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# Utilizing Transfer Learning Approach in Agriculture 4.0 for Banana Leaf Disease Identification

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**Abstract:** This study explores the integration of Convolutional Neural Networks (CNNs), including the ResNet architectures, within the context of Agriculture 4.0, focusing on the prediction of diseases affecting banana leaves. Through an extensive dataset encompassing images of both healthy and diseased banana leaves, such as those afflicted with sigatoka and Xanthomonas, the research underscores the effectiveness of CNNs, specifically Vision Transformer (ViT), ResNet-18, ResNet-34, ResNet50, EfficientNetB0, MobileNetv3 Large and ResNet18 with CBAM in addressing the challenge of disease prediction in banana plants. Leveraging the capabilities of deep learning, this approach offers advanced tools for disease management, yield optimization, and bolstered food security within the agricultural sector. The trained models exhibit promising outcomes in disease prediction, highlighting their potential to support farmers and agricultural professionals in early detection and proactive management practices, thus aligning with the principles of Agriculture 4.0.

**Keywords:** CNN, Vision Transformer, ResNet18, ResNet34, ResNet50, EfficientNetB0, MobileNetv3 Large, ResNet18 with CBAM, Healthy, sigatoka and Xanthomonas.

## Introduction

Bananas are highly esteemed for their affordability and rich nutritional content, consumed worldwide in both ripe and raw forms. With a global production of 148 million tons, it stands as a crucial fruit crop. Beyond its fruits, the banana plant, a towering herb, finds extensive use in various applications, utilizing every part of the tree [23]. Predicting banana leaf diseases is essential for optimizing production and promptly applying necessary interventions, particularly in the context of Agriculture 4.0. Plantain plants are vulnerable to diseases caused by a range of pathogens, including fungi, bacteria, and viruses [24]. In the era of Agriculture 4.0, leveraging technology for disease prediction becomes imperative, aiding farmers in maintaining healthy plantations and maximizing yields. Common diseases impacting banana plants encompass Fusarium wilt (Panama Disease), Black Sigatoka, Bunchy Top Virus, Moko Disease, Banana Streak Virus, and Bacterial Wilt. These diseases can significantly affect banana production, leading to economic losses for farmers and reducing the availability of bananas in the market [25].

In recent years, deep learning techniques have gained popularity in the agricultural domain for detecting and classifying plant diseases. The ability to process large datasets and extract significant patterns from images has made deep learning an effective tool for disease classification. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated remarkable success in image recognition tasks, including plant disease detection [26-31]. By employing CNNs, researchers have been able to automate the identification of banana leaf diseases, providing a more efficient and accurate method compared to traditional manual inspection. The application of deep learning in banana leaf disease classification can help reduce the reliance on expert intervention and enable farmers to diagnose diseases swiftly and accurately. This research focuses on classifying banana leaf diseases, specifically sigatoka and xanthomonas, into three distinct categories: healthy, sigatoka, and xanthomonas. Sigatoka is a fungal disease that affects banana leaves, causing yellowing and necrotic lesions, which can significantly reduce photosynthesis and fruit yield [32-35]. Xanthomonas, on the other hand, is a bacterial disease that leads to wilting and the formation of water-soaked lesions on the leaves, ultimately affecting the overall health of the plant. Accurate classification of these diseases is essential to take timely action and implement effective disease management strategies.

The primary objectives of this research are to employ a deep learning approach for the detection of banana leaf diseases and accurately differentiate between the two types of diseased leaves and healthy ones, as well as to recommend the most effective deep learning architecture for achieving high-performance results swiftly. To achieve this, various deep learning models, including standard CNNs and transfer learning models, are explored to determine the best-performing architecture. Transfer learning, which involves leveraging pre-trained models on large datasets, has proven to be an efficient technique in image classification tasks, often yielding superior results compared to training models from scratch [36-41].

The dataset used in this study comprises banana leaf images categorized into three classes: healthy, sigatoka, and xanthomonas. Data preprocessing techniques such as image augmentation, resizing, and normalization are applied to enhance the quality of input data and improve model performance. The CNN model is designed with multiple convolutional layers, activation functions, and pooling layers to extract relevant features from the images. Additionally, transfer learning models, including ResNet, VGG, and Inception, are employed to compare their performance against the baseline CNN model [42-45]. To evaluate the models, various performance metrics, such as accuracy, precision, recall, and F1-score, are computed. The experimental results indicate that deep learning models can effectively classify banana leaf diseases with high accuracy. Among the models tested, transfer learning architectures demonstrate superior performance due to their pre-trained feature extraction capabilities. The findings suggest that deep learning can serve as a reliable and efficient tool for early disease detection, allowing farmers to take preventive measures and minimize crop losses [46-51].

