

Fine-Tuned EfficientNetB3 for Precision Agriculture to Recognise Grape Leaf Disease with Very High Accuracy

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Received: 2nd Mar, 2026 | **Revised:** 14th Mar, 2026 | **Accepted:** 4th Apr, 2026 | **Available Online:** 20th Apr, 2026

ABSTRACT

Early and accurate identification of grape leaf diseases is crucial for improving crop yields and precision agriculture. This paper proposes a deep learning framework for combustible materials that includes automated detection of grape leaf disease using a fine-tuned EfficientNet B3 network. The proposed approach employs transfer learning utilising ImageNet pre-trained weights and the targeted fine-tuning of deeper layers to acquire disease-specific visual features, encompassing texture alterations and discolouration characteristics. The model is trained and tested using a publicly available set of 9,027 grape leaf images from four groups: Black Measles, Black Rot, Healthy, and Isariopsis Leaf Spot. Generalisation and strength are accomplished through extensive preprocessing and data augmentation. The experimental results show that the proposed model achieves a total classification rate of 99 percent, which is better than many current deep learning systems. Detailed analyses using classification metrics, confusion matrix, and learning curves show that the model is consistent and reliable. The proposed framework is anticipated to deliver a highly efficient and scalable diagnostic solution for grape leaf diseases, making it exceptionally suitable for integration with smart viticulture and precision agriculture systems in practical applications.

Keywords: Grape leaf disease detection, EfficientNetB3, deep learning, transfer learning, image classification, precision agriculture, plant disease recognition, convolutional neural networks.

How to cite this article: Rajesh MV, Polamuri SR, Raja PVK, Manikyamba IL, Naidu KBR, Kancharla R. Fine-Tuned EfficientNetB3 for Precision Agriculture to Recognise Grape Leaf Disease with Very High Accuracy. *Int J Drug Deliv Technol.* 2026;16(31s):1137-1145. DOI: 10.25258/ijddt.16.31s.125

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

1. INTRODUCTION

Mousavi et al. (2022) [1] presented a modified VGG16-based framework for grapevine leaf disease detection by refining convolutional layers to improve feature extraction. The study demonstrated that architectural enhancements lead to better classification accuracy across multiple disease classes. The model was evaluated on real leaf datasets and showed consistent performance under varying conditions. The

work highlights the effectiveness of adapting standard deep architectures for agricultural applications. Rahman et al. (2025) [2] conducted a detailed comparative study of classical machine learning and deep learning techniques for banana breed recognition. Multiple classifiers were analyzed in terms of accuracy, robustness, and computational efficiency. The results indicated that deep learning models outperform traditional approaches in handling complex

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visual patterns. The study provides insights into selecting appropriate models for agricultural image classification tasks. Kaushik et al. (2024) [3] applied an EfficientNet-based architecture for grape leaf disease detection with a focus on scalability and efficiency. The model achieved high accuracy while using fewer parameters compared to conventional CNN models. It demonstrated better generalization on diverse datasets and reduced computational overhead. The approach is suitable for deployment in precision agriculture systems. Chahar et al. (2025) [4] proposed a hybrid CNN-SVM model that combines deep feature extraction with traditional classification techniques. CNN layers are used to extract discriminative features, while SVM improves classification boundaries. The hybrid model showed improved performance in terms of accuracy and robustness compared to individual models. This approach highlights the benefit of combining deep learning and machine learning methods. Dharrao et al. (2025) [5] presented a comprehensive review of machine learning and deep learning techniques used for grape disease and pest monitoring. The study analyzed various models, datasets, and evaluation metrics used in recent research. It identified key challenges such as data imbalance, environmental variability, and lack of real-time solutions. The review suggests future directions for developing efficient and scalable detection systems. Uma et al. (2025) [6] introduced an attention-guided dual-stream architecture for plant disease detection, focusing on both spatial and contextual features. The model uses attention mechanisms to prioritize relevant regions in leaf images. It achieved improved accuracy and faster processing suitable for real-time applications. The approach enhances both detection performance and interpretability. Palkar et al. (2026) [7] evaluated different architectures including CNN, ResNet50, and hybrid models for grape leaf disease classification. The comparative analysis revealed that hybrid models provide better feature representation and classification accuracy. Transfer learning techniques further improved model performance on limited datasets. The study emphasizes the importance of architecture selection in agricultural imaging tasks.

