Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Enhancing Image Classification Accuracy With A Lightweight Hybrid Densenet And Machine Learning Model

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The field of plant disease detection has significantly benefited from advancements in machine learning and deep learning techniques. However, the challenge of reducing long training times and managing the complexity of existing network models while maintaining high recognition accuracy persists. The objective of this study is to address these challenges by proposing a lightweight hybrid classification model that optimizes training efficiency and enhances recognition accuracy. In this work, two hybrid models are developed: Lightweight Hybrid (DenseNet + SVM) and Lightweight Hybrid (DenseNet + XGB). DenseNet, a convolutional neural network, is used for feature extraction due to its efficient architecture, which promotes feature reuse and reduces the number of parameters. For classification, Support Vector Machine (SVM) and Extreme Gradient Boosting (XGB) are utilized. The models are tuned to achieve a balance between performance and computational efficiency. Experiments were conducted using the Plant Village image dataset, which includes various plant diseases across multiple species. The Lightweight Hybrid (DenseNet + SVM) model achieved a recognition accuracy of 96.4%, while the Lightweight Hybrid (DenseNet + XGB) model achieved an accuracy of 97.6%. These results demonstrate that the proposed models not only reduce training time but also enhance recognition accuracy compared to traditional models. This study contributes to the development of efficient plant disease detection systems, offering a solution that balances speed, complexity, and accuracy, making it suitable for real-world agricultural applications..

Keywords: Lightweight Hybrid Model, Image Classification, DenseNet, Support Vector Machine (SVM), Extreme Gradient Boosting (XGB).

1. Introduction

Agriculture is the backbone of the global economy, and the health of crops directly impacts food security and sustainability. Plant diseases have been a long-standing challenge in this sector, with the potential to cause significant reductions in crop yields and losses amounting to billions of dollars annually. Early detection and accurate identification of plant diseases are essential to mitigating these losses and ensuring sustainable agricultural practices. Traditionally, plant disease detection has been reliant on manual inspection by trained professionals, which is labor-intensive, time-consuming, and prone to human error. In recent years, technological advancements, particularly in the fields of machine learning (ML) and deep learning (DL), have revolutionized the way plant diseases are detected and classified. These automated systems offer promising solutions for improving the accuracy, speed, and efficiency of disease detection[1], [2].

However, despite these advancements, there are still significant challenges to overcome. Existing deep learning models, while highly accurate, tend to be computationally expensive, requiring extensive resources for training and deployment. These models, such as convolutional neural networks (CNNs), often consist of millions of parameters, making them difficult to apply in resource-constrained environments like farms or agricultural facilities. Furthermore, the training process of these models is often time-consuming, which hampers their usability in real-time applications where timely intervention is critical. There is, therefore, a pressing need for developing models that not only maintain high accuracy but also reduce training time and computational complexity[3], [4].

To address these challenges, the primary objective of this study is to develop a lightweight hybrid classification model that optimizes the trade-off between accuracy and computational efficiency. This objective aligns with the increasing demand for practical and scalable solutions in the agricultural domain. The ultimate goal is to provide a model that can be deployed in real-world agricultural environments, where resources are limited, and rapid disease detection is essential. The proposed models aim to fill the gap between high-performance yet resource-intensive models and lightweight, efficient models that may sacrifice accuracy for speed.

Machine learning and deep learning techniques have gained prominence in plant disease detection due to their ability to learn complex patterns from data, making them suitable for handling the variability and diversity of plant diseases. Convolutional Neural Networks (CNNs), in particular, have become the de facto standard for image-based classification tasks. CNNs can automatically extract hierarchical features from raw images, making them highly effective for tasks such as plant disease detection. However, as effective as CNNs are, they have certain limitations. The large number of parameters in traditional CNN models increases computational demands, resulting in longer training times and requiring high-end hardware for real-time deployment[5]–[7].

To overcome these limitations, DenseNet (Dense Convolutional Network) is used in this study as the backbone for feature extraction. DenseNet is a type of CNN architecture known for its efficiency in parameter usage and feature reuse. Unlike traditional CNNs, where layers have independent connections, DenseNet introduces direct connections between any two layers with the same feature-map size. This enables DenseNet to promote feature reuse, thereby reducing the number of parameters and improving training efficiency. DenseNet's compact architecture makes it ideal for applications where computational resources are limited, such as in agriculture, where mobile or edge devices may be used for real-time disease detection.