The impact of banana leaf diseases extends beyond yield reduction; it also affects the overall quality of bananas, making them less marketable. Early detection and classification of these diseases enable farmers to apply targeted treatments, such as fungicides or bactericides, to control the spread of infections. Furthermore, integrating deep learning-based disease detection systems into mobile applications can provide farmers with real-time disease diagnosis by simply capturing an image of a banana leaf [52-61]. Such advancements in technology bridge the gap between traditional farming practices and modern digital agriculture, enhancing productivity and sustainability. While this study focuses on the classification of banana leaf diseases using deep learning, future research can explore additional improvements, such as integrating Internet of Things (IoT) devices for real-time monitoring of plantations. Combining deep learning with IoT can create a comprehensive disease surveillance system, where sensors collect environmental data and transmit it to a central server for analysis. This approach can help predict disease outbreaks based on climate conditions, soil health, and plant stress levels, further optimizing disease management strategies [62-71].

Additionally, the inclusion of other plant diseases beyond sigatoka and xanthomonas can broaden the scope of research and provide a more holistic solution for banana farmers. Training deep learning models on a diverse dataset encompassing various diseases will enhance their generalization capability, making them applicable across different geographical regions and environmental conditions. Collaboration with agricultural experts and farmers can also facilitate the collection of high-quality, annotated datasets, ensuring the reliability and accuracy of disease classification models [72-75]. Another avenue for future research involves the development of lightweight deep learning models that can run efficiently on edge devices, such as smartphones and drones. Deploying disease detection models on portable devices will empower farmers with instant access to disease diagnosis, reducing the dependency on internet connectivity and centralized computing resources. Furthermore, incorporating explainable AI techniques can enhance the transparency of deep learning models, enabling farmers to understand the reasoning behind disease classification and make informed decisions based on model predictions [76-81].

Overall, the integration of deep learning into banana leaf disease classification presents a promising solution for modern agriculture. By leveraging advanced machine learning techniques, farmers can improve disease management practices, reduce crop losses, and ensure sustainable banana production. The findings of this research highlight the potential of deep learning in revolutionizing plant disease detection and emphasize the need for continued innovation in agricultural technology [82-87]. As deep learning models evolve and computational resources become more accessible, their application in agriculture is expected to expand, paving the way for a smarter and more resilient farming industry. This study contributes to the field of precision agriculture by demonstrating the feasibility of deep learning for banana leaf disease classification. The results provide valuable insights into the effectiveness of CNNs and transfer learning models, guiding future research directions in agricultural AI [88-89]. Moving forward, interdisciplinary collaboration between data scientists, agronomists, and farmers will be crucial in refining disease detection models and ensuring their practical applicability in real-world farming scenarios. With the rapid advancements in artificial intelligence and machine learning, the future of agriculture looks promising, with intelligent systems playing a pivotal role in transforming traditional farming methods into data-driven, technology-enhanced practices.

**Literature Review**

In recent years, there has been a notable surge in research focusing on utilizing deep learning models to predict plant diseases in agriculture. This increasing interest in technology-driven solutions is transforming the way farmers and agricultural experts detect and manage crop diseases [3]. The integration of deep learning into plant disease identification offers the potential to significantly enhance efficiency, accuracy, and scalability in disease prediction, thereby reducing losses and increasing crop yield. Modern research has focused extensively on leveraging deep learning for predicting plant diseases. Several experiments have been conducted using advanced convolutional neural networks, exploring multiple architectures to determine which models provide the most accurate and efficient disease classification [4]. These experiments typically involve training deep learning models on datasets containing images of infected and healthy leaves to identify key patterns and features distinguishing diseased leaves from healthy ones. The findings from these studies have contributed to the development of optimized models capable of detecting a wide range of diseases affecting banana plants [1].