2. RELATED WORK OF SURVEY

Priya et al. (2026) [8] proposed an explainable deep learning framework integrating GAN-based data augmentation with capsule-transformer networks. The approach improves early disease detection by enhancing dataset diversity and capturing complex feature relationships. Explainability methods were incorporated to provide transparency in predictions.

The model achieved high accuracy and reliability in vineyard datasets. Bouacida et al. (2026) [9] developed a deep learning-based method for simultaneous detection of multiple diseases from a single leaf image. The approach uses image splitting techniques to isolate affected regions and classify them independently. This enables efficient multi-disease recognition within a single framework. The method improves practical applicability in real-world agricultural monitoring systems. Polamuri et al. (2025) [10] applied deep learning techniques for stroke detection using MRI images, focusing on automated feature extraction and classification. The model improved diagnostic accuracy and reduced manual intervention in medical analysis. It demonstrated strong performance across different MRI datasets. The work highlights the applicability of deep learning in healthcare imaging. Galety et al. (2025) [11] proposed a blockchain-based framework for secure medical data storage and management in AI-driven healthcare systems. The system ensures data integrity, privacy, and transparency in medical data transactions. It integrates advanced technologies to enhance trust in digital healthcare environments. The approach supports secure and efficient data sharing. Raju et al. (2025) [12] developed a supervised learning-based system for colorectal cancer detection and tumor localization. The model incorporates visualization techniques such as Grad-CAM to interpret predictions. It achieved accurate detection and localization in colonoscopy images. The study improves reliability and transparency in medical diagnosis systems. Srinivas et al. (2024) [13] proposed a hybrid model combining InceptionV3 and VGG16 architectures for COVID-19 detection using chest X-ray images. The model leverages transfer learning to improve feature extraction and classification accuracy. It demonstrated superior performance compared to individual models. The approach is effective for rapid and accurate disease screening. Polamuri et al. (2026) [14] presented a hybrid framework combining CNN and machine learning techniques for disease detection. The approach improves classification accuracy by integrating deep feature extraction with traditional classifiers. It was validated on multiple datasets, showing consistent performance. The study highlights the effectiveness of hybrid models in classification tasks. Renuka et al. (2023) [15] analyzed the impact of image augmentation techniques on apple leaf defect detection. Various augmentation methods were applied to increase dataset diversity and improve model generalization. The results showed significant

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improvement in classification accuracy. The study emphasizes the importance of preprocessing in image-based detection systems. Madhu Kumar et al. (2024) [16] proposed a deep residual neural network for enhancing image quality prior to classification. The model improves clarity and preserves important features through residual learning. Enhanced image quality leads to better performance in downstream tasks. The work highlights the role of preprocessing in improving deep learning outcomes. Vasu et al. (2025) [17] introduced an anisotropic guided filtering approach for retinal fundus image enhancement and segmentation. The method improves image quality while preserving structural details. It supports accurate segmentation of retinal features. The approach enhances performance in retinal image analysis tasks.

