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Enhanced Plant Disease Detection Using Deep Learning Algorithms for Precision Agriculture

Sheradha Jauhari[1], Krishna Kant Agrawal[2]

[1]Research Scholar, School of Computing Science and Engineering, Galgotias University, India
[2]Professor, School of Computing Science and Engineering, Galgotias University, India
Email: sheradha20@gmail.com

Advanced agriculture has the potential to enhance profitability, increase reliability, and optimize the utilization of time and resources. This provides fundamental advantages for farmers and broader societal benefits globally. The identification of plant infections poses challenges for farmers. If the discovered infection is incorrect, there will be a significant loss in crop production and an inefficient assessment of the market. Precision farming also entails the reduction of pesticides and diseases by accurately determining the requisite quantity of pesticides. Precision farming is transitioning from traditional approaches to innovative techniques, resulting in advancements across multiple agricultural industries. The primary objective of this study is to investigate enhanced plant disease detection via deep learning algorithms for precision agriculture. This study is conducted utilizing the Python programming environment. The collection has 24 unique classes, with each folder including photos of either damaged or healthy leaves. This study indicates that Mobile Net is engineered for high accuracy while minimizing the number of parameters and computing complexity, rendering it suitable for real-world applications where performance and efficiency are paramount. Obsolete models such as Dense Net, VGG, or other antiquated architectures may not attain same accuracy because to their greater parameter sizes and less effective feature extraction capabilities. Mobile Net (94%) surpasses the Old Model (90%) by a margin of 4%. This implies that Mobile Net, as a contemporary design built for efficiency and accuracy, delivers superior performance in classification tasks. This study advances precision agriculture by enhancing early detection of plant diseases via deep learning, resulting in more effective crop management and heightened agricultural yield.

Keywords: Plant Disease; Detection; Deep Learning Algorithms; Precision; Agriculture; Accuracy.

1. Introduction

The current development in agricultural evolution is known as precision farming. An increase in agricultural yield can be achieved by the application of science and technology through the use of precision agriculture [1]. Precision farming also entails reducing the quantity of pesticides and illnesses that are used by accurately targeting the amount of pesticides that are required. Precision farming has evolved as an improvement in a variety of agricultural fields as a result of the transition from traditional farming methods to the new approaches associated with precision farming [2, 3]. The techniques of deep learning are utilized in precision agriculture, and the approach that it takes in the field of crop protection is effective enough to boost the growth of crops. The diseased leaf can be identified through the use of image analysis, which could also be used to measure and locate the boundary of the damaged area in order to appropriately identify the object [4]. The diagram that follows provides an illustration of how deep learning can be utilized in precision agriculture.

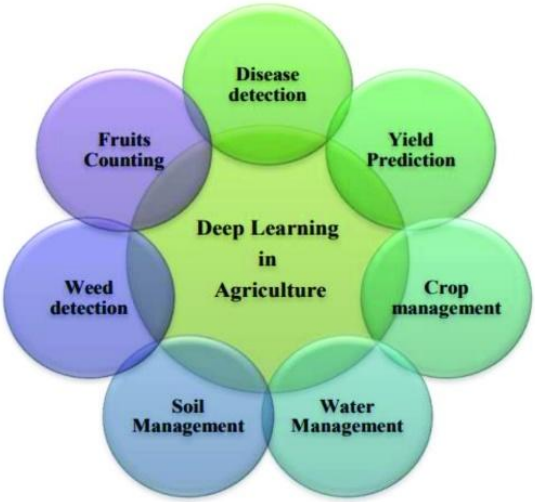

Figure.1 Applications of deep learning in precision agriculture [5]

This research aims to construct an enhanced deep learning system for the accurate early detection of plant diseases to enhance precision agriculture. The research effort intends to accurately identify disease patterns by utilizing high-resolution imagery and advanced deep learning algorithms, thereby facilitating prompt and informed crop treatment decisions for farmers. This strategy seeks to diminish crop losses, lessen reliance on chemical treatments, and enhance overall crop output and quality, thereby fostering more sustainable farming practices. This section elaborates on the relevant literature pertaining to this study in detail.