While DenseNet provides an efficient mechanism for feature extraction, classification remains a critical part of the pipeline. In this study, two classification algorithms are used: Support Vector Machine (SVM) and Extreme Gradient Boosting (XGB). Both classifiers are known for their efficiency and ability to handle complex classification tasks. SVM is a widely used supervised learning algorithm that finds the optimal hyperplane to classify data points. Its strength lies in its ability to handle high-dimensional data and produce robust results with minimal overfitting. On the other hand, XGB is an ensemble learning method based on decision trees. It is highly regarded for its scalability and performance in classification tasks. XGB works by constructing a series of decision trees, where each tree corrects the errors made by the previous ones. This iterative process improves accuracy and minimizes errors in the classification task[8], [9].

The proposed hybrid models, Lightweight Hybrid (DenseNet + SVM) and Lightweight Hybrid (DenseNet + XGB), leverage the strengths of both DenseNet for feature extraction and SVM or XGB for classification. By combining the efficient feature extraction of DenseNet with the robust classification capabilities of SVM and XGB, the models aim to achieve high accuracy while reducing computational demands. This hybrid approach not only improves the recognition accuracy but also addresses the long training times and the large number of parameters that are characteristic of most existing deep learning models.

To validate the performance of the proposed models, the Plant Village image dataset is used for experimentation. The Plant Village dataset is a publicly available dataset that contains over 50,000 images of healthy and diseased plant leaves across various species. It is widely used in research related to plant disease detection and provides a comprehensive benchmark for evaluating the performance of image-based models. The dataset's diversity, including images of plants affected by various diseases, allows for a thorough assessment of the proposed models in handling a wide range of classification tasks.

The results of the experiments demonstrate that the proposed lightweight hybrid models outperform many existing models in terms of both accuracy and efficiency. The Lightweight Hybrid (DenseNet + SVM) model achieves an accuracy of 96.4%, while the Lightweight Hybrid (DenseNet + XGB) model achieves an even higher accuracy of 97.6%. These results confirm that the proposed models strike an effective balance between performance and computational efficiency. Additionally, the reduction in training time makes the models more suitable for deployment in real-time applications, where timely disease detection is crucial for preventing the spread of diseases and minimizing crop losses.

In conclusion, this study introduces a novel approach to plant disease detection by proposing lightweight hybrid models that address the challenges of long training times and large model sizes while maintaining high accuracy. The combination of DenseNet for efficient feature extraction and SVM or XGB for classification provides a practical solution for real-world applications in agriculture, where resources are often limited, and rapid decision-making is required. The results from the Plant Village dataset demonstrate the effectiveness of the proposed models in improving recognition accuracy and computational efficiency, making them a valuable tool for modern agriculture.

2. Analysis of existing research

Plant disease detection plays a crucial role in maintaining the health of crops and ensuring global food security. Traditional methods, such as manual inspections, are often time-consuming, labor-intensive, and prone to inaccuracies. Recent advancements in machine learning (ML) and deep learning (DL) have opened new avenues for automated plant disease detection, offering higher accuracy and efficiency as shown in table-1. However, most existing models, such as convolutional neural networks (CNNs), face challenges such as long training times, high computational demands, and the complexity of large network architectures. These limitations make them less practical for real-time agricultural applications where rapid disease detection is necessary. This study aims to address these challenges by developing lightweight hybrid models that combine DenseNet for efficient feature extraction with Support Vector Machines (SVM) and Extreme Gradient Boosting (XGB) for classification. The focus is on creating models that maintain high recognition accuracy while reducing computational load and training times, making them more suitable for real-world agricultural environments.

