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Evaluation of RESNET50 and EfficientNETB0 Models for Maize Leaf Disease Detection

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Abstract—**Maize leaf diseases significantly affect crop yield and quality, making early and accurate detection essential. This research examines the effectiveness of two deep learning models, ResNet50 and EfficientNetB0, in classifying maize leaf diseases. The dataset images were categorized into four classes: Blight, Common Rust, Gray Leaf Spot, and Healthy. Both models were fine-tuned using transfer learning, and their performance was evaluated based on accuracy, precision, recall, and F1- score. ResNet50 achieved 95.25% accuracy, demonstrating strong generalization and balanced classification, particularly for Blight. EfficientNetB0 attained 93.92% accuracy, excelling in detecting Gray Leaf Spot. The study provides a comparative analysis of ResNet50 and EfficientNetB0, highlighting their respective strengths and limitations in maize leaf disease classification. ResNet50 demonstrated higher accuracy and balanced classification, while EfficientNetB0 excelled in detecting specific disease categories. These findings offer valuable insights into model selection based on application requirements, aiding in the adoption of deep learning for agricultural disease detection.**

Keywords—Maize leaf disease, deep learning, ResNet50, EfficientNetB0, and transfer learning.

I. INTRODUCTION

MAIZE, is one of the most important staple crops worldwide, providing food security and economic stability for millions of farmers. However, its production is often affected by various diseases that can significantly reduce yield and quality. De- tecting these diseases at an early stage is crucial for effective management, yet traditional methods rely on manual inspec- tion, which is time-consuming, labor-intensive, and prone to errors [1]. To overcome these challenges, researchers have been exploring deep learning-based automated solutions for disease detection.

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image-based classification tasks, including plant disease identification. Among these, ResNet (Residual Networks) and EfficientNet have gained particular attention due to their strong performance in handling complex image datasets [2]. ResNet, with its residual learning approach, addresses the vanishing gradient issue, allowing deeper networks to be trained effectively. In contrast, EfficientNet optimizes model scaling by balancing depth, width, and resolution, achieving high accuracy while being computationally efficient [3].

Despite these advancements, selecting the most suitable model for maize leaf disease detection remains a challenge, as different architectures perform differently based on dataset quality, environmental conditions, and computational constraints. A comparative study of ResNet50 and EfficientNet is, therefore, necessary to understand their strengths and limitations in this specific application [4].

This research aims to evaluate and compare the performance of ResNet50 and EfficientNet in identifying maize leaf diseases. By analyzing key performance metrics such as accuracy, precision, recall, and computational efficiency, this study provides insights into which model is more suitable for real- world deployment. The findings contribute to the ongoing development of AI-driven solutions in precision agriculture, helping researchers and farmers adopt more efficient disease detection techniques.

II. RELATED WORKS

The exploration of deep learning architectures for the detection of maize leaf diseases has garnered significant attention in recent years, as evidenced by a series of studies that highlight the efficacy of various models in this domain. In 2020, A comparative evaluation of convolutional neural networks (CNNs) and deep learning optimizers, emphasizing the superior performance of models like ResNet in classifying plant diseases [5]. The findings revealed that deep learning approaches consistently outperformed traditional machine learning techniques, showcasing the potential of modified architectures to enhance classification accuracy for maize leaf diseases.

Building on these insights, a lightweight deep neural network for tomato leaf disease classification was introduced, which achieved an impressive accuracy of 99.30% [6]. Their work underscored the importance of adaptive techniques to address illumination challenges and class imbalances, suggesting that such methodologies could also benefit maize leaf disease detection by improving model robustness in diverse environmental conditions. In 2022, a hybrid model was explored that combined modified deep transfer learning and ensemble approaches for leaf disease classification, utilizing an improved version of ResNet [7]. This study highlighted the adaptability of ResNet structures in identifying various leaf diseases, including those in maize, and demonstrated the potential for enhanced accuracy through effective feature extraction. Concurrently, the importance of image quality assessment in disease identification emphasized, proposing architectures that outperformed existing benchmarks on both laboratory and self-collected datasets, thereby reinforcing the need for robust models that can generalize well in real-world scenarios [8]. The systematic review provided a comprehensive overview of deep learning models applied to leaf disease diagnosis, noting the limitations of existing approaches and the promising capabilities of transformer-based models [9]. This review highlighted the necessity for improved feature representation and data handling, which are critical challenges that need to be addressed for effective maize disease detection. Further investigation reaffirmed the effectiveness of deeper models like ResNet-101 and DenseNet-201 for plant disease detection, while also considering the applicability of lightweight models for real-time applications [10]. This research emphasized the need for a balance between model complexity and performance, a theme that resonates with the ongoing quest for efficiency in agricultural AI solutions.