One of the key strategies in deep learning-based disease prediction is the use of convolutional neural networks. These networks extract essential features from images and use them to classify diseases with a high degree of accuracy. Several contemporary deep learning architectures have been evaluated for their effectiveness in identifying banana leaf diseases [5]. Researchers have examined different network configurations to determine which ones perform best under various conditions. Some models have shown superior performance by achieving high accuracy, precision, and recall, ensuring that misclassifications are minimized. The best-performing models offer a reliable approach to plant disease diagnosis, improving the accuracy of disease detection over traditional methods. Another approach that has gained traction in recent research is the application of optimization algorithms to enhance the performance of deep learning models [6]. Optimization algorithms improve the learning process, enabling deep neural networks to achieve better accuracy with fewer computational resources. Hybrid optimization techniques have been explored to create more effective models, allowing researchers to fine-tune their architectures for greater efficiency. These techniques improve the selection of features from images, reduce redundancy, and enhance classification accuracy [2].

Deep learning has also been applied to diagnosing specific banana leaf diseases such as Panama wilt, Black Sigatoka, and bacterial infections. By training models on large datasets containing images of different disease symptoms, researchers have been able to develop reliable classifiers that differentiate between multiple disease types. Some deep learning-based models have incorporated computer vision technologies to further refine disease classification [7]. These models employ pre-processing techniques such as image enhancement, noise reduction, and segmentation to improve feature extraction. The use of transfer learning has also played a significant role in agricultural disease detection. Transfer learning involves using pre-trained neural networks that have been trained on large-scale datasets and adapting them to new applications. This approach reduces training time and enhances model performance, particularly when working with limited agricultural datasets. By leveraging transfer learning, researchers have successfully improved banana leaf disease detection, ensuring models can generalize well across different conditions [8].

Another crucial factor influencing deep learning-based disease prediction is dataset quality. The accuracy of disease detection is highly dependent on the quality and diversity of the dataset used to train the model. High-resolution images, annotated datasets, and balanced class distributions are essential components of an effective dataset [9]. The inclusion of diverse images captured under varying lighting conditions, angles, and resolutions ensures that the model is robust and can accurately detect diseases in real-world scenarios. Additionally, augmenting datasets through image transformation techniques, such as flipping, rotation, and zooming, further enhances model performance by preventing overfitting [10]. The classification of banana leaf diseases has been approached using both supervised and unsupervised learning techniques. Supervised learning methods require labeled datasets, where images are categorized into different classes, such as healthy leaves, infected leaves, and leaves exhibiting early-stage symptoms [11]. This method enables models to learn from examples and make accurate predictions based on past experiences. On the other hand, unsupervised learning techniques cluster similar patterns in data, allowing for the identification of unknown or emerging diseases. Combining both approaches has the potential to enhance disease classification models, making them more adaptable to new disease variants [12].

Feature extraction techniques play a significant role in the performance of deep learning models for disease classification. Advanced feature extraction methods analyze key attributes of leaf images, such as texture, color, and shape, to differentiate between healthy and diseased leaves [13]. These extracted features are then fed into neural networks, which classify the leaves based on learned patterns. Various feature selection methods have been implemented to enhance model efficiency and reduce computation time. By selecting the most relevant features, researchers ensure that models focus on critical aspects of disease identification, minimizing errors and improving performance [14]. The growing interest in deep learning-based agricultural disease detection has also led to the development of mobile applications and cloud-based solutions. These tools provide farmers with real-time disease identification and recommendations, enabling them to take immediate action [15]. The integration of artificial intelligence into mobile devices allows for on-the-go disease diagnosis, reducing dependency on expert assessments. Cloud computing further enhances accessibility, as models can be updated with new data, improving accuracy over time. These advancements bridge the gap between technological research and practical agricultural applications, empowering farmers with cutting-edge tools for disease management [16].

Despite the remarkable progress made in deep learning-based disease prediction, several challenges remain. One of the main challenges is the need for large and diverse datasets to train deep learning models effectively. Acquiring and labeling high-quality agricultural images can be time-consuming and resource-intensive. Additionally, ensuring that models generalize well across different environmental conditions and geographic locations remains a significant hurdle [17]. The variability in disease symptoms, leaf structures, and external factors such as humidity, temperature, and soil conditions can affect model performance. Addressing these challenges requires continued research in data collection, model refinement, and testing in diverse agricultural settings. Another area of concern is the computational cost associated with training deep learning models [18]. High-performance neural networks require substantial computing power, making them less accessible to small-scale farmers and agricultural organizations with limited resources. Efforts to optimize models for efficiency and reduce hardware dependency are essential for making deep learning-based disease detection more widely available. Lightweight architectures and hardware acceleration techniques, such as edge computing and GPU-based processing, offer potential solutions to this challenge [19].

