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Smart Farming: Deep Learning for Accurate Plant Leaf Disease Diagnosis

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Abstract- This paper presents a strong deep learning framework for automatically diagnosing plant leaf diseases, which is a step forward in precision agriculture. The method combines two high-performing models, MobileNetV2 and EfficientNet, using a broad dataset of CLAHE-enhanced images of 15 diseased and healthy plant classes. The first steps in preprocessing include converting the image to greyscale and shrinking it to 256×256 pixels. Then, the Grey Level Co-occurrence Matrix (GLCM) is used to extract texture features that show important patterns. We use important measures like accuracy, precision, recall and loss to judge how well a model works. MobileNetV2 does better than older models like VGG19 (87%) and InceptionV3 (84%) with an accuracy of 97.38%. EfficientNet does well too, with an accuracy of 93.8%. The suggested models are reliable and effective, as shown by comparative assessments, confusion matrices and cross-validation. They greatly reduce the number of misclassifications. The results show that deep learning could be a reliable and scalable way to discover diseases early and better manage crops in precision farming.

Keywords- Deep learning, Diagnosis, Agriculture, MobileNetV2, EfficientNet

Introduction

The growing need for sustainable agriculture methods has made creative solutions necessary to improve crop output and reduce losses resulting from plant diseases adopted. Affecting crop productivity and food security, plant leaf diseases seriously impair world agriculture. Effective management depends on early identification and precise diagnosis of these diseases since delayed or erroneous identification can result in significant financial losses and environmental harm from too strong pesticide use. Conventional approaches for plant disease diagnosis can depend on time-consuming, labour-intensive inspections done by agricultural professionals, prone to human mistake.[1]–[3]. Moreover, for large-scale agricultural activities these approaches are not scalable. Deep learning has transformed several disciplines and its use in precision agriculture has provided fresh paths for automating and optimising plant disease diagnostics. Deep learning-based methods analyse photos of plant leaves and precisely diagnose diseases using the capabilities of convolutional neural systems (CNNs) and other sophisticated architectures. These models understand intricate patterns and delicate details that might be invisible to the human eye by means of large sets of labelled photos. Deep learning approaches let one create strong and effective algorithms able to detect a variety of plant leaf diseases in real-time. These technologies not only help farmers to take quick corrective action, therefore reducing crop damage and optimising resource use, but also increase the accuracy of disease identification. Deep learning combined with precision agriculture has many benefits. First of all, it makes scalability possible so that the technique may be used under various farming environments and across several crops. Second, by lowering the need for recurrent interventions and hence reducing the reliance on human knowledge, it improves costefficiencies. Third, fast processing of enormous amounts of data made possible by automated systems helps real-time monitoring and decision-making [4]–[6].

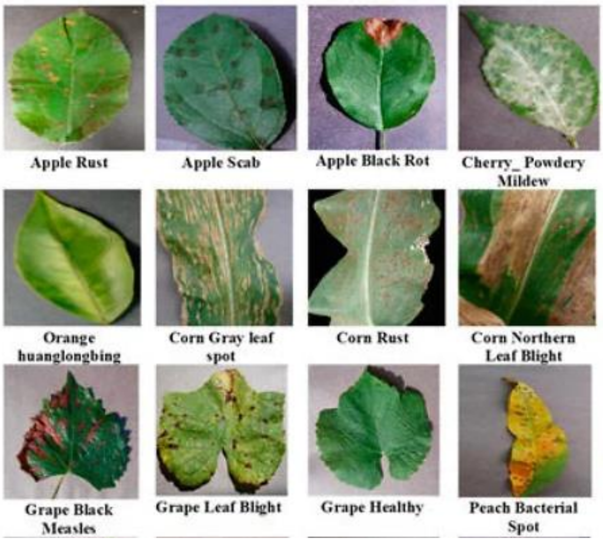

Fig. 1 Automated Plant Leaf Disease Diagnosis [7]