Recent advancements have seen the introduction of novel methodologies, such as the RGB-D post-segmentation image data approach, which aims to enhance disease classification accuracy in complex field environments by utilizing depth information alongside traditional RGB images [11]. This innovative approach seeks to overcome challenges posed by varying lighting and perspectives, which are common in field settings. By evaluating RESNET50 and EfficientNET specifically for maize leaf disease detection, illustrating the growing body of literature focused on optimizing model performance through various deep learning techniques [12].

The review highlighted the increasing trend in research aimed at improving plant disease classification accuracy, reflecting a collective effort to refine and innovate in this critical area of agricultural technology. As the field continues to evolve, it is evident that the integration of advanced deep learning techniques, coupled with innovative data handling strategies, will play a pivotal role in enhancing the detection and classification of maize leaf diseases, ultimately contributing to more effective agricultural practices.

II. Applied Methodology

A. Dataset Description

The dataset used in this study comprises images of corn leaves categorized into four distinct classes: Blight, Common Rust, Gray Leaf Spot, and Healthy. These images were sourced from popular plant village datasets [13]. A total of 4198 images were collected and split into training, test, and validation subsets. The training set contains 3606 images; the validation and test sets consist of 296 images each.

Fig. 1. Number of data of different classes.

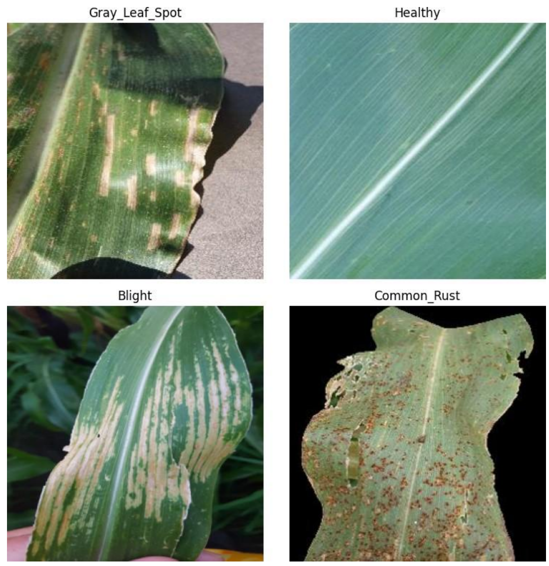

Fig. 2. Sample data.

B. Data Preprocessing

The collected data images were originally sized at 256x256x3. These datasets were resized to match the input requirements of different CNN architectures. For the ResNet50 and EfficientNetB0 networks, the data images were adjusted to 224x224x3. This resizing ensures compatibility with the pre-trained ResNet50 and EfficientNetB0 architecture. Proper resizing helps maintain the model's efficiency and ensures that spatial features are preserved for optimal feature extraction.

C. Transfer Learning

Transfer learning is a deep learning technique in which a pre-trained model is used as a starting point for a new but related task. A pre-trained model is customized to the new applications and re-trained on new datasets [14].

D. Training with ResNet50 and EfficientNetB0 Transfer Learning

ResNet50 is a deep neural network architecture that consists of 50 weight layers, including convolutional, pooling, and fully