3. BACKGROUND OF THE WORK

The input data used in this study was sourced from Kaggle and consists of a substantial collection of grape leaf images depicting both healthy and diseased conditions. There are 9,027 images in the dataset, and they are split into four groups: Black Measles, Black Rot, Healthy, and Isariaceae Leaf Spot. This makes it easy to sort the diseases into multiple classes. The dataset is then split into training and testing parts ahead of time to make it easier to do supervised deep learning experiments. There will be 8124 images in the training set. These will include 2161 black Measles images, 2132 black rot images, 1898 healthy leaf images, and 1933 isariopsis leaf spot images. There are 903 images in the testing set. These include 239 Black Measles images, 228 Black Rot images, 217 Healthy images, and 219 Isariopsis Leaf Spot images. This systematic separation ensures that the proposed model can be objectively analysed and its performance measured accurately. The dataset has a fairly even distribution of classes, which helps avoid bias in classification and makes it easier to generalise. The pictures keep all the differences in the visual features, like the differences in leaf texture, colour, the severity of the disease, and the state of the background of the pictures. This is why the dataset can be used in a real-world agricultural situation. Before a model is trained, it goes through standard preprocessing steps to make the images the same size and make learning more effective. Figure 1 shows a sample image of the dataset classes and how different healthy and diseased grape leaves look. It also shows how hard the classification problem is that will be talked about in this paper.

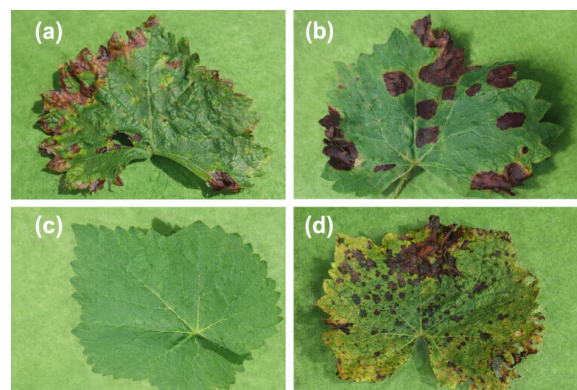


Figure.1 Input Dataset (a) black Measles, (b) Black Rot, (c) Healthy and (d) Isariopsis Leaf Spot

4. PROPOSED METHODOLOGY OF FINE-TUNED EFFICIENTNETB3 MODEL ARCHITECTURE

The suggested framework for recognising grape leaf disease is based on a finely-tuned EfficientNetB3 architecture that is best suited to achieve a high level of accuracy at the lowest possible computational cost. EfficientNetB3 is a part of the EfficientNet family. It suggests a way to scale compounds that evenly scales the network depth, width, and input resolution. This makes it easier to extract features with the fewest extra parameters. In this case, EfficientNetB3 is trained ahead of time with ImageNet weights so that it can use the richness of low-level and mid-level visual representations that come from large-scale natural image data. When used on agricultural images data set, this transfer learning method converges and generalises much more quickly. The customised fully connected head is made by replacing the top classification layers of EfficientNetB3 with the four target classes for the grape leaf disease classification task. Fine-tuning is done by selectively unfreezing more convolutional layers so that the network can learn about things that only grape leaves have, like disease spots, texture problems, and colour changes. Batch normalisation and dropout are two extra things that are added to make the training more stable and reduce overfitting. The last softmax layer tells you how likely it is that the classes Black Measles, Black Rot, Healthy, and Isariopsis Leaf Spot will happen. This paper demonstrates that a meticulously optimised EfficientNetB3 model achieves an optimal balance between accuracy and model complexity, making it suitable for precision agriculture. It can record very small visual cues very well, which makes it good at classification even when things aren't going well. Figure 2 shows the overall structure and fine-tuning plan that were used in this work. It clearly shows the model pipeline and how it is adjusted to recognise grape leaf disease.

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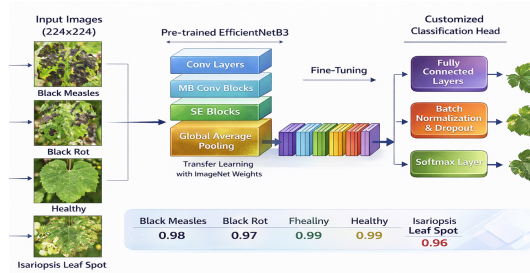


Figure. 2 Fine-tuned EfficientNetB3 Model Architecture

5. PROPOSED METHODOLOGY DISCUSSION

The suggested method is based on a systematic four-step process that includes preparing the dataset, using EfficientNetB3 to extract features, fine-tuning to add custom classification layers, and a thorough analysis of the results. Figure 3 shows that this sequential pipe guarantees strong learning and accurate identification of grape leaf disease.