In the framework of precise farming, where the objective is to maximise crop output while lowering environmental effect, these advantages are especially important. By encouraging focused treatments and lowering needless pesticide use, automated disease diagnosis systems match this goal. Creating deep learning-based techniques for plant disease diagnostics calls for various important phases. The first is a set of high-quality imagery datasets spanning both healthy and ill plant leaves under different environments. These preprocessed datasets then help to improve image quality and eliminate noise, therefore enabling the models to train efficiently. Design and training of deep learning models, including CNNs, customised to highly accurately diagnose particular diseases will come next. To guarantee dependability, model evaluation is carried out applying measures including accuracy, F1-score, precision and recall. Once perfect, these models can be used on drones or mobile apps to give farmers easily available and intuitive tools for real-time disease monitoring. Even although deep learning shows great promise for the identification of plant diseases, various difficulties still exist.[8]–[10]. These models' effectiveness mostly relies on the quality and variety of training data. Restricted datasets or those skewed towards particular conditions could lead to models unable to broadly apply across many crops and surroundings. Furthermore, putting these systems into use in environments with limited resources, such as farms, calls for addressing problems including computational needs and cost. More thorough datasets, lightweight model optimisation for edge devices and frameworks integrating disease detection with other precision agriculture technologies for total farm management should be the main priorities of future research. Using deep learning and automated plant leaf disease diagnostics offers a revolutionary way to solve one of the most important problems facing agriculture. This technology has the ability to transform farming methods, increase crop health and strengthen food security by combining cutting-edge computer technologies with precision agriculture concepts. Improvements in this field must be progressed with attention to current issues and guarantee that these solutions are scalable and easily available for farmers all around. Adoption of deep learning-powered systems in agriculture is a major step towards reaching sustainable and effective farming methods for the next generations.[11], [12].

Literature review

Habaragamuwa 2024 et al. The goal is to create a variation autos encoder (VAE) framework based approach for categorisation and explanation. This approach creates images that fairly depict the numerous variations in important features, therefore graphically showing their disparities. The Plant Village dataset attained a good degree of explain ability without sacrificing the accuracy of classification. The suggested approach applies to different crops as well as several photo classification problems. Furthermore in development are applications for software using this approach to recognise diseases such potato blackleg, potato virus Y and other picture classification chores [13].

Kaur 2023 et al. Ant Colony Optimisation with Convolution Neural Network, or ACO-CNN for short, is one of modern deep learning methods for disease categorisation and diagnosis. The scientists set out to investigate whether the optimisation of ant colonies (ACO) may aid in the diagnosis of illnesses impacting plant leaves. The convolutional neural networks (CNN) approach eliminates surface features, leaf colour and spatial layouts prior to photo classification. We evaluate the problem using several efficacy measures and derive a solution; these tests show that the proposed approach beats the current state of affairs when used with great precision. One must first take pictures, then segment those images, eliminate the nose and then classify the findings to identify disorders[14].

Alshammari 2023 et al. This research introduces the HL-FO technique, which combines the Lion and Firefly optimization methods. This hybrid strategy targets olive leaves within Saudi Arabia with the goal of improving disease diagnosis and classification through the use of feature selection & categorization approaches. This is how to use a Convolutional Neural Network (CNN) to categorise images without overfitting. It makes sense to utilise Convolutional Neural Networks (CNNs) to correctly diagnose distinct olive leaf diseases because they have been found to work well for categorising pictures. We thoroughly test the suggested hybrid approach using ROC curve analysis, F1-score, recall, accuracy and precision[15].

Umamageswari 2023 et al. Innovative approach to classifying diseases that affect the leaves of plants. The suggested method consists of three stages: preparation, division and categorization. Raising the image's contrast and eliminating noise and overfitting are the initial steps. Researchers employ the FCM-CSA, or Chameleon Swarm Algorithm based on Fuzzy C-Means, to detect damaged areas of plant leaves. Step three involves extracting features using a quick GLCM feature extraction model. To identify diseases that affect plant leaves, researchers use PNAS, or Progressive Neural Architecture Search. Combining the Mandalay database with the MATLAB software allows for the execution of the experiments[16].

Shewale 2023 et al. It is crucial to closely observe plant leaf diseases in an agroecosystem. Farmers can mitigate financial losses by detecting plant leaf diseases in a timely manner. Recognizing large datasets manually is time-consuming and skill-dependent, which frequently produces erroneous results. Convolutional neural networks (CNNs) for deep learning have lately seen increased use in AI. It is widely recognized that these procedures can cut down on diagnostic time and resources without sacrificing accuracy. Utilizing methods for image processing to images of the leaves taken at certain intervals, plant diseases can be recognized. Research into tomato plant diseases is currently focused on disease detection, classification and diagnosis. We collect data from Jargon city's farms in real-time for our study. By doing away with feature engineering and threshold segmentation, the suggested method can successfully detect diseases through the automated extraction of features. We enhance our network by incorporating spatial images shot in challenging environments. The idea is to train deep learning models on publicly available, continuously growing datasets of real-time images. With this strategy, we hope to finally have a way to diagnose agricultural diseases on a global scale [17].