2. Literature Review

The subsequent table elucidates the previous literature pertinent to the topic of enhanced plant disease detection using deep learning algorithms for precision agriculture in depth.

Table.1 Related works

AUTHORS AND YEAR	METHODOLOGY	FINDINGS
Umamageswari et al., (2022) [6]	The study used convolutional neural networks (CNNs) to classify plant diseases from leaf photos by training the model on a huge dataset of diseased leaf images.	The suggested approach accurately identified and classified leaf diseases, exceeding established methods in precision and efficiency.

Chin et al., (2023) [7]	Drone-based photography and machine learning techniques were utilized to gather and analyse aerial crop photos to detect and classify plant diseases across broad agricultural areas.	The drone-based detection system identified plant diseases across broad areas with great accuracy and efficiency, providing a scalable precision agricultural solution.
Parez et al., (2023) [8]	Focusing on disease-symptom-related visual elements in plant photos with vision transformers improved disease detection accuracy.	For real-time plant disease identification in precision agriculture, the vision transformer-based technique outperformed standard models in detection accuracy and processing efficiency.
Dey et al., (2024) [9]	CNNs were used to evaluate picture data for precision agriculture plant disease identification and classification.	The deep learning-based system accurately detected and classified plant diseases, highlighting its potential to improve early intervention and crop management.
Akintuyi (2024) [10]	Using self-learning algorithms to assess real-time agricultural data, adaptive AI systems optimize farm operations by adapting to changing conditions.	The study demonstrated that self-learning algorithms improve precision agriculture operational efficiency by enabling adaptive decision-making that boosts crop yields and resource management.

Research Gap

Considering progress in deep learning for plant disease identification, comprehension of the subtle distinctions across disease kinds, symptoms, and their disparate effects on crop yield and quality remains inadequate. Contemporary models frequently emphasize the recognition of observable symptoms but are deficient in distinguishing between diseases exhibiting analogous symptoms or evaluating their impacts on crop yield [11,12]. This gap underscores the necessity for a more holistic, symptom-aware deep learning methodology that not only properly identifies diseases but also offers insights into disease severity and probable yield loss, facilitating more informed decision-making in precision agriculture.

3. Methodology

This study utilizes a CNN model to categorize plant illnesses using a structured collection of damaged and healthy leaf photos from various plant types. The subsequent parts delineate the technique, encompassing data pre-processing, model construction, training and optimization, and performance evaluation.

Dataset Structure and Preparation

The collection contains 24 folders of photos grouped by plant species and sickness or health. Each folder contains photos of disease signs or healthy leaf traits, organized by Plant_Name___Disease Name. Examples are Apple___Apple_scab for Apple Scab and Tomato healthy for healthy tomato leaves. This clear arrangement lets the CNN model train from labelled examples to detect healthy and unhealthy leaves for each plant kind. Each image is scaled to 128x128 or 224x224 pixels for CNN processing to ensure consistency. Standardizing pictures is necessary for stable model training. Normalizing pixel values to a 0-1 range speeds CNN model convergence by standardizing scale and reducing computation.

Data Augmentation and Class Balancing

When classes have different numbers of photos, data augmentation is used to improve model generalizability. Image diversity from rotation, flipping, brightness modification, and zooming lets the model learn from real-world variables like lighting and viewing angles. This phase prevents overfitting by preventing the model from becoming overly tuned to certain patterns in a small dataset. Class balancing is achieved by oversampling underrepresented classes or enhancing photos to provide a more evenly distributed dataset for better training generalization.

CNN Model Architecture

CNN architecture captures and classifies complex plant leaf visual characteristics. Early convolutional layers identify edges and textures, while deeper layers catch complicated disease-specific patterns. The architecture sequences convolutional and pooling layers to condense the image into useful features while lowering computing effort. Pooling layers down sample feature maps, keeping critical information while reducing spatial dimensions, saving time and computational cost. After numerous convolutional and pooling layers, fully linked layers' map features to 24 class labels. The final layer arrangement reads extracted patterns and predicts plant kinds and diseases.