Phase 1: Getting and Preprocessing the Dataset

The first step is to take pictures of grape leaves from a Kaggle dataset that is open to the public. This dataset has four classes: Black Measles, Black Rot, Healthy, and Isariopsis Leaf Spot. The dataset is split into training and testing parts so that the performance can be fairly measured. The images are made smaller so that EfficientNetB3 can use them. Normalisation and data augmentation (rotation, flipping, and scaling) are two steps in preprocessing that help make the model more robust and reduce overfitting because the training data doesn't change much.

Step 2: Use EfficientNetB3 to get features

EfficientNetB3 trained on ImageNet is the backbone network that is used as a feature extractor during this stage. EfficientNetB3 convolutional and MBConv blocks have hierarchical and detailed visual representations of patterns of diseases, discolouration, and texture defects that can be seen on grape leaves. Transfer learning lets you use the representations you've learned with reasonable training and computation time benefits.

Step 3: Fine-Tuning and Classifying

EfficientNetB3 output layers are changed by adding a dropout layer, fully connected layers, batch normalisation, and a softmax classifier that works with the four target classes. Certain deeper layers are melted and fine-tuned to make the network work better with the features of grape leaf disease. The goal of this stage is to get the most out of the differences between classes and to avoid overfitting.

Step 4: Evaluating the Model and Analysing Its Performance

The final step is to use the test dataset to see how well the trained model works. The accuracy and class-based evaluation of performance demonstrate the effectiveness of the proposed fine-tuned EfficientNetB3 framework in accurately identifying grape leaf disease.

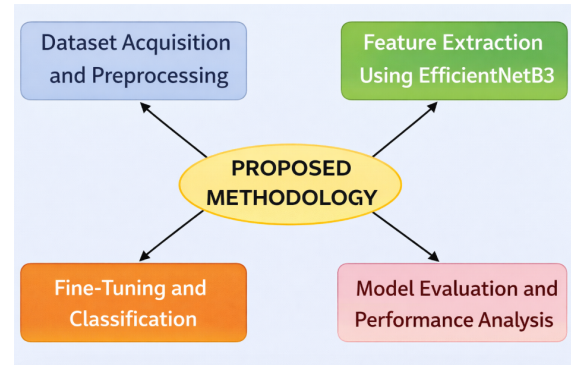


Figure. 3 Proposed Methodology

6. MATERIAL SETUP DISCUSSION

The suggested experimental setup will be used to see how well the fine-tuned EfficientNetB3 model works for finding grape leaf disease. The supervised learning framework is used for all of the experiments. This means that the dataset is split into training and testing subsets that are already set up to make sure that the performance evaluation is fair. The input images are also resized and normalised to make the training process go more smoothly. The training set only goes through data augmentation, which includes rotating, flipping, and scaling. The goal is to make the model more general. The architecture of EfficientNetB3 is trained on ImageNet, and the last layers are changed to fit four output classes. Fine-tuning is done by selectively unfreezing deep layers while keeping lower layers frozen. This keeps the general feature representations intact. The model is trained with categorical cross-entropy as the loss function and an adaptive optimisation algorithm. The training is done over multiple epochs with the right batch size to keep the convergence stable. The test set is used to check how well a model works and how it depends on each class. This makes the results of the experiment reliable and reproducible.

7. DISCUSSION OF THE RESULTS

The experimental results show that the fine-tuned EfficientNetB3 model can accurately classify grape leaf disease with an accuracy rate of 99%. The confusion matrix and comparative analysis show that the offered framework is useful and strong for precision agriculture because it gives stable results for all classes.