Table 1 literature summary

Author / Year	**Method**	**Accuracy**	**Ref.**
Oishi /2021	YOLO Faster R-CNN Without	Acc= 96.7% Precision= 78.2%	[18]
Ahmed / 2021	CNN	Acc= 94%	[19]
Fenu/ 2021	VGG-16, VGG-19, ResNet50, InceptionV3, MobileNetV2 and EfficientNet	Acc= 78.31%	[20]
Rinu/ 2021	VGG16	Acc = 94.8%	[21]
Sagar/ 2021	VGG16, ResNet50, InceptionV3, InceptionResNet and DenseNet169	Acc= 98.2%	[22]

Proposed methodology

The suggested method for automatically diagnosing plant leaf diseases uses deep learning techniques. It starts with getting a large Kaggle dataset of 20,636 CLAHE-enhanced photos of plant leaves in 15 categories, including both healthy and diseased leaves. All images are converted to greyscale, shrunk to 256×256 pixels, then saved as NumPy arrays to make sure they are all the same and to speed up processing. To keep the evaluation framework balanced, 80% of the dataset is used for training and 20% for validation. The Gray-Level Co-occurrence Matrix (GLCM) and AlexNet work together to extract features that capture important texture properties including Energy, Contrast and Homogeneity. Using visual tools like histograms and frequency charts, Exploratory Data Analysis (EDA) shows patterns in class distribution and imbalances in the dataset. Custom deep learning architectures are implemented, including EfficientNet and MobileNetV2. EfficientNet uses identity and convolutional blocks to facilitate efficient feature extraction and gradient flow, while MobileNetV2 incorporates dense connectivity and attention mechanisms to enhance focus and classification accuracy. Both models are designed for scalability and high performance, offering reliable and precise disease detection capabilities suitable for real-time precision agriculture applications.

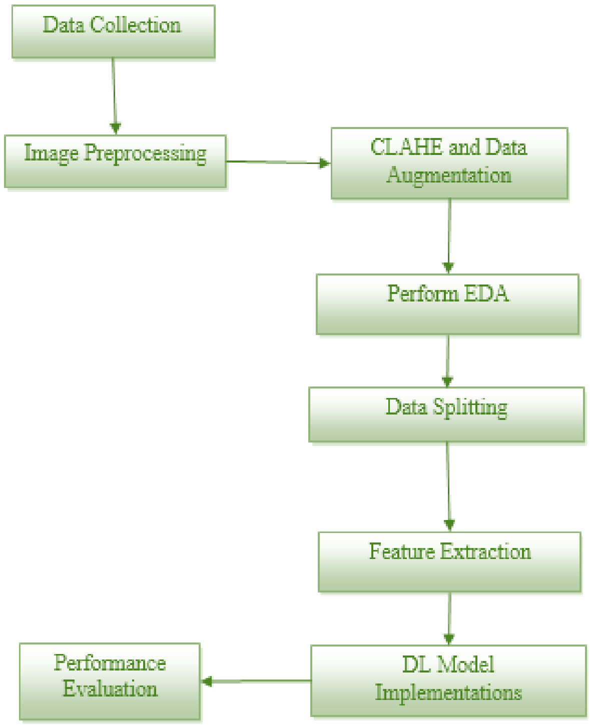

Fig. 2 Proposed Flowchart

A. Data collection

One important part of the automated plant leaf disease diagnostic system is the Kaggle dataset, which has 20,636 CLAHE-enhanced photos sorted into 15 groups that show different plant illnesses and healthy leaf situations. https://www.kaggle.com/datasets/rahimanshu/plant-village-clahe-processed-data/code.

These classes have healthy leaves from crops like tomatoes, potatoes and peppers, as well as bacterial spots, early and late blight, mosaic viruses, yellow leaf curl virus, septoria leaf spot and spider mite damage. The dataset's wide range of well-prepared photos makes it a great starting point for training and testing deep learning models. Its quality and consistency make it great for convolutional neural network (CNN)-based methods since they can extract features and classify data accurately. This dataset is very important for enhancing crop health monitoring and promoting sustainable farming methods since it makes it possible to find diseases accurately and on a large scale.

