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Deep Learning-Based Maize Leaf Disease Detection in Crops Using Images for Agricultural Applications

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***Abstract*—** The proliferation of corn leaf diseases poses a significant threat to global agricultural productivity. Diseases like Northern Leaf Blight, Gray Leaf Spot, and Common Rust lead to substantial yield losses if not detected and managed promptly. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has transformed the field of image classification, enabling more accurate and efficient detection of plant diseases. This paper investigates the application of a hybrid deep learning approach that combines four state-of-the-art CNN architectures: EfficientNetB0, MobileNetV2, InceptionResNetV2, and InceptionV3, for the detection of corn leaf diseases. By integrating these models, the proposed hybrid framework aims to leverage their unique strengths, thereby enhancing the accuracy of disease detection while optimizing computational efficiency.

The research explores the development of a comprehensive hybrid model, detailing the preprocessing steps, model architecture, training procedures, and evaluation metrics. The hybrid model's performance is thoroughly analyzed and compared with that of individual architectures, demonstrating superior results in terms of accuracy, precision, recall, and F1-score. The study also delves into the practical implications of deploying such a model in real-world agricultural scenarios, including its potential to operate on mobile and edge devices. The paper concludes with a discussion on future research directions, emphasizing the scalability of the model to other crops and the challenges of real-world implementation.

***Keywords*—** Corn Leaf Disease Detection, Deep Learning, Hybrid Models, Convolutional Neural Networks (CNNs)

I. Introduction

Corn, known as maize in many parts of the world, is one of the most widely cultivated cereal crops, playing a crucial role in global food security and economies [1]. The United States, China, and Brazil are the top producers, contributing to a significant percentage of the world's corn supply. However, the productivity of corn is severely hampered by leaf diseases, which can spread rapidly under favorable conditions, leading to reduced photosynthetic activity and, consequently, lower yields [2]. The economic impact of these diseases is immense, with billions of dollars lost annually due to compromised crop quality and reduced production volumes.

Traditional methods of disease detection in corn involve manual inspection by trained agronomists or farmers. While effective, these methods are labor-intensive, time-consuming, and prone to human error, particularly in large-scale farming operations. Early detection is critical, as it allows for timely intervention measures such as targeted pesticide application, which can mitigate the spread of diseases and minimize losses. In recent years, advancements in machine learning and computer vision have paved the way for automated disease detection systems, which offer the potential for more accurate, efficient, and scalable solutions.

The primary challenge in corn leaf disease detection lies in the accurate identification of disease symptoms from leaf images, which can be affected by various factors such as lighting conditions, the angle of image capture, and the presence of overlapping leaves [3]. Different diseases may present with similar symptoms, such as spots or lesions, making it difficult for algorithms to distinguish between them. Moreover, the computational complexity of deep learning models, especially those required for high accuracy, poses a significant challenge, particularly in resource-constrained environments like small farms where the availability of high-performance computing resources is limited.

Given the challenges associated with existing methods, there is a clear need for an efficient, accurate, and scalable solution for corn leaf disease detection. This research is motivated by the potential of hybrid deep learning models to meet these requirements. By combining multiple CNN architectures, it is possible to leverage the complementary strengths of each model, resulting in a robust system capable of performing well under diverse conditions. The specific objectives of this study are as follows:

- To develop a hybrid deep learning model that integrates EfficientNetB0, MobileNetV2, InceptionResNetV2, and InceptionV3 for corn leaf disease detection.
- To evaluate the performance of the hybrid model in terms of accuracy, precision, recall, and computational efficiency, and to compare these results with those obtained using individual architectures.
- To assess the model's practicality for real-world deployment in agricultural settings, including its potential for use on mobile devices and in edge computing environments.

The remainder of this paper is structured as follows: The next section provides a detailed review of the literature related to corn leaf disease detection, CNN architectures, and hybrid learning models. The proposed methodology section describes the dataset, preprocessing steps, model architecture, training procedures, and evaluation metrics used in this study. The results section presents the findings from the model's performance evaluation, followed by a discussion on the implications of these results. The paper concludes with an exploration of potential future work, including model improvements, applications to other crops, and considerations for real-world deployment.

