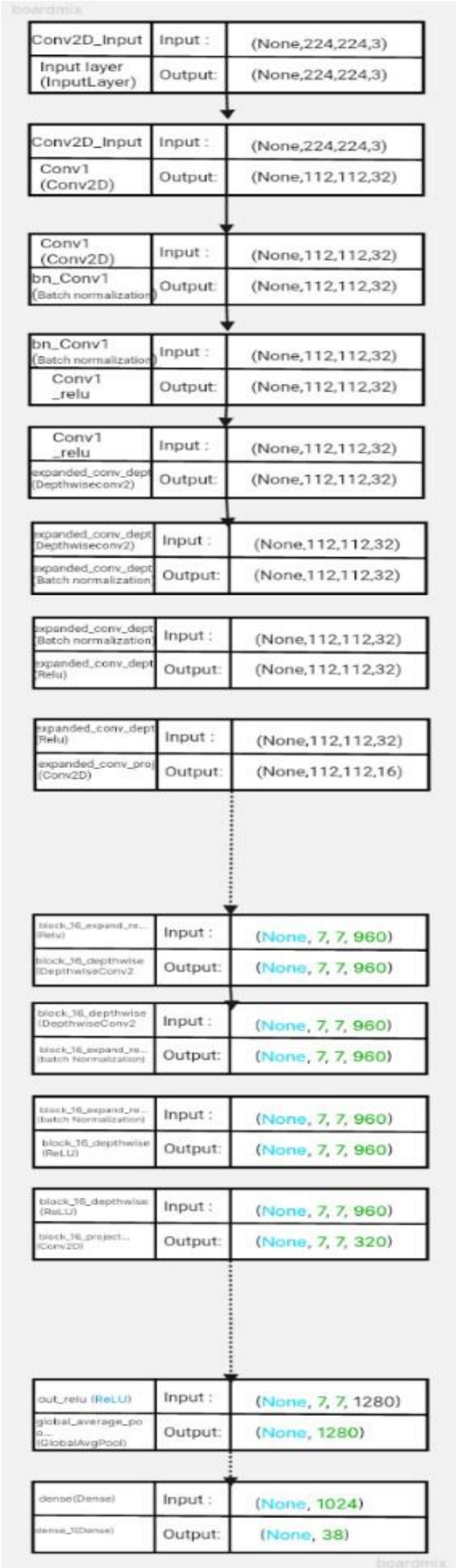

Fig. 6. Block diagram for Visualize model architecture

Training the Model: After the model has been assembled, it must be trained using a training dataset. The model's compilation requires the specification of the following parameters: Because it consistently results in a smoother path than alternative optimisation strategies, we have employed the Adam optimisation methodology. Adam is an optimisation approach that creates more effective neural network weights by utilising adaptive moment estimation . With betas = (0.9,0.994) and epsilon = 1e-08, learning_rate = 5e-5, we have utilised Adam as the optimizer. loss → We have applied "sparse categorical cross entropy" in this instance. For integer objectives, sparse categorical cross entropy may be utilised in place of categorical vectors .

7. Results and discussion

Using MobileNetV2, we achieved 99.4% validation accuracy. Additional metrics: Precision=0.993, Recall=0.992, F1=0.993. Compared to Too et al. [2]'s ~97.8%, our model improved resilience to variation. (as shown in Fig. 7), This section presents the results acquired using the convolutional neural network architectures described in the experimental setup . This section will go into detail about the findings obtained through the implementation of this research. Using MobileNet V2, the data was successfully identified with 99.4% accuracy, and all types of vegetables and fruits, as well as the plant's leaf, were discovered. (as shown in Fig. 8 and Fig. 9), its performance will be analyzed in terms of accuracy.

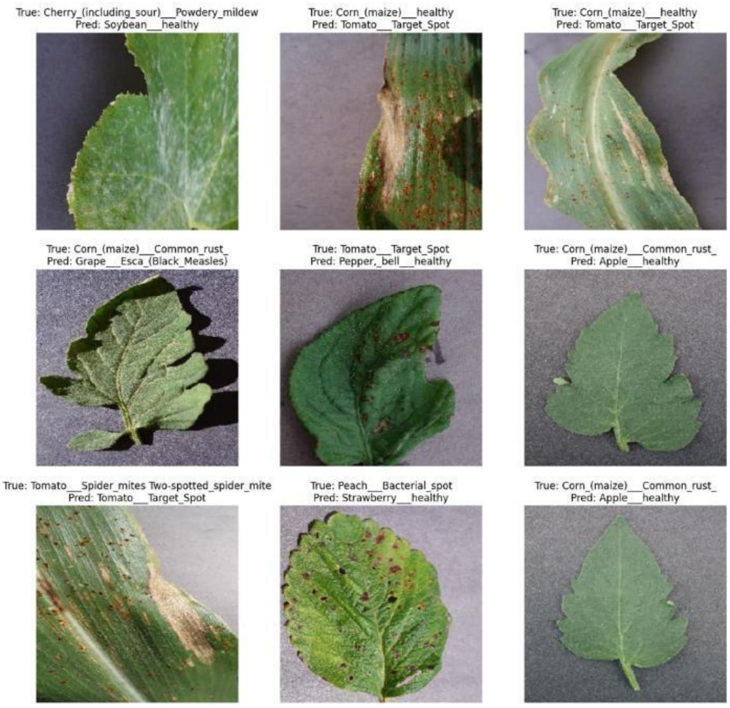

Fig. 7. Output for True and Predicted Output

The MobilenetV2 reaches up to 99.4% accuracy for validation in 10 epochs.