B. Loading and Preprocessing Images

A crucial initial step in preparing images for feature extraction and model training is the image loading and preprocessing process. Using cv2.imread, images are read in grayscale mode to reduce computational complexity while preserving essential structural patterns relevant to disease detection. Each image is uniformly resized to 256×256 pixels, ensuring consistent input dimensions compatible with machine learning architectures. The grayscale conversion minimizes color-related noise and enhances focus on texture and shape—key characteristics for accurate disease classification. Processed images are stored efficiently as NumPy arrays, facilitating streamlined handling during training and evaluation. This preprocessing step ensures dataset uniformity and lays the foundation for effective downstream tasks such as feature extraction and normalization, ultimately contributing to the robustness and accuracy of the disease detection model.

- CLAHE Technique

Contrast Limited Adaptive Histogram Equalisation (CLAHE) makes leaf images much better, which helps automated plant disease detection systems be more accurate. CLAHE uses histogram equalisation on small, non-overlapping parts of an image (tiles) to boost local contrast. This makes it easier to see minor textural and structural details that are important for finding disease signs. Unlike global histogram equalization, CLAHE includes a clipping limit that prevents excessive contrast amplification, reducing noise in uniform areas while preserving important details. This localized enhancement is particularly beneficial for highlighting disease-related anomalies such as spots or lesions. By improving visual clarity and compensating for variations in lighting and exposure—common challenges in agricultural imaging—CLAHE ensures more consistent and reliable input data for deep learning models, ultimately supporting robust and accurate feature extraction during training.

C. Dataset Splitting

Splitting the dataset is an important step to make sure that the model's performance is fairly and effectively evaluated. This method splits the dataset into two parts: training and validation. The split is 80% for training and 20% for validation and it is done with the train_test_split function from

sklearn.model_selection. A fixed random_state is set so that the results of different tests may be compared. The training set is used to train the model and the validation set checks how well it can work with new data. This separation helps keep the model from overfitting and provide trustworthy performance measures. This stage establishes the groundwork for creating strong and accurate deep learning models by making sure that data is evenly distributed between learning and testing.

D. Feature Extraction

–To find plant leaf diseases, we use a feature extraction algorithm that combines VGG19 with the Gray-Level Co-occurrence Matrix (GLCM) to improve texture-based analysis. We calculate GLCM at different distances and angles to get a full picture of the texture patterns. Key properties including Energy, Correlation, Dissimilarity, Homogeneity and Contrast are pulled out. These features are very important for telling healthy leaf tissue from unhealthy leaf tissue. Then, these features are put into a Pandas DataFrame so that they may be easily used with machine learning models. Combining VGG19 with different GLCM settings makes sure that texture properties are extracted in a strong and consistent way, which greatly increases the accuracy of illness categorisation.

E. EDA

Exploratory Data Analysis (EDA) is an important first step in figuring out how the dataset is structured, how the data is spread out and what patterns are already there. This is especially true when using deep learning to automatically diagnose plant leaf diseases. EDA helps uncover class imbalances, disease frequency and the diversity of disease types through visualizations such as histograms and frequency plots. These insights inform model design and preprocessing strategies by revealing data-driven trends that could affect training performance. Sample images of diseased tomato leaves, showcasing symptoms like spots and lesions, provide visual cues that aid in identifying distinguishing features. Comparisons between healthy and diseased leaves against neutral backgrounds further enhance the understanding of structural and symptomatic differences. This comprehensive analysis supports effective feature extraction, model optimization and overall system robustness—key to achieving accurate and reliable results in precision agriculture.