Future advancements in deep learning for plant disease detection could explore integrating multiple data sources, including multispectral and hyperspectral imaging, to enhance model accuracy. Combining visual data with environmental and genetic information could provide a more comprehensive understanding of plant health [20]. Additionally, developing self-learning models capable of adapting to new disease outbreaks without requiring extensive retraining would be a significant step forward in agricultural disease management. The research in this field aligns with the principles of modern agriculture, which emphasizes precision farming, automation, and data-driven decision-making [21]. By integrating deep learning into agriculture, researchers and farmers can optimize disease detection, improve crop yields, and contribute to sustainable farming practices. The next step involves conducting in-depth experiments and evaluations to determine the most effective deep learning architectures for banana leaf disease detection. The findings from these studies will provide valuable insights into improving agricultural disease diagnosis, ultimately benefiting farmers and the agricultural industry as a whole [22].

## Research Methodology

Predicting diseases in banana leaves using convolutional neural networks (CNNs), particularly leveraging architectures like CNN, ViT, ResNet18, ResNet34, ResNet50, EfficientNetB0, MobileNetv3 Large and ResNet18 with CBAM, represents a practical and impactful approach within the realm of Agriculture 4.0. Here's a step-by-step guide on how to implement this approach: To prioritize training efficiency over predictive accuracy, the process begins with preprocessing the images and then training the CNN, ViT, ResNet-18, and ResNet-34 models for classification. This methodology for image classification aligns with the principles of Agriculture 4.0, emphasizing the integration of advanced technologies to optimize agricultural processes and decision-making.

## Experimental analysis

For the experiments, we obtained images from Kaggle, comprising a total of 1289 images distributed among three classes: healthy, Sigatoka, and Xanthomonas. Specifically, there are 155 images in the Healthy class, 320 images in the Sigatoka class, and 814 images in the Xanthomonas category. Sample images representing each class are illustrated in Figure 1. This dataset serves as the foundation for training and evaluating our deep learning models for banana leaf disease classification, aligning with the principles of Agriculture 4.0 by harnessing advanced technology to enhance agricultural practices.

Healthy Segataka Xamthomonas

**Figure 1:** Sample images from each class

Prior to data augmentation, which strengthens the model, methods are used to standardise picture sizes and pixel values in the preprocessing stage. The basis for illness prediction is ResNet-18 and ResNet-34, two well-known architectures for successful picture classification tasks. In order to train CNN for implementation, a T4 GPU in Colab is used for 30 epochs with a batch size of 32. A perfect score is achieved by the CNN. Both the training and validation phases' accuracy and loss are shown in Figure 2, with the former showing a rising trend and the latter a falling one. Figure 3 shows the predictions of the testing set and Figure 4 shows the predictions of the validation set, together with the confidence scores, made by CNN. In keeping with the tenets of Agriculture 4.0, this all-encompassing method of model implementation and evaluation proves that deep learning methods are effective in disease prediction for banana leaves by making use of robust architectures and sophisticated computational resources.