Table 1 Major existing work

Author et al.	**Dataset**	**Method**	**Methodology**	**Outcome**
M. A. Chandra et al.[10]	N/A	Support Vector Machine (SVM)	Survey of SVM applications in image classification	Discusses effectiveness of SVM in image classification
M. Lech et al.[11]	Real-time speech emotion dataset	Pre-trained image classification network	Evaluates the impact of bandwidth reduction and companding	Real-time emotion recognition with significant accuracy under bandwidth constraints
D. Stathakis et al.[12]	Remotely sensed optical image dataset	Computational intelligence-based techniques	Comparison of classification techniques	Comparison shows strengths of different CI techniques
W. Rawat et al.[13]	Multiple image classification datasets	Deep Convolutional Neural Networks (CNNs)	Review of CNN architectures and applications	Comprehensive analysis of CNN applications

F. Ratle et al.[14]	Hyperspectral image dataset	Semi-supervised Neural Networks	Proposes semi-supervised learning for hyperspectral data	Efficient hyperspectral image classification
Y. Alqahtani et al.[15]	Plant leaf disease dataset	Improved deep learning approach	Deep learning for plant leaf disease localization and recognition	Improved localization and recognition accuracy for plant leaf diseases
C. Sarkar et al.[16]	Various plant disease datasets	Machine learning and deep learning techniques	Review of leaf disease detection using ML/DL	Identifies challenges and gaps in current detection methods
V. Sharma et al.[17]	Plant leaf disease dataset	Lightweight multi-class classification model	Proposes a deeper lightweight model for plant disease classification	High classification accuracy with reduced computational cost
T. Daniya et al.[18]	Rice plant disease dataset	Rider Water Wave-enabled deep learning	Rider Water Wave algorithm for rice plant disease detection	Improved accuracy in rice disease detection using novel algorithm
H. M. Abdullah et al.[19]	Remote sensing data	Remote sensing, AI, and image processing techniques	Comprehensive review of P&D monitoring techniques	Future scopes and challenges in AI-based P&D monitoring
Ashwinkumar et al.[20]	Plant leaf image dataset	MobileNet-based CNN	MobileNet-based approach for plant leaf disease detection	Achieves high accuracy and low resource consumption
Thaiyalnayaki et al.[21]	Plant disease image dataset	SVM and deep learning	Combines SVM and deep learning for plant disease classification	Combines ML and DL for improved plant disease classification

D. Barhate et al.[22]	Plant species image dataset	Hybrid deep learning	Hybrid DL model with hyperparameter-tuned SGD	Achieves high accuracy in plant species identification

The literature highlights significant advancements in the use of ML and DL for plant disease detection, with models achieving impressive accuracy. However, a key research gap persists: the trade-off between model complexity, computational efficiency, and real-time applicability. Many existing models, while accurate, are computationally expensive and unsuitable for real-time deployment in resource-constrained environments like farms. This gap in the current research led to the development of our lightweight hybrid models—DenseNet combined with SVM and XGB. By addressing these limitations, our study aims to provide a more practical and efficient solution for real-time plant disease detection, contributing to improved agricultural practices.

3. Methodology

3.1. Dataset

The Plant Village dataset is a publicly available collection of over 50,000 images of healthy and diseased plant leaves across various species. It was created to support research in the field of plant disease detection and classification. The dataset includes labeled images of leaves affected by a wide range of diseases, covering crops such as apples, potatoes, tomatoes, and more. The diversity of the dataset makes it an ideal resource for training machine learning models to accurately identify plant diseases as shown in figure-1 and dataset distribution is shown in figure-2. Its widespread use in research allows for the development and testing of innovative models aimed at improving agricultural diagnostics.