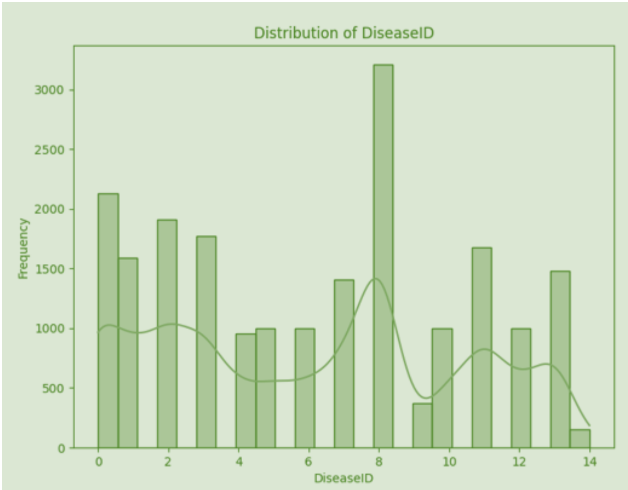

Fig. 3 Disease ID Frequency Distribution

Figure 3 illustrates the frequency distribution of disease IDs within the dataset, highlighting how often each specific disease appears. This visualization effectively reveals data imbalances and trends, making it easier to identify overrepresented or underrepresented classes and informing model training strategies accordingly

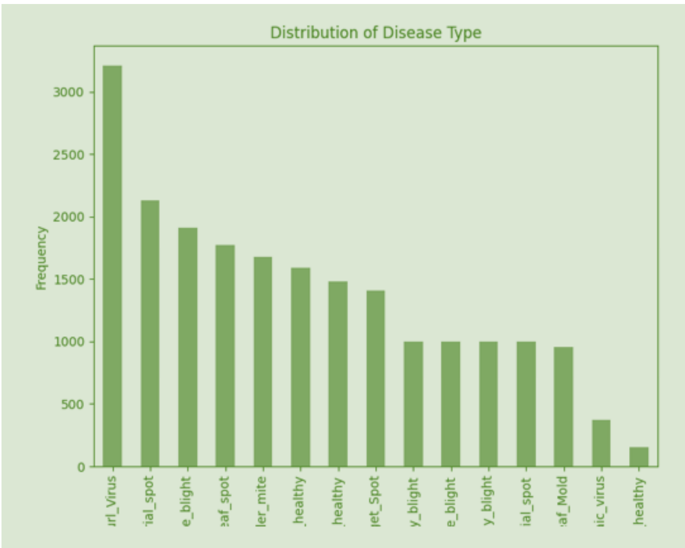

Fig. 4 Disease Type Frequency Distribution

Figure 4 presents the frequency distribution of different disease types, highlighting the prevalence of each category within the dataset. This visualization is essential for identifying class imbalances or anomalies, which can significantly impact model training and the overall effectiveness of disease classification.

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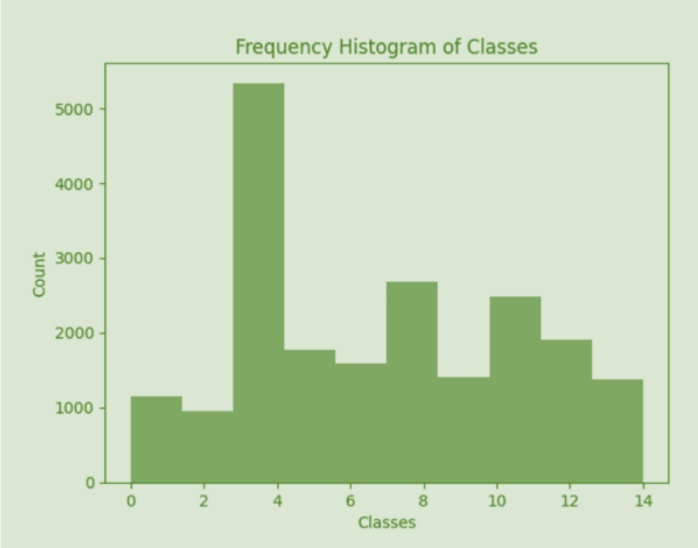

Fig. 5 Class Frequency Distribution Histogram

Figure 5 shows the histogram presented illustrates the frequency distribution of instances across different classes within the dataset. Each bar represents the number of samples associated with a specific class, allowing for an immediate visual assessment of class representation. This visualization is crucial for identifying potential class imbalances, where some classes may have significantly more or fewer instances than others. Such imbalances can introduce bias in model training, leading to poor generalization or underperformance on minority classes. By analyzing the histogram, researchers and practitioners can determine the need for techniques such as resampling, weighting, or augmentation to ensure fair and effective model training.

Fig. 6 Tomato Leaf with Disease Spots

Figure 6 shows a close-up image of a cherry leaf clearly marked with disease spots. These affected areas indicate a specific plant disease, highlighting its impact on the leaf's appearance. This image serves as a valuable reference for identifying disease symptoms in plant health monitoring.