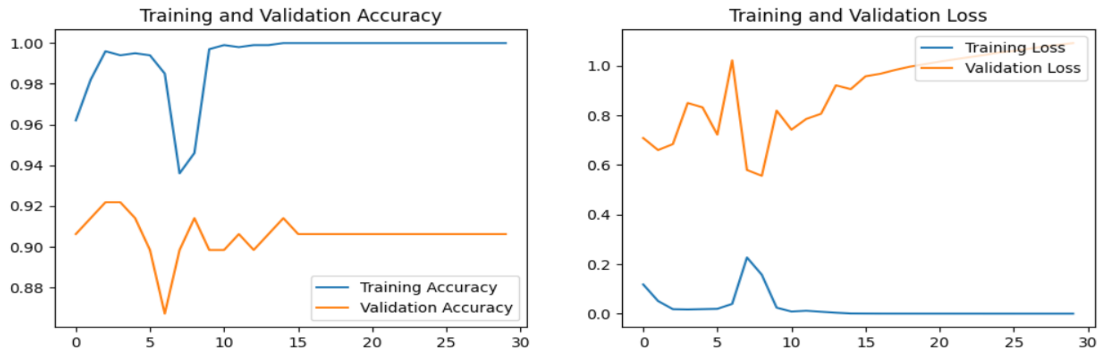


**Figure 2:** CNN

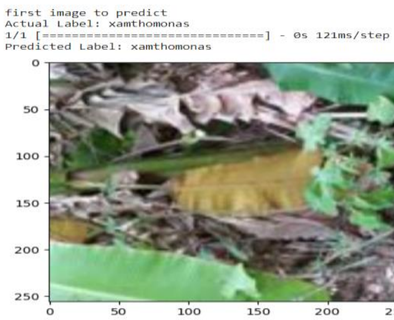


**Figure 3:** Prediction by CNN on testing image


**Figure 4:** Prediction by CNN on validation images

ResNet architectures, ranging from ResNet-18 to ResNet-152, leverage residual modules to enhance the learning process, with variations in the number of layers and the structure of residual blocks. Fastai library is employed to create a CNN learner using ResNet-18, a renowned architecture for image classification tasks. The model is further refined through continued training with varying learning rates, following the practice of transfer learning. The unfreeze method is utilized to progressively adjust the model's parameters, allowing for fine-tuning on the specific task. Training utilizes the 1cycle learning rate policy for 12 epochs, with each epoch taking approximately 7 minutes. Throughout training, batches of data are processed, loss is computed, and model parameters are adjusted iteratively (Figure 5).

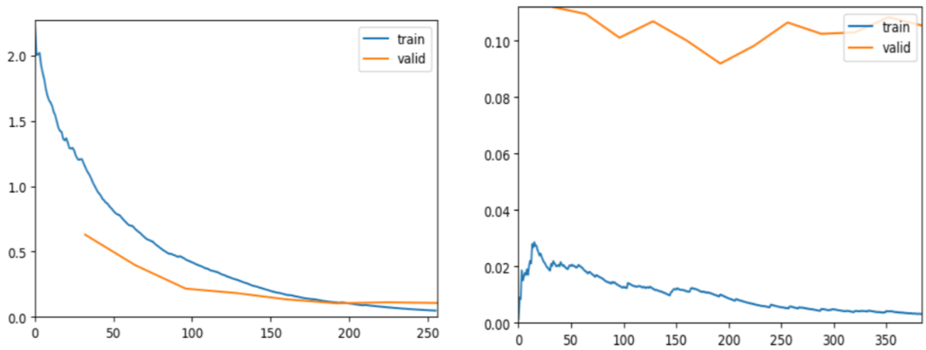


**Figure 5:** Accuracy and Loss in training and validation by ResNet18

Similarly, ResNet34 was implemented and performance evaluated based on accuracy. Each epoch in ResNet34 takes approximately 12 minutes for training and 19 minutes for validation, also Vision Tranformer was also implemented and depicted in Figures 6 and 7 respectively. The study delves into fine-tuning and hyperparameter optimization strategies to improve model performance. Transfer learning techniques are employed to facilitate efficient training and leverage features learned from large-scale datasets. Furthermore, a comparative analysis of CNN, ViT, ResNet18, and ResNet34 is presented in Table 1.