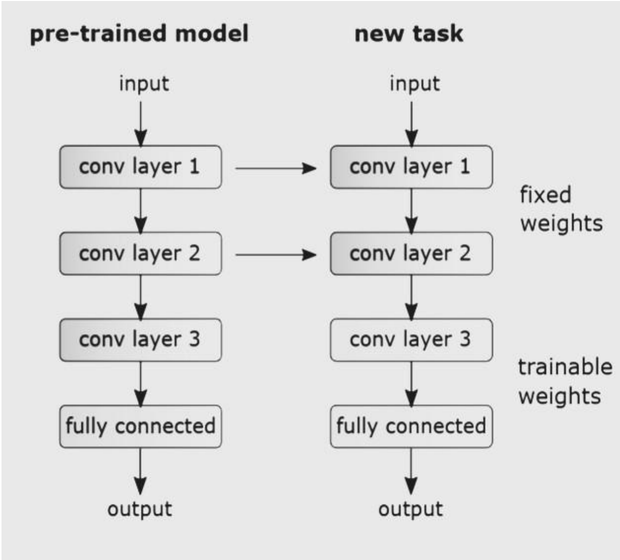

Fig. 3. Concept of transfer learning [15].

TABLE I: TRAINING CONFIGURATION

Parameter	Value
Model	ResNet50/EfficientNetB0
Optimizer	Adam
Batch Size	32
Epochs	20
Learning Rate	0.00001

connected layers, and is pre-trained on the ImageNet dataset. EfficientNet is a lightweight deep learning model that uses compound scaling to balance network depth, width, and resolution, making it computationally efficient while maintaining high accuracy. Transfer learning is applied by using ResNet50 and EfficientNetB0 as a feature extractor, where the initial layers remain frozen to retain general features while the last 30 layers are fine-tuned to adapt to the specific task of corn leaf disease classification. This significantly reduces training time while improving performance. The model was optimized using the Adam optimizer.

E. CNN Architecture: ResNet50 and EfficientNetB0

A particular kind of deep learning model designed for image processing and recognition applications is called a convolutional neural network (CNN). It has completely changed the area of computer vision and is widely utilized in applications including image segmentation, object recognition, and image classification [16]. CNNs are very successful because they eliminate the requirement for human feature engineering by using convolutional layers to automatically extract spatial characteristics from images. The use of backpropagation and optimization algorithms enables CNNs to improve performance continuously through iterative learning. To use the ResNet50 and EfficientNetB0 model for corn leaf disease classification, the original fully connected layers were removed. A GlobalAveragePooling2D layer was introduced to reduce the dimensionality of the feature map while retaining

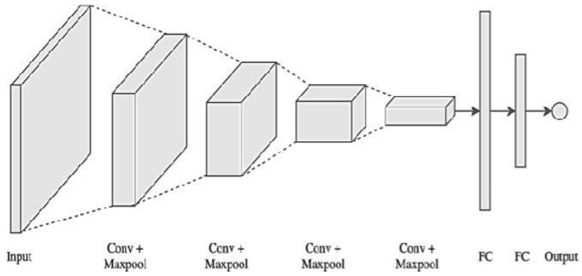

Fig. 4. Basic Architecture of CNN Model [17].

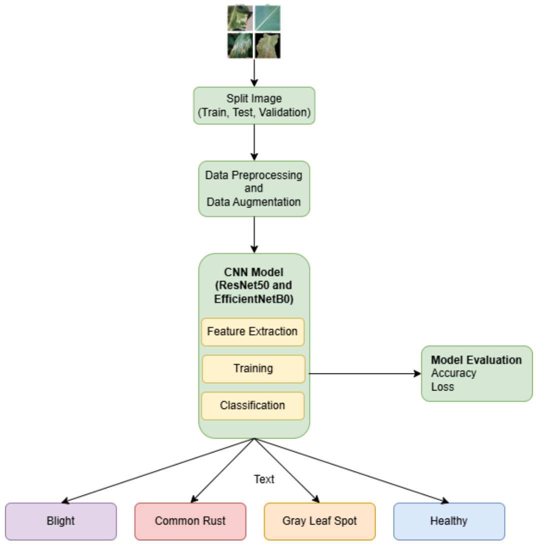

Fig. 5. Block diagram of the model.

spatial information. This helps minimize computational complexity and prevents overfitting. Two fully connected layers with 512 and 256 neurons, both activated using ReLU, were used to enable the model to learn more complex patterns of corn leaf disease. To further improve generalization, dropout layers (0.4 and 0.3) are introduced to reduce overfitting by randomly deactivating neurons during training. Finally, a softmax output layer with 4 neurons is added, corresponding to the four diseases in the dataset. This layer assigns probabilities to each class, ensuring that the model provides a good classification output.