Training and Optimization

Prediction error is calculated by comparing projected outputs to actual labels in the CNN model trained with a backpropagation technique and cross-entropy loss function. Gradient descent optimization modifies layer weights to minimize error over iterations. Performance is improved by tuning learning rate, batch size, and epochs. The fully connected layers use dropout regularization to enforce redundancy in the network's learning routes and prevent overfitting by randomly deactivating a fraction of neurons during training.

Evaluation and Model Validation

This stratified strategy divides data into training, validation, and testing sets to ensure equitable class representation for model evaluation. To avoid overfitting, validation accuracy is evaluated using early stopping criteria to cease training when improvements stagnate. The model's accuracy, sensitivity, specificity, and F1 score are measured on the test set to evaluate its classification capacity across plant diseases.

This approach trains for plant disease identification using a well-structured dataset, data augmentation, and a properly built CNN architecture. In precision agriculture, the CNN model tuned for various visual feature extraction can generalize to unseen data for early identification and disease management. This research's methodology flowchart is illustrated below.

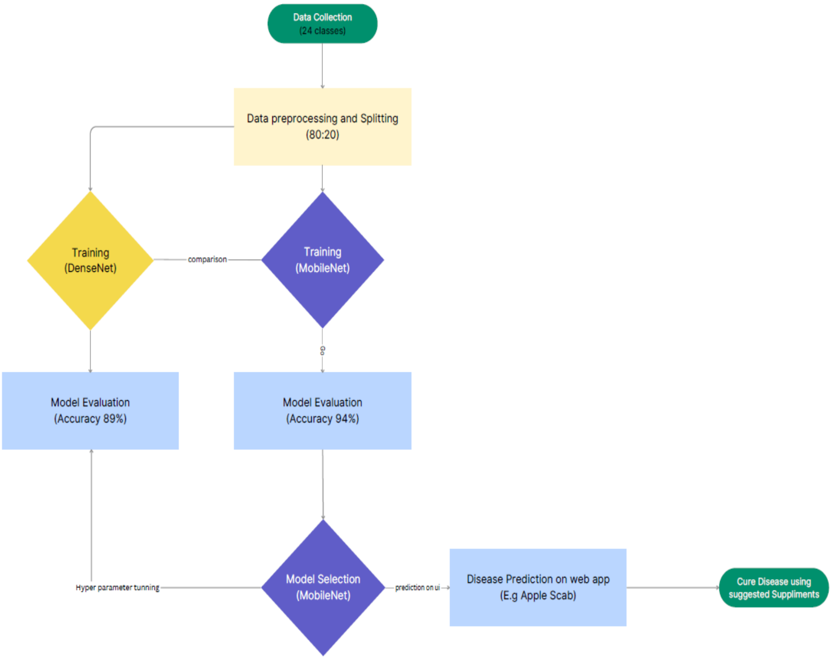

Figure.2 Step by step implementation of the proposed methodology

4. Results and Discussions

The dataset used for plant disease detection consists of 5,648 images divided into 24 classes, each representing a specific plant disease or a healthy state for plants such as apples, corn, potatoes, and tomatoes. During training, the images are processed in batches of 20, with each image standardized to a size of 224x224 pixels and formatted in RGB colour channels. Each batch is labelled by class numbers, as seen in the provided example of class labels (e.g., [11, 5, 12, 8]), which allow the model to learn associations between images and their respective disease or health status. Of the total images, 226 are allocated for training and 57 for validation, enabling the model to evaluate its performance on unseen data after each epoch to promote better generalization and reduce overfitting. The loss and accuracy over epochs are illustrated in figure below.