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Fig. 7 Diseased Tomato Leaf Sample

Figure 7 presents another example of a diseased tomato leaf, displaying distinct lesions or patches caused by the disease. This image illustrates the various manifestations of the disease on tomato leaves, providing additional insight into the specific symptoms observed during plant health assessments.

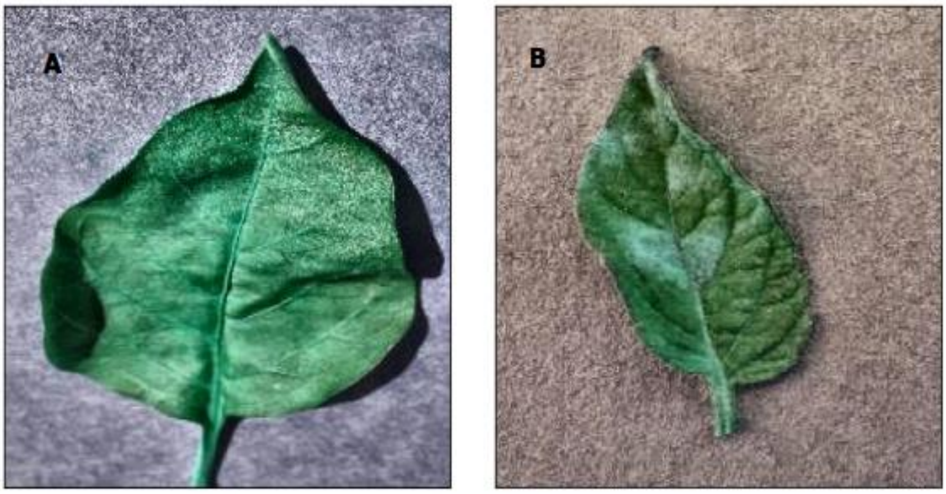

Fig. 8 A) Green Leaf on Gray Background B) Diseased Green Leaf on Brown Background

Figure 8 displays a close-up of a healthy green leaf against a grey background. The vibrant color and detailed natural texture of the leaf stand out sharply against the neutral backdrop, making it useful for studies on plant health or leaf morphology. In contrast, Figures B show a diseased green leaf set against a brown background. This contrasting backdrop accentuates the visible signs of disease, such as discoloration and lesions, clearly illustrating the damage and providing a valuable visual reference for disease diagnosis and analysis.

F. Deep Learning Models Implementation

EfficientNet and MobileNetV2 are cutting-edge deep learning models tailored for robotic plant leaf disease detection in precision agriculture. EfficientNet employs a compound scaling method to optimally balance network depth, width and resolution, enabling it to efficiently extract detailed features from leaf images while maintaining computational efficiency. The model is customized to process grayscale and texture-rich datasets, incorporating squeeze-and-excitation blocks and global average pooling to enhance feature representation and classification accuracy. MobileNetV2, designed for lightweight and resource-constrained environments, uses inverted residuals and linear bottlenecks to effectively capture fine-grained texture details with minimal computational cost. Both models utilize dynamic learning rate schedulers, dropout regularization and adaptive optimizers to improve generalization and robustness, providing accurate and real-time disease diagnosis suitable for deployment in robotic systems.

- EfficientNet

EfficientNet is a group of convolutional neural networks that were made to get high accuracy while also being fast to compute. Traditional CNNs can change the size of the network in any way they like, while EfficientNet uses a compound scaling method that uniformly changes the network's depth, width and input resolution using a set of scaling coefficients that don't change. This method of balanced scaling lets the model expand in a more organised and effective way, which leads to greater performance with fewer parameters and less computing power. EfficientNet models use mobile inverted bottleneck convolution (MBConv) blocks, which are based on MobileNetV2 and squeeze-and-excitation (SE) modules to change the way channel-wise features respond in real time. These design decisions let EfficientNet find a lot of useful and unique properties, which makes it quite good at classifying images in many fields, such as medicine and farming. EfficientNet's optimised architecture gives it the best accuracy possible while being light enough to run on edge devices. This makes it perfect for real-time applications that need both precision and speed.