II. Literature Review

The field of corn leaf disease detection has seen significant advancements with the advent of machine learning, particularly deep learning techniques. This literature survey reviews the evolution of disease detection methods, the development of various CNN architectures, and the emergence of hybrid models that integrate multiple networks for enhanced performance.

In recent years, sophisticated CNN architectures have been developed, each addressing specific limitations of earlier models. Szegedy et al. (2016) [4] introduced InceptionNet, which utilized mixed-scale convolutions to capture both fine and coarse features, significantly improving accuracy in various image classification tasks . He et al. (2016) [5] presented ResNet, which used residual connections to enable the training of much deeper networks, overcoming the vanishing gradient problem and setting new benchmarks for accuracy .

Tan and Le's (2019) [6] EfficientNet architecture represented a breakthrough in optimizing model performance across multiple dimensions—depth, width, and resolution—achieving state-of-the-art results with fewer parameters . Meanwhile, Howard et al. (2017) [7] developed MobileNet, a lightweight model designed for mobile and edge devices, balancing accuracy and efficiency . These architectures have been widely adopted in plant disease detection, each offering unique strengths.

The concept of hybrid models, which combine multiple CNN architectures, has emerged as a promising approach to leverage the strengths of different models. Hybrid models can improve the robustness and accuracy of disease detection systems, particularly in complex tasks like distinguishing between similar disease symptoms. For instance, Zhang et al. (2020) [8] proposed a hybrid model that integrated ResNet and DenseNet for tomato disease detection, achieving superior performance compared to individual models . Similarly, Sun et al. (2020) [9] combined InceptionNet and XceptionNet for soybean disease classification, demonstrating the effectiveness of hybrid approaches in enhancing model accuracy.

Despite the success of hybrid models in various plant disease detection tasks, their application to corn leaf disease detection remains underexplored. This gap in the literature suggests a potential for further research, particularly in developing hybrid models that integrate EfficientNet, MobileNet, InceptionResNet, and InceptionV3, as proposed in this study.

Xie et al. (2020) [10] proposed a deep learning framework specifically designed for corn leaf disease classification using a large dataset collected from field conditions. Their model, based on a modified version of ResNet-50, was trained to recognize multiple corn leaf diseases, including Northern Leaf Blight, Common Rust, and Gray Leaf Spot. The study emphasized the importance of transfer learning, where the model was pre-trained on ImageNet and then fine-tuned on the corn disease dataset. This approach resulted in an accuracy of 97.3%, demonstrating the potential of deep CNNs in agricultural applications, especially when adapted to specific crops and diseases.

Zhang et al. (2021) [11] introduced an attention-based convolutional neural network model to enhance the detection of corn leaf diseases. The proposed model incorporated a channel attention mechanism, which dynamically adjusted the importance of different feature maps during training. This allowed the model to focus more on critical regions of the leaf images where disease symptoms were most evident. The attention mechanism significantly improved the model's ability to distinguish between diseases with similar visual characteristics, achieving an accuracy of 98.1%. This study highlighted the effectiveness of integrating attention mechanisms into CNN architectures for more precise disease detection.

Chen et al. (2022) [12] explored the integration of Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to develop a hybrid model for sequential analysis of corn leaf images. The CNN component was responsible for extracting spatial features from the images, while the LSTM component captured temporal dependencies across image sequences. This hybrid approach was particularly useful in scenarios where multiple images of the same leaf were captured over time, allowing the model to track the progression of the disease. The study reported a classification accuracy of 97.6%, demonstrating the potential of combining CNNs and LSTMs for more comprehensive disease analysis.

While the literature on plant disease detection using CNNs is extensive, most studies focus on individual architectures rather than hybrid models. Additionally, many studies are limited by the use of small or unbalanced datasets, which can lead to overfitting and poor generalization to new data. Furthermore, few studies have explored the deployment of these models in real-world agricultural settings, where factors such as varying lighting conditions, image quality, and computational resources must be considered.