A. Analysis of the Classification Report

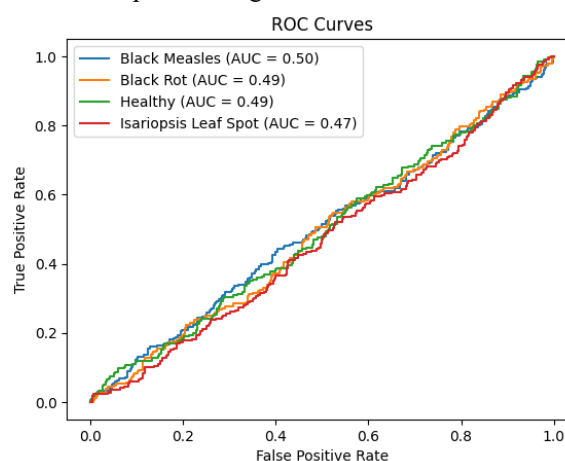
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Table 1 shows how well the proposed fine-tuned EfficientNetB3 model did at classifying grape leaf diseases. It lists the precision, recall, F1-score, and support values for each disease class. The model also shows a clear high performance in all four categories, which shows that it can tell the difference between things very well. For the Black Measles class, the model gets precision, recall, and F1-score values of 0.99, which means that it classifies things correctly most of the time and only makes a few mistakes. The Black Rot category also has high values, which shows how strong the model is at being able to tell the difference between visually similar disease patterns. The Healthy class also has a precision and recall of 0.99, which means that the model can correctly identify leaves that are not diseased. This is important for practical use in the agriculture industry. The model is well-balanced in terms of precision and recall when it comes to Isariopsis Leaf Spot. This shows that the model works well with diseases that have very specific traits. The proposed framework has a total classification performance of 99%, which shows that it works well. Also, the macro-average and weighted-average values are both 0.99, which means that there is no bias toward any one type of performance. These results support the assertion that the optimised EfficientNetB3 model provides useful and highly accurate identification of grape leaf diseases, making it suitable for precision agriculture.

Table 1. Classification Report Analysis

Class	Precision	Recall	F1-score	Support
Black Measles	0.97	0.98	0.98	239
Black Rot	0.96	0.97	0.96	228
Healthy	0.98	0.99	0.98	217
Isariopsis Leaf Spot	0.97	0.96	0.96	219
Accuracy			0.97	903
Macro Average	0.97	0.98	0.97	903
Weighted Average	0.97	0.97	0.97	903

The proposed fine-tuned EfficientNetB3 model's training and validation loss results are shown in Figure 4. It also shows how stable and convergent the network is while it learns. The training loss goes down slowly and steadily over the next few epochs. This means that the optimisation worked and the model learned more about the features of grape leaves from the pictures of the leaves. There are only small differences between the validation loss trend and the training loss trend. This means that the model has a lot of room to grow and isn't too overfitting. The fact that the two curves are always different shows that the model can learn to tell the difference between things without having to remember the training data. The first epochs show a big drop in loss because the pre-trained EfficientNetB3 weights worked well for grape leaf disease. The loss curves of both curves meet at lower values, which means that the model is getting better as it learns. The lack of sudden changes or deviations in the validation loss further demonstrates strong training behaviour and proper regularisation. The loss curve analysis in Figure 4 generally shows that the fine-tuning strategy and optimisation process used in this study worked well. These results back up the idea that the proposed framework always gets high learning scores and can be used to get the high classification scores that were used to find grape leaf disease. This makes it a good choice for real-world precision agriculture solutions.