- MobileNetV2

MobileNetV2 is a lightweight convolutional neural network architecture that works well on mobile and embedded devices. It builds on the original MobileNet by adding inverted residual blocks with linear bottlenecks. These blocks cut down on the amount of parameters and calculations by a lot without losing accuracy. The inverted residual structure adds more channels before applying depthwise convolutions and then projects back to a lower-dimensional space. This keeps important features while making the process more efficient. MobileNetV2 additionally uses depthwise separable convolutions, which break the convolution operation into steps for each spatial and channel, which lowers the cost of computing even further. This architecture is great at picking out little details in images, which makes it perfect for things like real-time image classification and object detection. MobileNetV2 is perfect for use in places where resources are limited, including mobile devices, drones and robotics, since it strikes the right balance between speed and accuracy. This is especially important for applications like plant leaf disease detection, where lightweight models are essential.

G. Performance Evaluation

Study used standard benchmarks like precision, recall, accuracy, F1-score and confusion matrix to measure how well deep learning models work. Recall and precision can tell you how well the model can tell the difference between healthy and damaged leaves, while accuracy can tell you how well it can categorise things in general. The F1-score is a blend of recall and accuracy that gives a full picture of how well the model works. The confusion matrix shows where predictions are wrong and how they are spread out. Cross-valuation approaches assist lower the danger of overfitting and make the performance indicators more reliable by making sure that the model works well on a number of different data sets.

RESULTS AND DISCUSSION

The automated plant disease detection system shows that deep learning models are quite good at identifying the difference between different types of plant diseases. We trained and tested models like MobileNetV2 and EfficientNet on a carefully chosen dataset. To make the leaf images clearer before feature extraction, we used image augmentation techniques like CLAHE. We used key measures including accuracy, precision, recall and F1-score to thoroughly test the model's performance and make sure we had a full picture. MobileNet, which was made for greyscale inputs and included skip connections, did a great job at classifying data, especially when it had a lot of texture. EfficientNet made feature extraction even better by adding dense connection and built-in attention processes, which made classifications even more accurate. The confusion matrix and cross-validation results showed a big drop in misclassifications. This shows how strong these models are and how deep learning might be used to accurately find plant diseases in precision agriculture.

- Accuracy

Accuracy expresses, in relation to the total sample count, the proportion of accurately labelled samples. Although it is a fundamental indicator of general model performance, in imbalanced datasets it can be misleading and calls for complementary measurements like precision and recall.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

- Loss

Loss measures the inaccuracy between true and expected values throughout model development. It directs the optimising process; reduced loss indicates improved model performance. Common loss functions in classification are categorical cross-entropy; in regression, mean squared error.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} \mathcal{y}i.\log(\mathcal{y}i) \quad (2)$$

- Precision

Precision, the ratio of real positive predictions to all positive predictions, tests the model's dependability in positive case classification. In applications where false alarms are expensive, high precision suggests less false positives and is therefore quite important.

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

- Recall

Sensitivity, sometimes known as recall, gauges the true positive to actual positive ratio, therefore demonstrating the model's capacity to find all pertinent cases. In situations when reducing false negatives takes front stage, high recall is absolutely essential.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

TABLE 2 PERFORMANCE EVALUATION OF DEEP LEARNING MODEL

Model	Accuracy	Loss	Precision	Recall
MobileNetV2	0.9738	0.0339	0.9702	0.9613
EfficientNet	0.938	0.1002	0.9234	0.9318

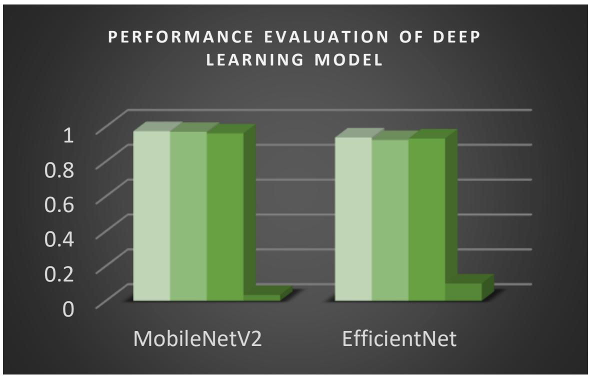

Fig. 9 Performance Evaluation of Proposed DL models

Table 2 shows how well the two deep learning models, MobileNetV2 and EfficientNet, did on important classification measures like accuracy, loss, precision and recall. EfficientNet does quite well, with an accuracy of 93.8% and a loss of 0.1002. Its precision and recall scores are 92.34% and 93.18%, respectively. MobileNet, on the other hand, beats EfficientNet on all metrics, with a greater accuracy of 97.38%, a lower loss of 0.0339 and better precision (97.02%) and recall (96.13%). These results show that MobileNetV2 is better at correctly classifying positive cases and reducing false negatives. In general, the metrics show that MobileNetV2 is the better and more trustworthy model for this task of classification. Figure 9 shows that MobileNetV2 works better than the others.