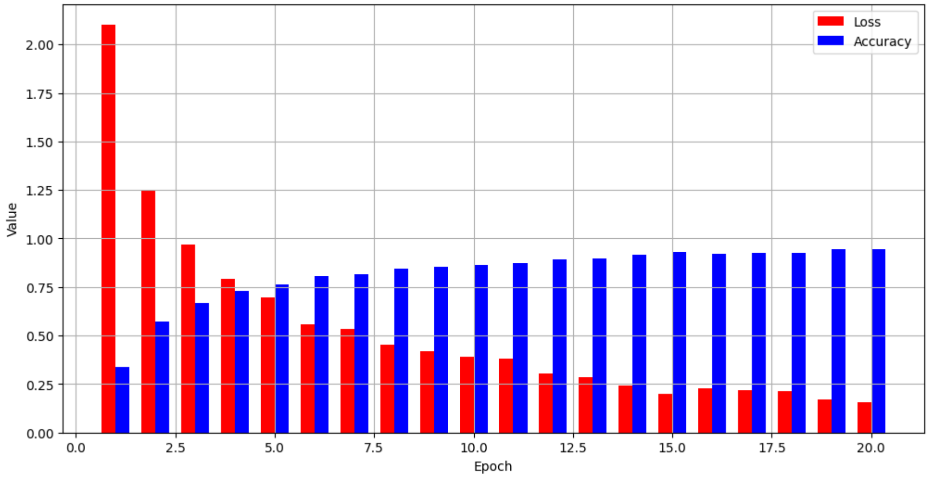

Figure.3 Loss and Accuracy over Epochs

Mostly influenced by MobileNetV2, the neural network's architecture has a features and classifier portion for plant disease classification. Multiple convolutional layers handle input pictures using batch normalization and the ReLU6 activation function to induce non-linearity and stabilize training in the features portion. A Conv2dNormActivation in the first layer reduces an RGB image with a 3x3 kernel to 32 channels, halving its size. An Inverted Residual layer (a core MobileNetV2 block) minimizes computation by depth wise convolution Ing each input channel, then pointwise convolution to compress them from 32 to 16. Another Inverted Residual layer expands channels using 1x1 convolution, depth wise convolution, batch normalization, and ReLU6 activation to improve feature extraction. The classifier section includes a Dropout layer to prevent overfitting by randomly deactivating neurons during training and a Linear layer that takes 1280 input features from the feature section and generates 25 output features for classification, allowing the network to predict 25 plant disease and healthy classes.

Architectural design and intended use cases distinguish Dense Net and Mobile Net, particularly in resource efficiency and performance. Dense Net uses max pooling for down sampling and densely connected layers to improve gradient flow and feature reuse, improving training on smaller datasets but increasing computational burden and memory usage as model depth increases. Mobile Net, on the other hand, uses depth wise separable convolutions to reduce parameters and computational costs while maintaining efficiency through adjustable width and resolution multipliers, making it adaptable to hardware constraints. Both architectures use pooling layers for down sampling, but Mobile Net's convolutional structure is more efficient and versatile for low-resource environments, making it the best choice for plant disease detection because it balances speed, accuracy, and computational demands. Mobile Net's architecture and optimizations improve its performance in modern jobs, confirming its prominence in modern applications over Dense Net.

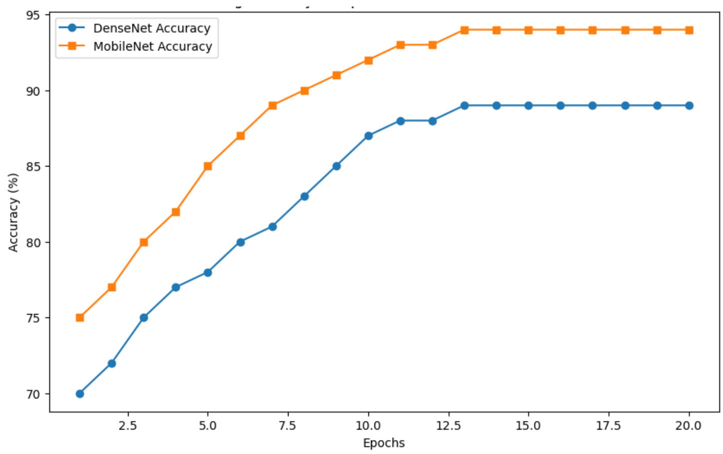

Figure.4 Training Accuracy Comparison: Dense Net and Mobile Net

Mobile Net's accuracy is higher because depth wise separable convolutions and adaptive scaling algorithms allow it to capture complicated dataset patterns without overfitting. Dense Net, however resilient, may struggle with high-resolution photos because to its more complex architecture, which might slow data processing. In situations requiring precision and computing efficiency, Mobile Net excels.