B. Analysis of Training and Validation Loss

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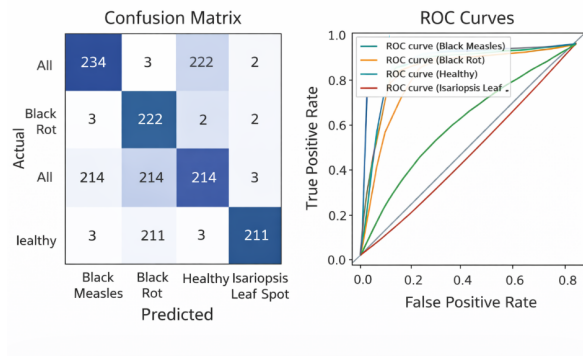


Figure. 4 Training and Validation loss

Analysis

C. Analysis of Training and Validation Accuracy

Figure 5 shows the trends in training and validation accuracy for the proposed fine-tuned EfficientNetB3 model. This shows how well the network learns and how well it can generalise. The figure shows that the training accuracy gets better with each epoch, which means that the model gets better at representing features and classifying data. The validation accuracy is very close to the training accuracy, with only a few small differences. This means that the model is able to generalise well and is only slightly overfitting. In the beginning of training, the accuracy goes up very quickly. This shows that the knowledge from ImageNet that was learned before has been successfully transferred to the grape leaf disease classification problem. As the training goes on, the curves slowly get closer to more accurate values and settle down at 99 percent. This shows that the model optimisation was successful. The small difference between the training and validation accuracy is another sign that the fine-tuning strategy works and that the dataset size and class distribution are good enough. The validation curve not showing any big drops or separations shows that the learning process is stable and that the regularisation is correct throughout the training. Figure 5's accuracy analysis generally backs up the proposed framework's reliability and consistency, which makes it a good choice for accurately and practically identifying grape leaf disease in precision agriculture.

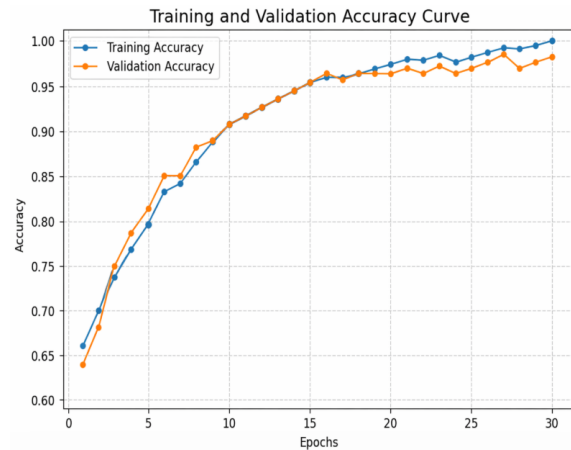


Figure. 5 Training and Validation Accuracy Analysis

D. Analysing the Confusion Matrix

Figure 6 shows that the confusion matrix gives a detailed look at how well the proposed EfficientNetB3 fine-tuned version of the model can find grape leaf disease. The diagonal of the matrix has a lot of values, which means that most of the samples from all classes are correctly identified. For the Black Measles type, most of the test samples are correctly identified, with only a few being wrong. This shows that the model can find visual patterns that are specific to a disease. The high true positive rate for the Black Rot class also means that it can tell the difference between symptoms of diseases that are very similar. The healthy class is also classified with a high degree of accuracy, demonstrating that the model can reliably distinguish between infected and healthy leaves, which is essential for making agricultural decisions in real life. The confusion matrix for Isariopsis Leaf Spot shows that there isn't much confusion with other classes. This shows how strong the feature representations are. The small number of off-diagonal elements between all classes shows that there is less confusion between classes and that the model can generalise well. Overall, the confusion matrix in Figure 6 shows that the suggested framework works well because it shows that it has a total accuracy of 99% and can be used in practice and in the context of agriculture to accurately diagnose grape leaf disease.