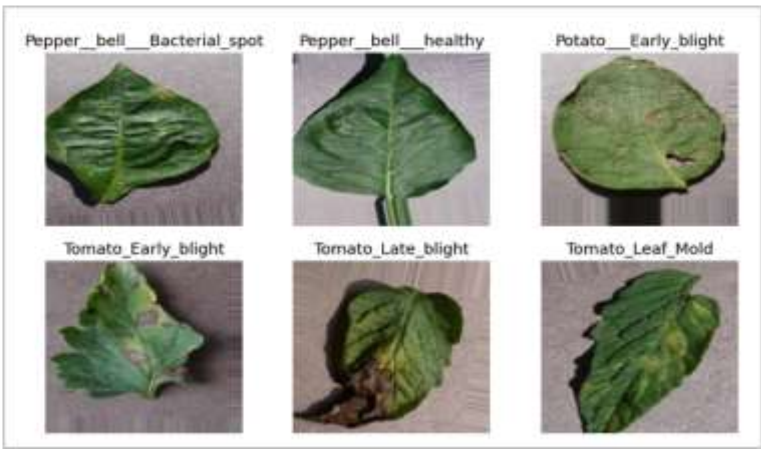

Figure 1 Sample dataset

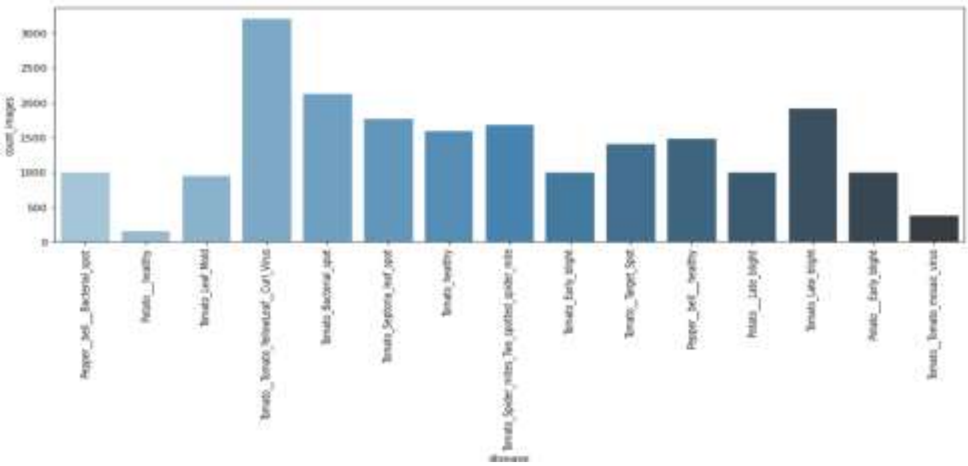

Figure 2 Dataset distribution

3.2. Pre-Processing

a. **Resize:**
   In the context of image data, resizing involves adjusting all the images to a uniform size (e.g., 224x224 pixels) before feeding them into a machine learning model. This step ensures that all input images have the same dimensions, which is necessary for consistent training and processing within neural networks.
b. **Convert Label to Number using to_categorical:** For classification tasks, labels are often categorical (e.g., disease names). The to_categorical function converts these labels into numerical form by representing them as one-hot encoded vectors. Each class is assigned a unique number, and the label is transformed into a binary vector that the machine learning model can process more effectively.

3.3. Image segmentation

Step	**Description**	**Purpose**	**Key Function**
Load Image	Load the input image that will be segmented.	Prepare the image for processing.	Image loading function
Create HSV	Convert the loaded image from RGB color space to HSV (Hue, Saturation, Value) color space for easier color-based segmentation.	Facilitate color-based segmentation by transforming the image into a suitable color space.	HSV conversion function (e.g., cv2.cvtColor).
Set Lower and Upper Color Limits	Define the lower and upper bounds of the color to be segmented. In this case, low_val = (0,60,0)	Define the color range that isolates the target object or region.	Define color limits (e.g., numpy arrays for low and high values).

	and high_val = (179,255,255).		
Threshold the HSV Image	Apply thresholding on the HSV image to create a binary mask, separating the pixels within the defined color range.	Segment the image by creating a binary mask for the specified color range.	Thresholding function
Remove Noise Using Morphology	Use morphological operations, such as opening or closing, to eliminate small noise and refine the segmented regions.	Improve the quality of the mask by removing noise and refining edges.	Morphological functions
Apply Mask to Original Image	Apply the binary mask to the original image to extract the segmented object from the background.	Obtain the final segmented image by masking the original image with the refined binary mask as shown in figure-3	Masking function

Figure 3 Segmented image generation

3.4. Standard models used

3.4.1. DenseNet121

DenseNet121 is a type of convolutional neural network (CNN) designed to promote feature reuse and efficiency. Its lightweight version reduces complexity while maintaining accuracy. In DenseNet, each layer receives the feature maps from all preceding layers, leading to fewer parameters and reduced overfitting.