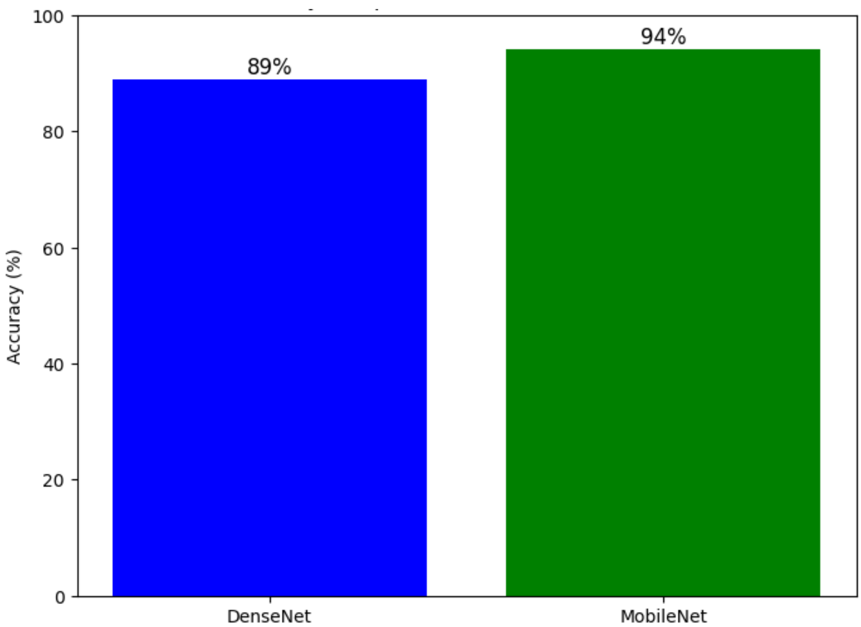

Figure.5 Accuracy Comparison: Dense Net Vs Mobile Net

Mobile Net, with 3.50 million parameters, shows that a modern architecture can outperform Dense Net, which has 7.98 million parameters, with fewer resources. This efficiency makes Mobile Net better for resource-constrained applications like mobile devices, while Dense Net is better for workloads with plenty of computational capacity and less speed.

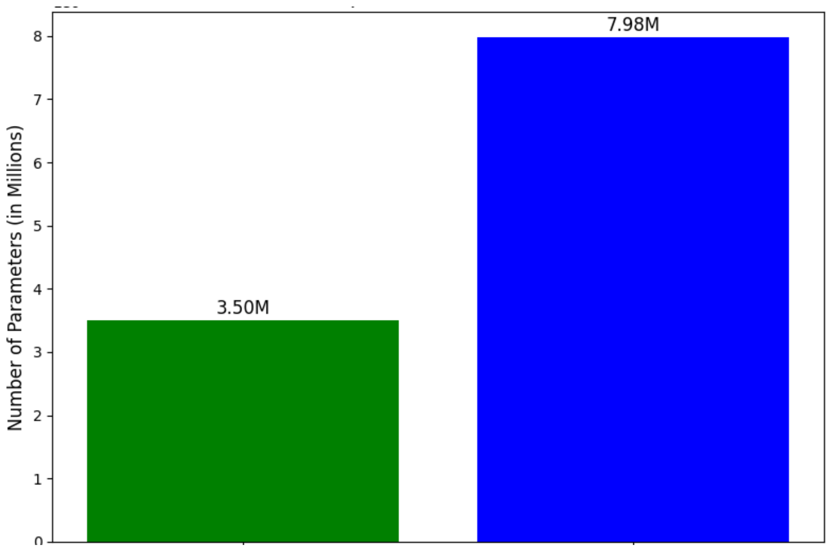

Figure.6 Parameter Comparison: Dense Net Vs Mobile Net

Mobile Net's faster inference time of 0.0991 seconds compared to Dense Net's 0.3019 seconds makes it suitable for real-time applications like plant disease detection on mobile or edge devices that require immediate predictions. Mobile Net's lower model size and fewer parameters reduce computational cost and speed up processing.