F. Performance Matrices

The performance of the model is evaluated using key metrics, accuracy and loss for both training and validation datasets. Accuracy measures how well the model classifies images correctly, while loss quantifies the difference between predicted and actual labels.

$$Accuracy = \frac{TP + PN}{TP + TN + FP + FN} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

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

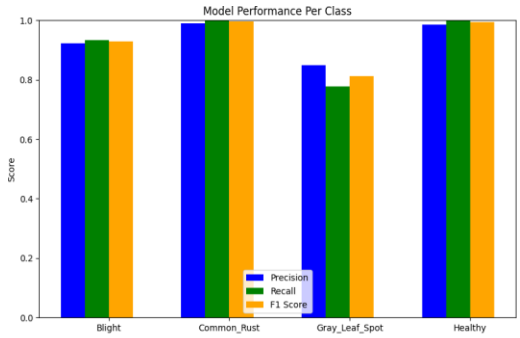

Fig. 6. ResNet50 model's performance per class.

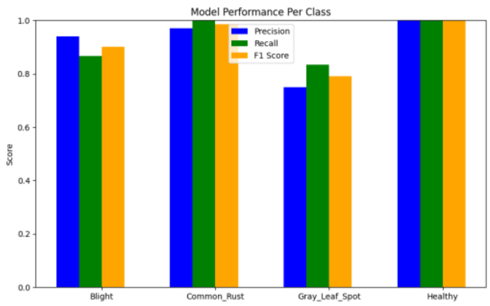

Fig. 7. EfficientNetB0 model's performance per class.

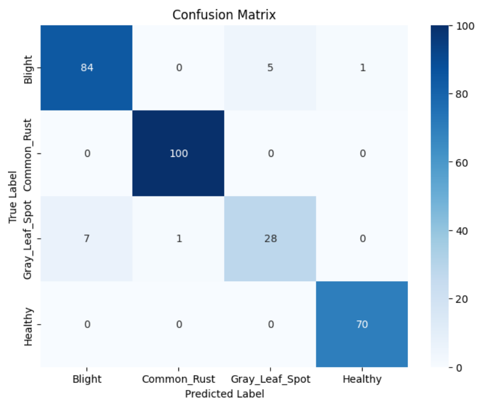

Fig. 8. Confusion matrix of ResNet50 model.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where, TP= True Positive, TN= True Negative, FP= False Positive, FN= False Negative.

III. Results and Discussion

This section evaluates the model's performance based on metrics such as accuracy, loss, precision, recall and F1-score. The trained model is tested on unseen data to evaluate its generalization ability. Performance curves, which include training vs. validation accuracy and loss, are plotted to examine the learning behavior of the model. Confusion matrices and classification reports help to understand the model's effectiveness in classifying different diseases of corn leaves.

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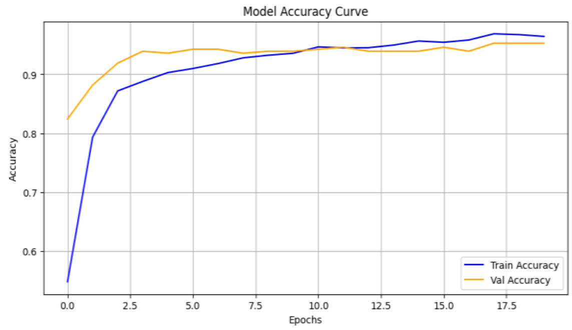

Fig. 10. Accuracy curve of ResNET50 model.

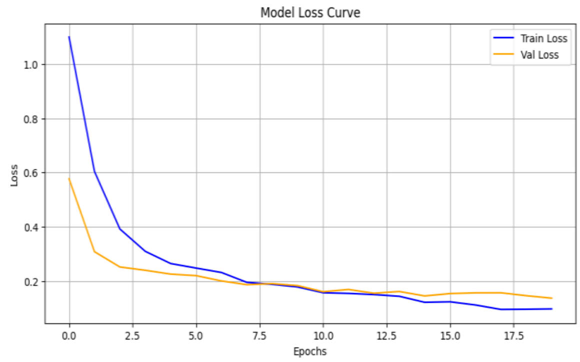

Fig. 11. Loss curve of ResNET50 model.