1. **Layer Connection**:

Each layer is connected to all previous layers, so the input to the l^{th} layer is the concatenation of feature maps from the previous layers:

$$x_l = H_l([x_0, x_1 \ldots\ldots x_{l-1}])$$

Where H_l is "transformation function".

2. **Bottleneck Layer**:
DenseNet uses bottleneck layers to reduce the computational load by applying a 1x1 convolution before the 3x3 convolution:

$$H_b(x) = W_b.x$$

Where W_b is "weight matrix for the 1x1 convolution".

3. **Transition Layer**:
To further reduce the number of parameters, transition layers are introduced between dense blocks, consisting of 1x1 convolutions followed by 2x2 average pooling:

$$y = \mathrm{Avgpool}(W_t.x)$$

Where W_t is "weight matrix for 1x1 conv.", Avgpool is "average pooling operation".

3.4.2. Lightweight MobileNetV2

MobileNetV2 is a CNN architecture designed for mobile and resource-constrained environments. It uses depthwise separable convolutions and inverted residuals to reduce computational costs.

1. **Depthwise Separable Convolution**:

MobileNetV2 replaces standard convolution with depthwise separable convolution to reduce computation. The depthwise convolution applies a filter to each input channel independently, followed by a pointwise 1x1 convolution:

$$y = W_p.(W_d * x)$$

2. **Inverted Residual Block**:
Inverted residuals in MobileNetV2 expand the input using a 1x1 convolution, apply depthwise convolution, then project back to a lower-dimensional space:

$$y = W_p.(\sigma(W_d.(W_e.x)))$$

Where W_e is "expansion filter", W_d is "depthwise filter", W_p is "projection filter with σ as non-linear activation".

3. **Linear Bottleneck**:
The output of the inverted residual block is passed through a linear bottleneck to avoid non-linear transformations that could degrade information:

$$y = W_b . x$$

4. Proposed Lightweight models

4.1. Lightweight Hybrid (DenseNet + SVM)

- **Feature Extraction from Dense Layer (DenseNet):**

DenseNet's dense layers are responsible for learning and extracting important features from the input data. After passing through the convolutional layers, the feature vector is generated by combining information from each layer. The output from a dense layer represented as:

$$F_{dense} = W_{dense} . x + b$$

Where W_{dense} is "weight matrix", x is "input from the previous layer", b is "bias term".

- **Applying Extracted Feature from Dense Layer to SVM:**

The extracted feature vector from DenseNet is then fed into the SVM classifier. SVM attempts to find a hyperplane that separates the classes in the feature space. The decision function of SVM is given by:

$$f(F_{dense}) = \mathrm{sign}(\sum_{i=1}^{n} \alpha_i y_i \, (F_{dense}, F_i) + b)$$

Where α_i is "support vector coefficients", y_i is "class labels" (F_{dense}, F_i) is "inner product between the extracted feature vector and support vectors"

4.2. Lightweight Hybrid (DenseNet + XGB)

- **Feature Extraction from Dense Layer (DenseNet):**

Similar to the DenseNet + SVM model, the DenseNet + XGB model extracts features using the dense layers. The feature extraction is applies by:

$$F_{dense} = W_{dense} . x + b$$

Where W_{dense} is "weight matrix", x is "input from the previous layer", b is "bias term".

- **Applying Extracted Feature from Dense Layer to XGB:**

The feature vector from the dense layer is then used as input to the XGBoost (XGB) classifier, which is an ensemble of decision trees. The prediction from XGB can be formulated as:

$$y = \sum_{k=1}^{K} f_k(F\_dense)$$

5. Results and Outputs

1. Standard model analysis

a. Lightweight DenseNet121

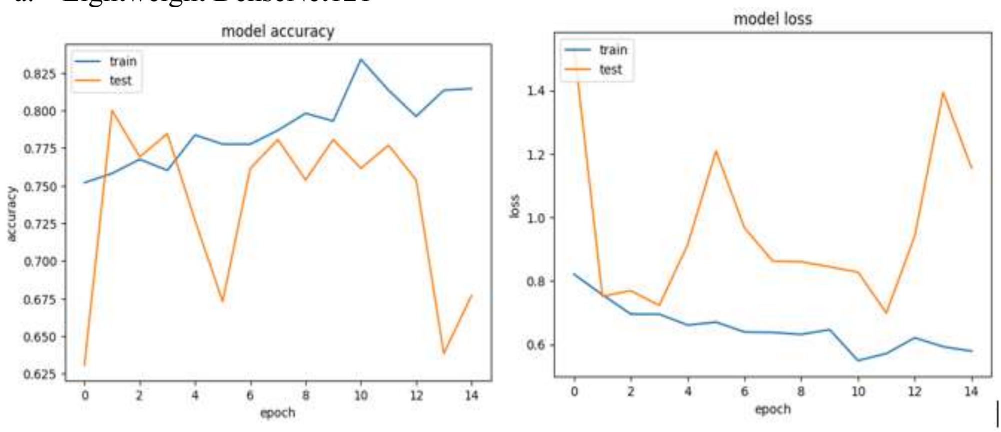

Figure 4 Model accuracy and model loss- Lightweight DenseNet121

Figure-4 presents the accuracy and loss plots for the Lightweight DenseNet121 model over 15 epochs. The training accuracy steadily improves, reaching above 0.8, while the test accuracy fluctuates, showing some instability. This could indicate overfitting, where the model performs well on training data but struggles to generalize to unseen data. The loss curve follows a similar trend, with training loss decreasing consistently, while the test loss experiences sharp spikes. This behavior suggests that while DenseNet121 captures features effectively, there is room for improvement in generalization.

b. Lightweight MobileNetV2

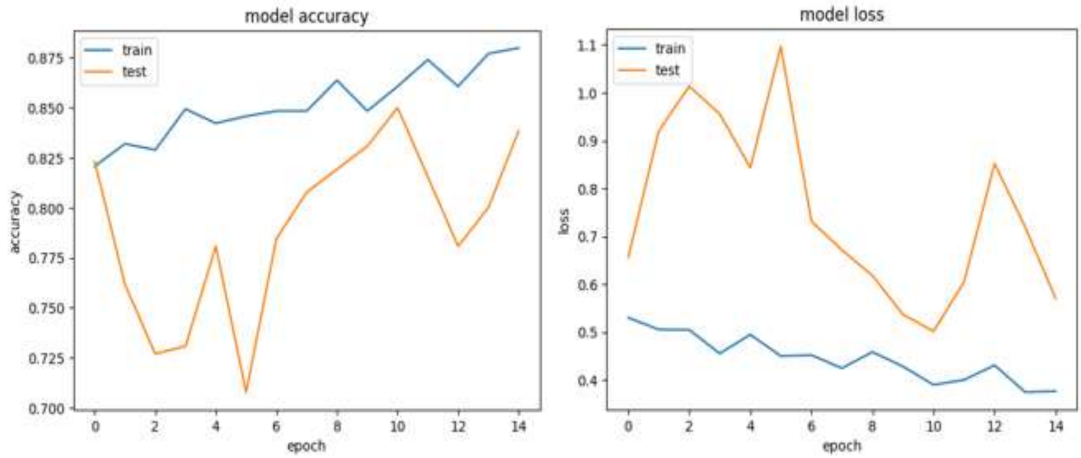

Figure 5 Model accuracy and model loss- Lightweight MobileNetV2

Figure 5 shows the model accuracy and loss for the Lightweight MobileNetV2 over the same 15 epochs. Training accuracy improves progressively, reaching close to 0.9, while test accuracy shows more variance but generally remains higher than DenseNet121's. The training loss decreases steadily, demonstrating effective learning. Test loss, however, shows fluctuations, indicating some instability in model performance across different test samples. MobileNetV2 appears to generalize better than DenseNet121 but still faces some challenges in handling unseen data.