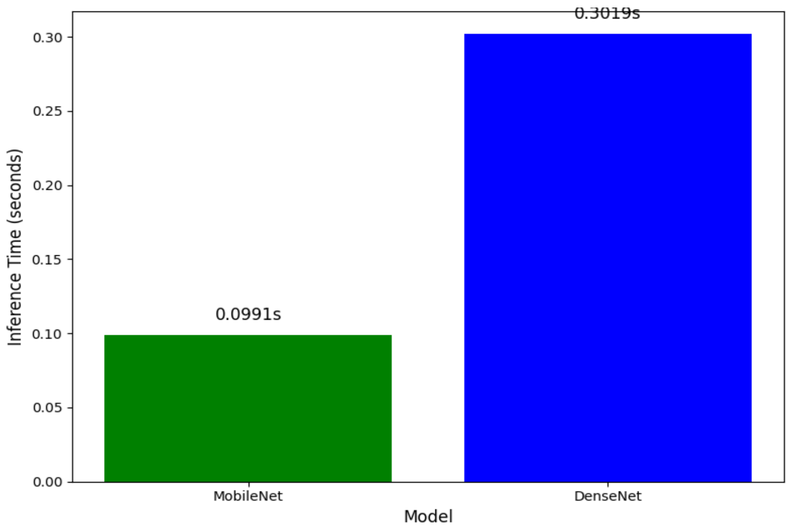

Figure.7 Inference Speed Comparison: Dense Net Vs Mobile Net

Mobile Net's accuracy of 94% surpasses Dense Net's 89%, indicating its superior performance for the plant disease prediction task. Furthermore, with only 3.5 million parameters compared to Dense Net's 7.98 million, Mobile Net demonstrates a more efficient balance between model size and accuracy, highlighting its effectiveness in maintaining high performance while minimizing complexity.

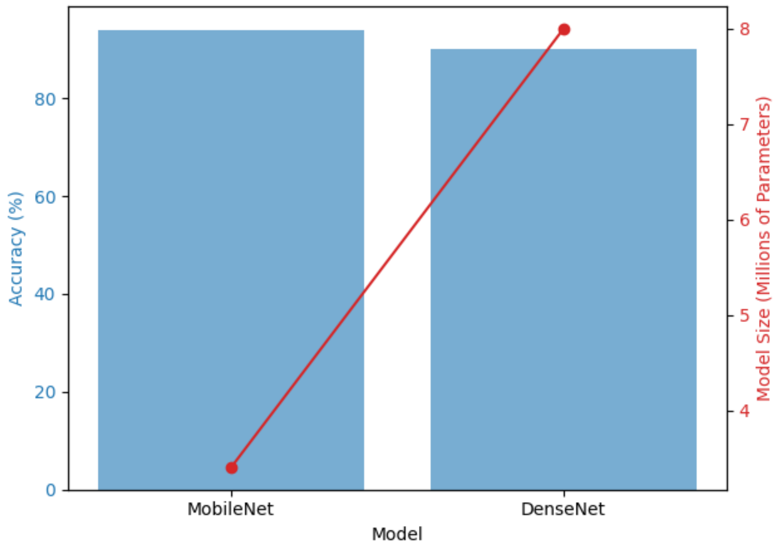

Figure.8 Accuracy Vs Model Size Comparison

Mobile Net demonstrates superior efficiency in both model size and inference time while achieving an impressive accuracy of 94%, making it a standout choice for applications requiring rapid processing and minimal resource consumption. In contrast, Dense Net, with its bulkier architecture, achieves a lower accuracy of 89%, reflecting its older design principles that prioritize accuracy over computational efficiency. Additionally, Reset follows with an accuracy of 87%, indicating that while it offers benefits in certain deep learning tasks, it still falls short compared to Mobile Net's optimized performance. Efficient Net, another modern architecture, achieves a commendable accuracy of 93%, showcasing its effectiveness but still not surpassing Mobile Net in efficiency and speed. Overall, Mobile Net's combination of high accuracy and low computational demand makes it an ideal candidate for deployment in environments where resources are limited and timely predictions are essential, particularly in the context of real-time applications like plant disease detection.