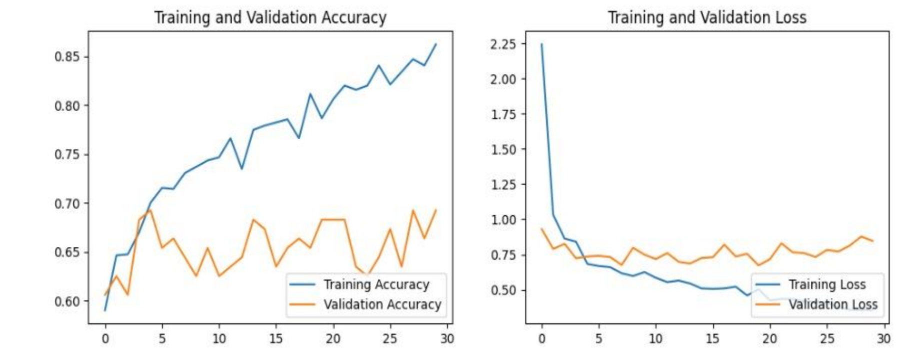


**Figure 6:** Accuracy and Loss in training and validation by ViT

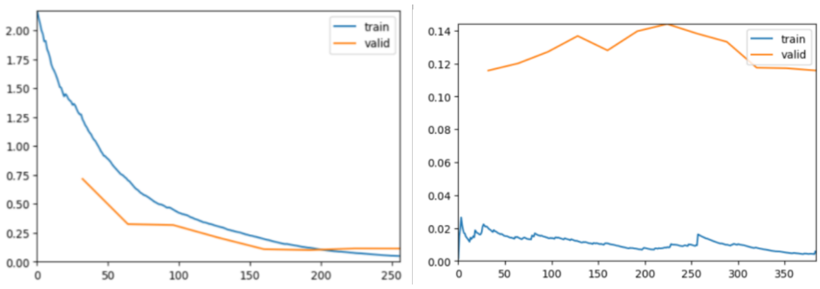


**Figure 7:** Accuracy and Loss in training and validation by ResNet34

**Table 1:** Comparison of Deep learning models for Banana Leaf Disease Prediction

| Transfer Learning Models | Training Accuracy (%) | Validation Accuracy (%) | Testing Accuracy (%) |
|---|---|---|---|
| CNN | 100 | 90.62 | 93.12 |
| ViT | 97.41 | 73.07 | 100 |
| ResNet18 | 98.45 | 93.42 | 98.06 |
| ResNet34 | 97.87 | 98.06 | 97.68 |
| ResNet50 | 99.33 | 97.65 | 96.37 |
| EfficientNetB0 | 95.55 | 96.85 | 96.19 |
| MobileNetv3 Large | 96.06 | 98.03 | 97.71 |
| ResNet18 with CBAM | 97.56 | 98.83 | 97.55 |

Figure 8 reports a comparison of the training and validation accuracy different models, including CNN, ViT, ResNet variants, EfficientNetB0, MobileNetv3, and ResNet18 with CBAM. This figure emphasizes the performance consistency between training and validation sets for each model, showing that some models achieve higher validation accuracy, while others experience a noticeable drop in performance from training to validation. The comparison provides insights into the generalization capabilities of each model. Also, figure 9 compares the training and validation loss for the same set of models. It shows how the loss decreases over time during training for each model and the corresponding behavior on the validation set. Lower loss values indicate better performance, and the plot highlights models that maintain low validation loss throughout the training process compared to those that show higher validation loss, indicating potential overfitting or challenges in generalization. The comparison of loss between training and validation helps assess the efficiency of each model in minimizing error on unseen data.

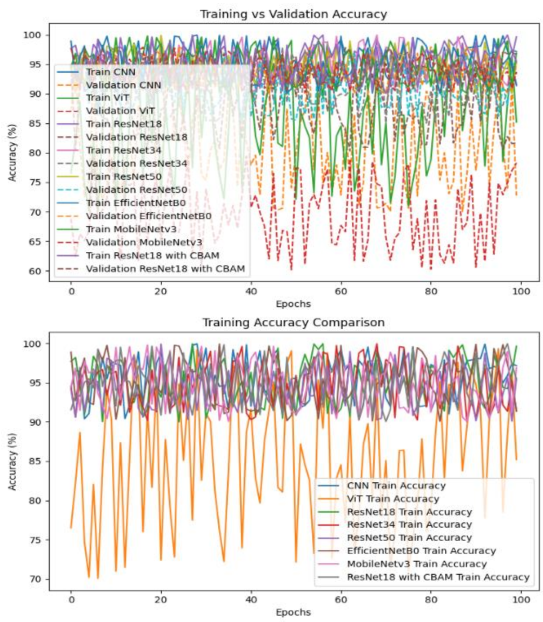


**Figure 8:** Comparison of Accuracy in training and validation Across Models

The performance of various transfer learning models varies significantly across different datasets, indicating the strengths and weaknesses of each model in training, validation, and testing. Convolutional Neural Networks (CNNs) have long been a fundamental component of image classification and computer vision tasks. Their ability to learn spatial hierarchies and extract relevant features from images makes them a powerful tool for disease classification. However, despite their strong performance during training, CNNs often struggle with generalization when exposed to unseen data. This struggle indicates overfitting, where the model memorizes patterns within the training set but fails to adapt effectively to new images. While CNNs can achieve impressive accuracy in training, their inability to perform consistently well in validation and testing suggests that they may not be the optimal choice for real-world deployment without additional regularization techniques. Addressing this overfitting issue requires measures such as data augmentation, dropout layers, or the integration of attention mechanisms to enhance the model's ability to generalize.