TABLE 3 COMPARATIVE ANALYSIS OF PROPOSED WORK AND EXISTING WORK

Model	Accuracy	References
MobileNetV2	**0.97**	--
EfficientNet	**0.93**	--
ViT	0.81	[23]
VGG19	0.87	[24]
InceptionV3	0.84	[25]

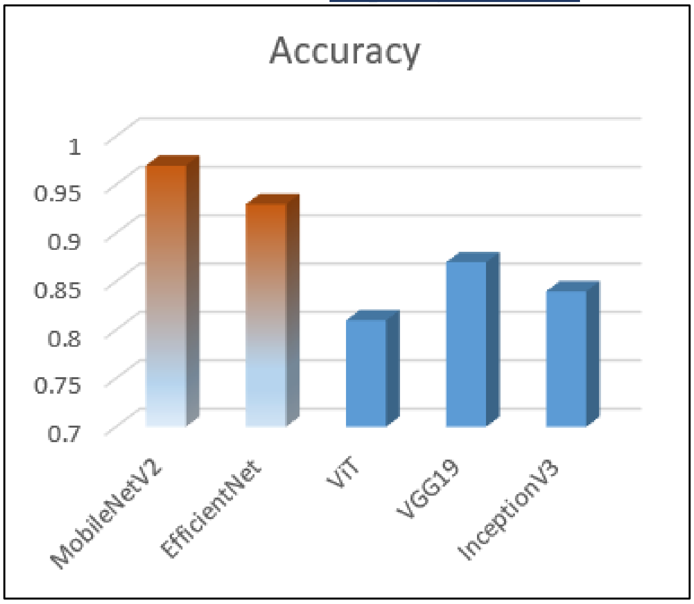

Fig. 10 Comparative Analysis Graph

Table 3 compares different deep learning models that are used in precision agriculture to automatically diagnose plant leaf diseases. The suggested models, MobileNetV2 and EfficientNet, perform better than the others, with accuracies of 97% and 93%, respectively, in correctly recognising plant illnesses. On the other hand, a version of ViT that was employed in prior research had an accuracy of only 81%. Other common models, including VGG19 and InceptionV3, don't work as well either, with accuracies of 87% and 84%, respectively. These results show that the suggested deep learning models, especially MobileNetV2, are very good at finding diseases with high accuracy, which is very important for precision farming. Figure 10 shows this comparison visually, highlighting how much better the suggested models are in diagnosing than standard structures. The better performance of MobileNetV2 is due to its strong capacity to extract features and its higher diagnostic reliability.

CONCLUSION

Precision agriculture relies heavily on automated plant leaf disease diagnosis to enable early detection and improve crop management strategies. This study proposes an advanced deep learning approach using MobileNetV2 and EfficientNet to identify plant diseases across 15 classes—both diseased and healthy—utilizing a large dataset of 20,636 CLAHE-enhanced images. To ensure consistency, all images are preprocessed through grayscale conversion and resized to 256×256 pixels. The Gray-Level Co-occurrence Matrix (GLCM) is used to get texture-based properties, focussing on important ones as energy and homogeneity. We train and test the models using metrics like accuracy, loss, precision and recall. MobileNetV2 has the best performance of all the models, with an accuracy of 97.38%. This is far better than traditional designs like VGG19 (87%) and InceptionV3 (84%). EfficientNet also does a great job of classifying things, because to its thick connections and attention techniques that help it get better at extracting features. The new MobileNetV2 model uses attention approaches to boost feature learning even more, which makes the diagnosis more accurate. This comparison shows that the proposed models, especially MobileNetV2, work better than models that have been reported before, including an earlier version of ViT that only got 81% of the answers right. Overall, the results show that deep learning could be a useful tool for finding plant diseases in precision agriculture that is precise, scalable and dependable.

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