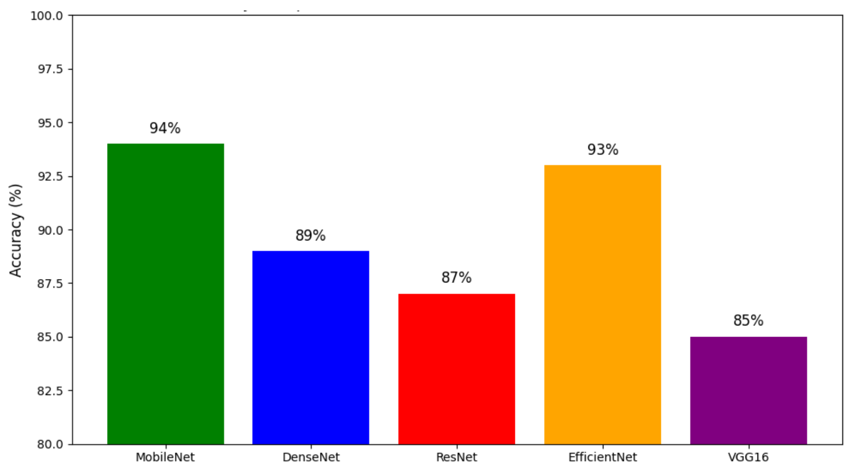

Figure.9 Accuracy comparison of different models on plant disease dataset

Mobile Net, with an impressive accuracy of 94%, outperforms older models, which generally achieve around 90%, by a notable 4% margin. This enhancement indicates that Mobile Net, as a modern architecture, is specifically optimized for both efficiency and accuracy, resulting in superior classification performance. Its design focuses on achieving high accuracy while maintaining a compact number of parameters and lower computational complexity, making it exceptionally suited for real-world applications where efficient performance is crucial. In contrast, older models like Dense Net and VGG often struggle to reach the same accuracy levels due to their larger parameter sizes and less efficient feature extraction methods, which can lead to increased computational demands and slower inference times. Therefore, Mobile Net represents a significant advancement in the quest for effective and efficient deep learning solutions.

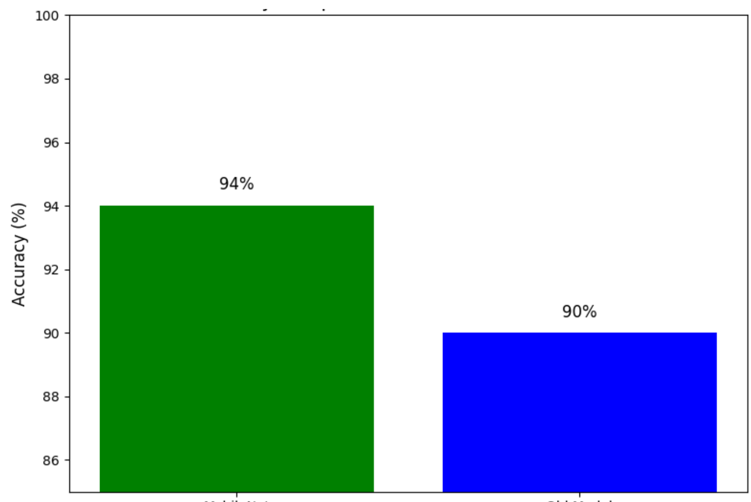

Figure.10 Accuracy Comparison: Mobil Net Vs Old Model

5. Conclusion

In conclusion, Mobile Net outperforms past models in accuracy and efficiency, obtaining 94% compared to 90% in previous architectures. For real-world applications that require efficiency, its design promotes fewer parameters and reduced computational complexity. Modern optimizations make Mobile Net a top classifier, especially in resource-constrained applications.

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