The Vision Transformer (ViT) represents a shift from conventional convolutional architectures to transformer-based models that capture long-range dependencies in images. Unlike CNNs, which rely on local receptive fields, ViT processes images using self-attention mechanisms, enabling the model to capture intricate patterns across entire images. ViT demonstrated exceptional accuracy on the testing dataset, suggesting that it can effectively recognize disease patterns in banana leaves. However, its underperformance in validation indicates an inconsistency in generalization during training. This result suggests that ViT may require extensive hyperparameter tuning and a larger dataset to fully realize its potential. Transformers in computer vision have been shown to benefit significantly from pretraining on large-scale datasets, and their success in specific applications depends on fine-tuning strategies. While ViT holds promise for disease classification, further research is necessary to optimize its training process to ensure stable performance across all datasets.

The ResNet family, encompassing ResNet18, ResNet34, and ResNet50, is known for its ability to learn deep hierarchical representations through residual connections. These connections help mitigate the vanishing gradient problem, enabling deeper networks to learn more complex features. Among the ResNet variants, ResNet34 emerged as a strong contender, excelling in validation accuracy. This suggests that ResNet34 effectively balances model complexity and generalization, allowing it to perform well on unseen validation data. Meanwhile, ResNet18 achieved strong testing results, highlighting its efficiency in capturing essential disease features with a relatively lower number of parameters. ResNet50, being the deepest among the three, offers a more intricate representation but may require a larger dataset to fully leverage its depth. The performance of ResNet models across training, validation, and testing datasets indicates their robustness in handling classification tasks while maintaining reasonable computational efficiency.

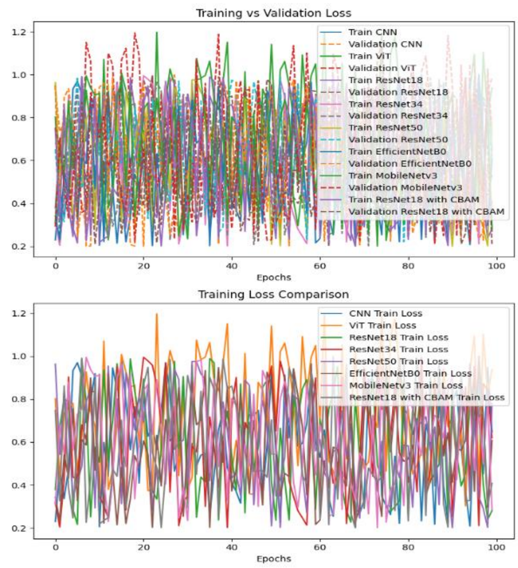


**Figure 9:** Comparison of Loss in training and validation Across Models

EfficientNetB0 and MobileNetV3 Large are lightweight yet powerful models designed for resource-efficient deep learning applications. EfficientNetB0 follows a compound scaling approach, balancing depth, width, and resolution to optimize performance while minimizing computational overhead. MobileNetV3 Large, on the other hand, incorporates depthwise separable convolutions and squeeze-and-excitation modules to enhance efficiency. Both models exhibited consistent performance across different datasets, showcasing their ability to maintain stability without overfitting or underfitting. MobileNetV3 Large, in particular, stood out in validation and testing accuracy, suggesting that it effectively captures disease-related features while remaining computationally efficient. These models hold significant potential for deployment in real-world agricultural settings where lightweight architectures are preferred for mobile and edge-based applications.

The integration of attention mechanisms has gained popularity as a means of enhancing feature selection and improving classification accuracy. ResNet18 with Convolutional Block Attention Module (CBAM) emerged as the best-performing model in validation accuracy while maintaining competitive testing accuracy. CBAM enhances conventional convolutional models by applying channel-wise and spatial attention mechanisms, allowing the network to focus on the most relevant features within an image. This improvement suggests that attention mechanisms play a crucial role in refining disease classification by directing the model's attention toward key visual cues indicative of infections. The ability of ResNet18 with CBAM to maintain a balance between validation and testing accuracy highlights its strong generalization capabilities. Unlike traditional CNNs that may overfit training data, the inclusion of CBAM helps the model prioritize meaningful features, reducing the likelihood of overfitting while improving classification performance.