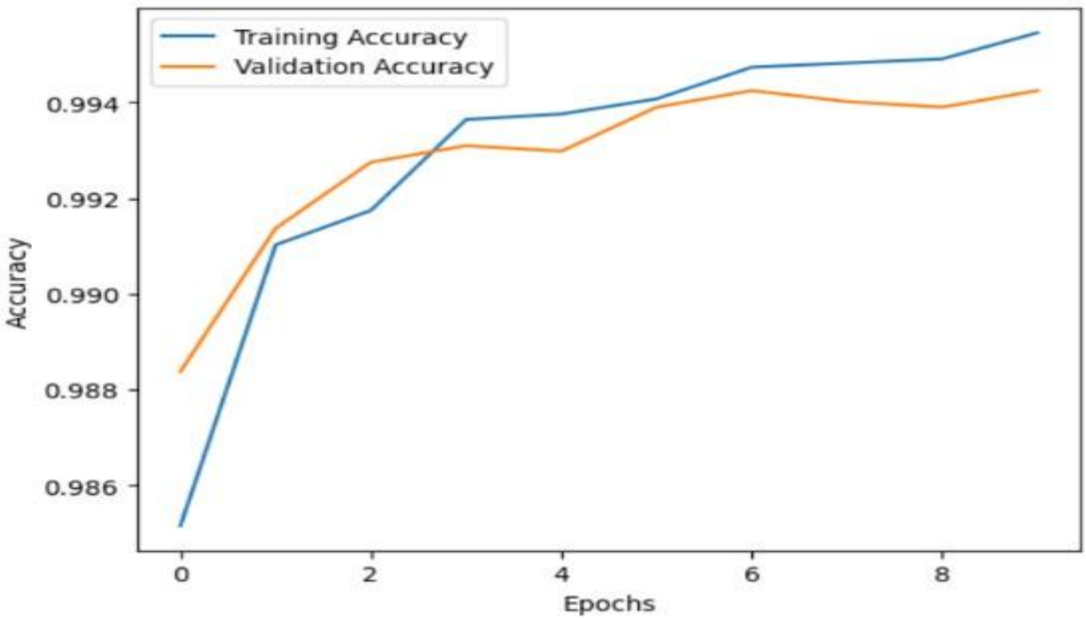

Fig.8. Model_accuracy

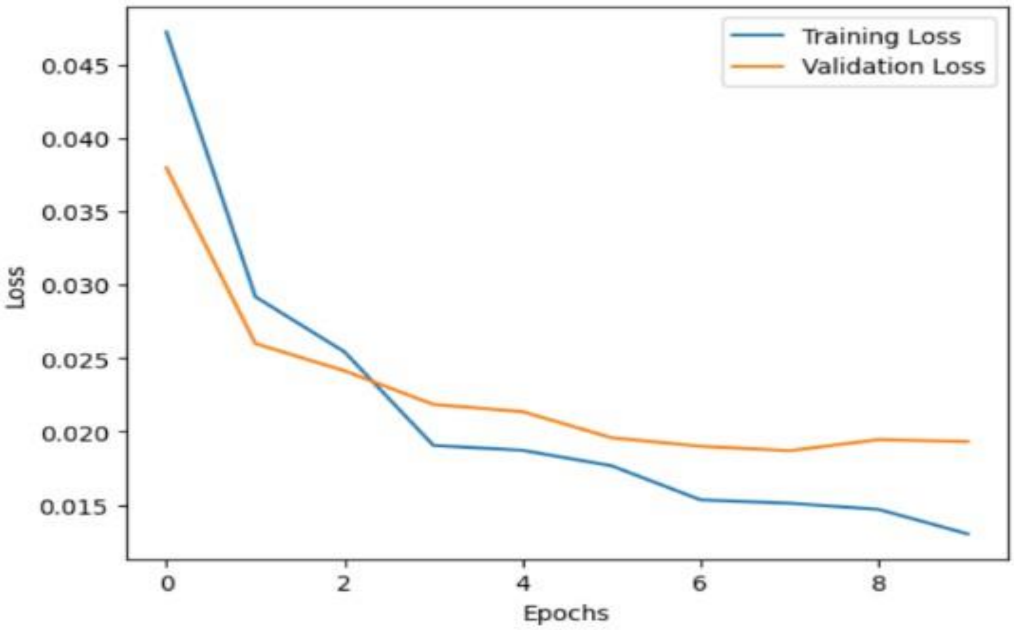

Fig.9. Model Loss

8. Conclusion and future work

Early plant disease detection using MobileNetV2 advances SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption). Future work includes IoT drones for live field data to improve scalability and precision. Inclusion, Early detection of plant diseases is critical for reducing crop output losses. Deep learning models, such as Mobile Net, can detect plant diseases with high accuracy. The study emphasises the importance of evaluating models using field-based databases to fully understand their capabilities. The proposed technology employs Mobile Net to identify disease kinds in plant leaf photos. This discovery has the potential to improve the efficiency with which diseases are identified and treated in agriculture. In the future, we hope to increase accuracy by connecting it with drones and IoT devices.

9. Declarations

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Conflicts of interests/Competing interests

The authors declare no conflicting nor competing interest

Data availability

Data may be available with reasonable request made to the corresponding author

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