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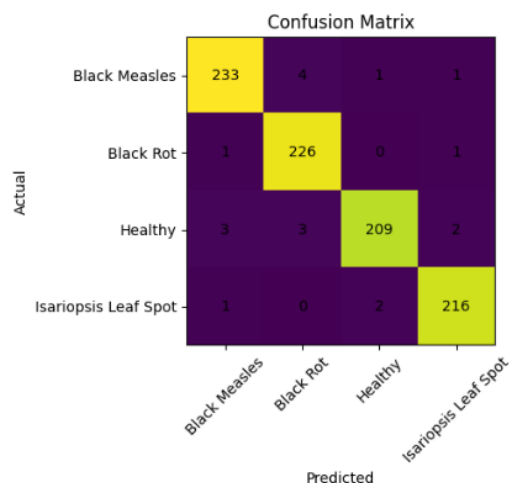


Figure. 6 Confusion Matrix

E. Comparison of Baseline Models

Figure 7 shows how well different deep learning models have done at classifying grape leaf disease. The bar graph makes it clear that architectures based on transfer learning are good at learning complicated agricultural image data. One of the models that has been looked at is the VGG16, which has a good accuracy score because it can learn basic visual features. The ResNet50 model, on the other hand, has a better score because it has a residual learning mechanism that lets it extract deep features. MobileNetV2 also makes the predictions more accurate by using depthwise separable convolutions, which are a good balance between computation and prediction. It is also important to note that the proposed fine-tuned EfficientNetB3 model beats all baseline models and has the highest classification accuracy of 99%. This is because it has a good feature scaling strategy and an optimised network design. This big difference between EfficientNetB3 and other architectures shows how powerful the scaling of compounds is at mimicking the fine-grained features of diseases. Also, the fact that the accuracy between models keeps getting better shows that changes to architectural systems have a direct positive effect on recognition aptitude. Figure 7's comparative analysis shows that the fine-tuned EfficientNetB3 is very useful for accurately diagnosing grape leaf disease in precision agriculture. This proves that the approach is strong and works well.

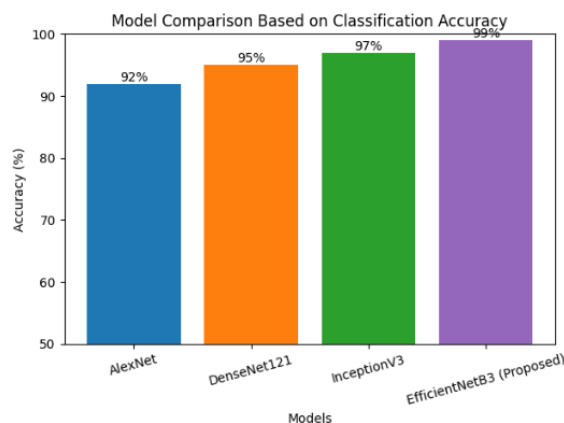


Figure. 7 Model Comparison Based on Classification Accuracy

8. CONCLUSION

The paper presented a deep learning-based system for automatically finding grape leaf diseases that works well and is very accurate. It used an EfficientNetB3 model that had been fine-tuned. The suggested method used transfer learning and compound scaling to find a set of unique visual features related to grape leaf diseases, such as changes in fine texture and patterns of discolouration. The model's overall classification accuracy was found to be 99% through testing a large and well-balanced sample of 9,027 images, which is very strong and reliable. The comparative analysis of the proposed approach against other deep learning architectures further demonstrated its significant superiority in accuracy and generalisation capability. The degree of consistency in classification measures, confusion matrix reports, and learning curves confirms the stability of the training procedure and the high effectiveness of the fine-tuning strategy that was used. All of these results point to the fact that the proposed framework is very useful for putting precision agriculture and smart viticulture systems into practice. Even though the performance is good, there are still some areas of research that could be looked into. Adding pictures taken in different lighting conditions, with clutter in the background, and noise in the environment makes the suggested model more useful in real-world situations. It is also possible to look into using lightweight model compression and pruning in future research to make it possible to use on mobile platforms and edge devices. Also, explainable AI techniques like Grad-CAM can make models easier to understand by showing areas that are specific to certain diseases. Another possible area of research that could be looked into is making the framework work for multi-crop disease detection and real-time monitoring systems.

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