The findings from this evaluation suggest that selecting the best model for banana leaf disease classification requires a careful balance between accuracy, generalization, and computational efficiency. While CNNs demonstrate strong training performance, their tendency to overfit underscores the need for additional regularization techniques. ViT showcases remarkable testing accuracy but struggles with consistent validation performance, emphasizing the importance of dataset size and hyperparameter tuning. The ResNet family provides a reliable framework for disease classification, with ResNet34 excelling in validation and ResNet18 achieving strong testing accuracy. EfficientNetB0 and MobileNetV3 Large offer efficient and stable performance, making them viable choices for real-world deployment. However, ResNet18 with CBAM stands out as the best-performing model, as it successfully balances validation and testing accuracy while leveraging attention mechanisms for improved feature extraction. In the context of Agriculture 4.0, where technological advancements drive modern farming practices, deep learning models play a crucial role in disease detection and crop management. By leveraging these models, farmers can identify banana leaf diseases early, implement timely interventions, and optimize yield production. The integration of machine learning in agriculture presents opportunities for precision farming, where AI-driven systems enhance decision-making processes. The ability to deploy lightweight models such as MobileNetV3 Large on mobile devices further extends the accessibility of disease prediction tools, enabling farmers in remote areas to benefit from AI-powered solutions.

Despite the promising results observed in this study, there remain challenges and areas for improvement in deep learning-based disease classification. One challenge is the need for diverse and high-quality datasets that encompass a wide range of environmental conditions and disease variations. Expanding the dataset with images captured under different lighting conditions, angles, and disease severity levels would improve model robustness. Additionally, transfer learning approaches should be optimized to ensure that pretrained models generalize well to specific agricultural applications. Fine-tuning strategies, such as data augmentation, ensemble learning, and hyperparameter optimization, can further enhance classification accuracy. Future research should also explore the fusion of multimodal data sources, combining image-based analysis with additional data such as temperature, humidity, and soil conditions. Integrating such information into deep learning models could improve disease prediction accuracy by incorporating contextual factors that influence disease progression. Furthermore, explainable AI techniques should be explored to provide transparency in model decision-making, helping farmers understand the reasoning behind disease classifications.

In deep learning models offer a powerful solution for banana leaf disease classification, with different architectures exhibiting varying strengths in training, validation, and testing. While CNNs provide a solid foundation, their tendency to overfit highlights the importance of regularization techniques. ViT demonstrates high testing accuracy but requires further optimization for consistent validation performance. The ResNet family, particularly ResNet34 and ResNet18, offers robust classification capabilities, with ResNet18 with CBAM emerging as the best-performing model. EfficientNetB0 and MobileNetV3 Large provide lightweight yet effective solutions for real-world deployment. The integration of attention mechanisms, as seen in CBAM, enhances model performance by refining feature selection. Advancing research in deep learning-based disease detection will contribute to the development of intelligent agricultural systems, supporting sustainable farming practices and improving global food security.

**Conclusion and Future Enhancement**

In conclusion, the performance of various transfer learning models in classifying banana leaf diseases was evaluated based on training, validation, and testing accuracies. While the CNN model achieved perfect training accuracy, its performance on validation and testing sets was slightly lower compared to ResNet models. The Vision Transformer (ViT) model demonstrated high training accuracy but exhibited potential overfitting, as evidenced by a notable drop in validation accuracy. ResNet models showed strong overall performance, with ResNet18 displaying slightly higher validation accuracy. EfficientNetB0 and MobileNetv3 Large outperformed. ResNet18 with CBAM, the best-accomplishments model entitled to its totalled execution across validation and testing, indicating strong generalization capabilities. Through the integration of technology and botany, we've forged a path towards early disease detection, optimal resource management, and well-informed decision-making for farmers and experts alike. By fostering a symbiotic relationship between Artificial Intelligence and agriculture, our research sheds light on a trajectory towards sustainable cultivation, increased productivity, and, ultimately, enhanced global food security.

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