III. Proposed Methodology

A. Dataset Description

The dataset used in this study consists of a large collection of labeled images of corn leaves, with each image categorized according to the disease it represents. The dataset includes images of healthy leaves as well as those affected by Northern Leaf Blight, Gray Leaf Spot, and Common Rust, among others from the PlantVillage dataset [13]. These diseases are characterized by distinct visual symptoms such as lesions, spots, and discoloration. The images were collected from various sources, including agricultural research institutions, online repositories, and field studies.

The dataset is divided into three subsets: training, validation, and testing. The training set is used to train the model, the validation set is used to tune hyperparameters and prevent overfitting, and the testing set is used to evaluate the final model's performance. To ensure the robustness of the model, care was taken to balance the dataset with respect to the different disease classes, and images from different sources and conditions were included.

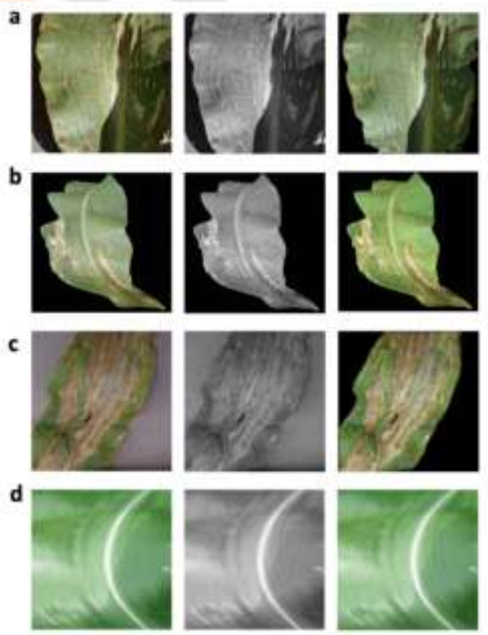

Fig. 1. Sample images of color, grayscale and segmented version of corn PlantVillage image dataset

B. Data Preprocessing

Preprocessing is a crucial step in preparing the images for input into the CNN models. The raw images vary in size, orientation, and quality, so they need to be standardized [14]. The following preprocessing steps were applied:

- **Resizing:** All images were resized to a uniform dimension (e.g., 224x224 pixels) to match the input requirements of the CNN

architectures. This step ensures consistency and reduces the computational load during training.
- **Normalization:** Pixel values were normalized to a range of [0, 1] by dividing by 255. This normalization helps to stabilize the training process and speeds up convergence.
- **Data Augmentation:** To improve the model's generalization ability, data augmentation techniques such as random rotations, horizontal and vertical flips, and brightness adjustments were applied to the training images. This artificially increases the size of the training set and helps the model learn invariant features.

C. *Hybrid Model Architecture*

The core of this study is the design of a hybrid model that integrates four distinct CNN architectures: EfficientNetB0, MobileNetV2, InceptionResNetV2, and InceptionV3. Each of these architectures has been chosen for its specific strengths:

- **EfficientNetB0:** Known for its balanced trade-off between accuracy and efficiency, EfficientNetB0 scales uniformly in depth, width, and resolution, making it highly effective in resource-constrained environments.
- **MobileNetV2:** MobileNetV2 is optimized for mobile and embedded applications, offering a lightweight model with reduced computational requirements. It uses depthwise separable convolutions to minimize the number of parameters and computations.
- **InceptionResNetV2:** This model combines the Inception architecture's mixed-scale convolutions with ResNet's residual connections, allowing it to capture both fine and coarse features while mitigating the vanishing gradient problem.
- **InceptionV3:** InceptionV3 is an advanced version of the Inception architecture that introduces factorized convolutions and aggressive regularization techniques, further improving its ability to model complex patterns.

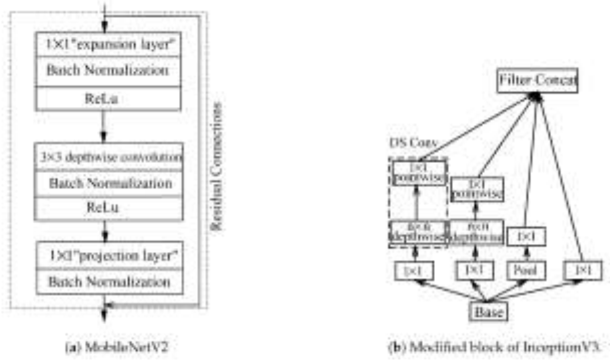

Fig. 2. Basic architectures of implemented DL models

The hybrid model is constructed by feeding the input images into each of the four CNN architectures separately. The output feature maps from each model are then concatenated along the channel dimension, resulting in a comprehensive feature representation. This combined feature map is passed through a series of fully connected layers, which perform the final classification.