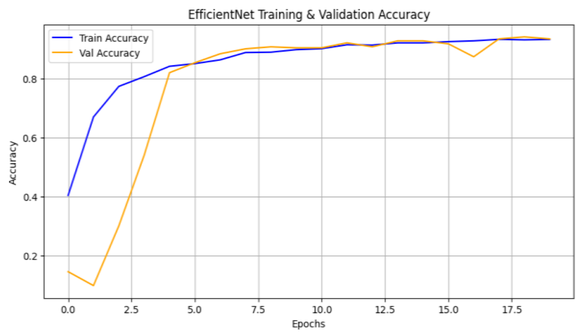

Fig. 12. Accuracy curve of EfficientNetB0 model.

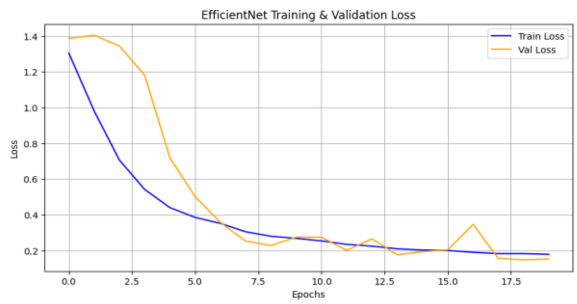

Fig. 13. Loss curve of EfficientNetB0 model.

Based on the two bar graphs and confusion metrics, Common Rust and Healthy classes have good precision, recall and f1-scores in both models. The key difference is in the Blight and Gray Leaf Spot classesFor the Blight class, the EfficientNetB0 has higher precision than recall, meaning it is more selective in predicting Blight cases. On the other hand, ResNet50 maintains a more balanced performance across precision and recall, ensuring consistent classification. The Gray Leaf Spot class presents the most noticeable variation between the two models. The bar graphs suggest that EfficientNetB0 is better suited when detecting all potential cases is a priority.

Overall, while both models perform well, ResNet50 offers more balanced predictions, particularly for the Blight class, whereas EfficientNetB0 is slightly better at capturing all possible cases of Gray Leaf Spot. If maximizing disease detection is crucial, EfficientNet is advantageous, while ResNet50 is preferable for minimizing misclassifications. The evaluation curves of two models (ResNet50 and EfficientNetB0) for corn leaf disease classification showed distinct performance in their ability to identify diseased and healthy leaves.

The ResNet50 model reached an accuracy of 95.25% slightly outperforming EfficientNetB0. The validation curve closely follows the training curve, indicating minimal overfitting and strong model generalization. The ability of ResNet50 to learn deep hierarchical feature, made it a highly effective architecture for this classification task.

The EfficientNetB0 model achieved an accuracy of 93.92%, as shown in figure 12. The performance of this model can be attributed to EfficientNet's compound scaling, which balances depth, width, and resolution to extract hierarchical features from the input images. The use of fine-tuning and regularization techniques helped reduce overfitting, allowing the model to maintain high validation accuracy throughout the training process.

V. Conclusion

This study conducted a comparative analysis of ResNet50 and EfficientNetB0 for maize leaf disease classification, assessing their accuracy, precision, recall, and F1-score. ResNet50 achieved an accuracy of 95.25%, demonstrating strong generalization and balanced performance, particularly in detecting Blight. EfficientNetB0 attained 93.92% accuracy, excelling in identifying Gray Leaf Spot. While ResNet50 minimized misclassifications, EfficientNetB0 was more effective in detecting a broader range of diseases. The findings highlight the importance of selecting a model based on application- specific requirements: ResNet50 for high-precision classification and EfficientNetB0 for comprehensive disease detection. This comparative evaluation provides valuable insights for the adoption of deep learning in agricultural disease identification, contributing to the advancement of automated solutions in precision farming.

Future research can explore incorporating Explainable AI (XAI) techniques would provide better interpretability, and increase trust in model predictions. Expanding the dataset to include images from diverse environmental conditions and geographic regions would enhance the model's adaptability.

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