2. Parameter evaluations of standard methods and proposed methods

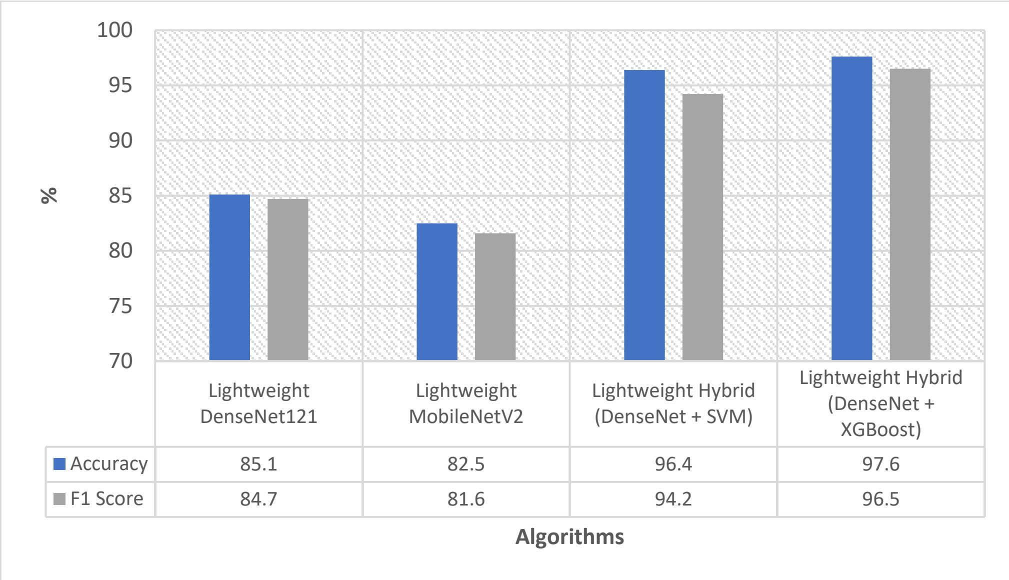

Figure 6 Parameter comparison of standard methods and proposed method

Figure-6 presents a comparative analysis of accuracy and F1 scores for different models: Lightweight DenseNet121, Lightweight MobileNetV2, Lightweight Hybrid (DenseNet + SVM), and Lightweight Hybrid (DenseNet + XGBoost). Among the models, the hybrid approaches (DenseNet + SVM and DenseNet + XGBoost) achieve the highest performance, with the DenseNet + XGBoost model showing the best accuracy (97.6%) and F1 score (96.5%). In comparison, the Lightweight DenseNet121 and MobileNetV2 achieve lower accuracy, with DenseNet121 performing slightly better than MobileNetV2 in both accuracy (85.1% vs. 82.5%) and F1 score (84.7% vs. 81.6%). This illustrates that combining DenseNet with classifiers like SVM and XGBoost significantly boosts performance.

6. Conclusion and Future scope

This study explored the development of a lightweight hybrid model combining DenseNet with machine learning classifiers (SVM and XGBoost) to enhance image classification accuracy, particularly for plant disease detection. The proposed approach aimed to address the challenges of long training times and high computational costs, which are common in deep learning models like DenseNet. By leveraging the feature extraction capabilities of DenseNet and the classification strength of SVM and XGBoost, the hybrid models achieved superior performance compared to standard lightweight architectures like DenseNet121 and MobileNetV2. The hybrid models demonstrated a significant improvement in accuracy, with DenseNet + SVM achieving 96.4% and DenseNet + XGBoost reaching 97.6%. These results confirm that the hybrid approach not only reduces training time and computational complexity but also significantly improves the classification performance, making it a suitable solution for real-world applications, such as agricultural diagnostics.

Despite these advancements, some limitations and areas for improvement remain. The DenseNet + SVM model, although highly accurate, exhibited some sensitivity to tuning parameters. Moreover, while the hybrid models outperformed their standard counterparts, further optimization could be explored to improve their adaptability to varying datasets and real-time applications.

Future Scope

- Model Optimization for Real-Time Applications: Further refinement of the model's architecture and training process can improve its ability to work in real-time, especially in resource-constrained environments such as mobile devices used in agriculture.
- Expansion to Multi-Modal Data: Incorporating additional data types, such as sensor data or time-series information, alongside image data could enhance model robustness and classification accuracy across diverse datasets.
- Transfer Learning and Domain Adaptation: Applying transfer learning techniques and domain adaptation can improve the model's generalization across different plant species or disease types, allowing for broader applicability in agriculture.

The lightweight hybrid DenseNet models show great promise in improving image classification tasks, and future developments can further enhance their effectiveness and practicality in various fields.

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