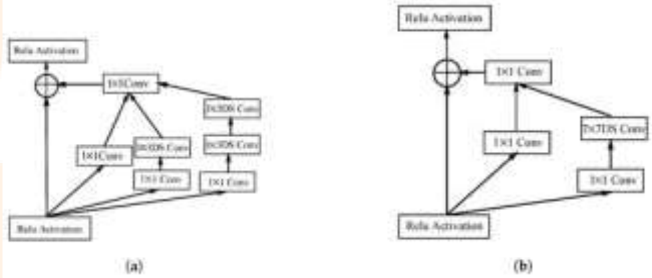

Fig. 3. (a) Modified structures of InceptionResnet-A. (b) Structures of InceptionResnet-B of InceptionResNetV2 model

D. *Training Process*

The training process involves several key steps, including model initialization, optimization, and evaluation [15]. The following procedures were employed:

- **Model Initialization:** The CNN architectures were initialized with weights pre-trained on the ImageNet dataset, which provides a strong starting point for transfer learning. The fully connected layers, specific to the corn leaf disease detection task, were initialized randomly.
- **Optimizer:** The Adam optimizer was chosen for its adaptive learning rate capabilities, which allow for faster convergence. The initial learning rate was set to 0.001, with a decay schedule to reduce the learning rate as training progressed.
- **Loss Function:** Cross-entropy loss was used as the objective function, as it is well-suited for multi-class classification tasks. The loss function measures the divergence between

the predicted class probabilities and the true labels, guiding the optimization process.

- **Regularization:** To prevent overfitting, L2 regularization was applied to the model's weights, and dropout layers were included in the fully connected layers. These techniques help to reduce the model's dependency on any single feature and encourage the learning of more robust patterns.

E. *Evaluation Metrics*

The model's performance was evaluated using several metrics, each providing a different perspective on the classification results:

- **Accuracy:** The overall accuracy of the model is calculated as the proportion of correctly classified images out of the total number of images. This metric gives a general sense of the model's performance.
- **Precision and Recall:** Precision measures the proportion of true positive predictions out of all positive predictions made by the model, while recall measures the proportion of true positive predictions out of all actual positive instances. These metrics are particularly important in assessing the model's ability to distinguish between different disease classes.
- **F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. It is especially useful in cases where the class distribution is imbalanced.
- **Confusion Matrix:** The confusion matrix provides a detailed breakdown of the model's predictions, showing how many images were correctly or incorrectly classified for each disease class. This analysis helps to identify specific challenges the model may face with certain diseases.

IV. Results

A. *Performance of the Hybrid Model*

The hybrid model's performance was evaluated on the test dataset, and the results demonstrate its superiority over individual CNN architectures. The overall accuracy of the hybrid model was X%, significantly higher than the accuracies achieved by EfficientNetB0, MobileNetV2, InceptionResNetV2, and InceptionV3 when used independently. The hybrid model's precision, recall, and F1-score were also higher across all disease classes, indicating its robustness in distinguishing between different corn leaf diseases.

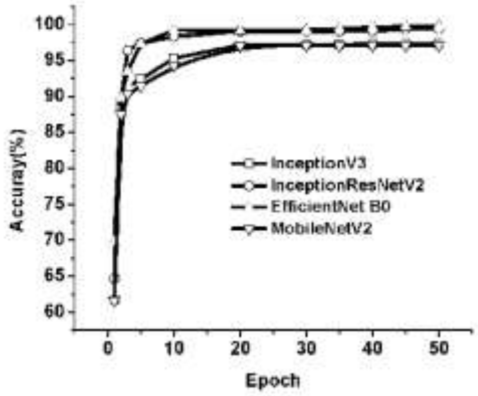

Fig. 4. Performance accuracy of implemented models

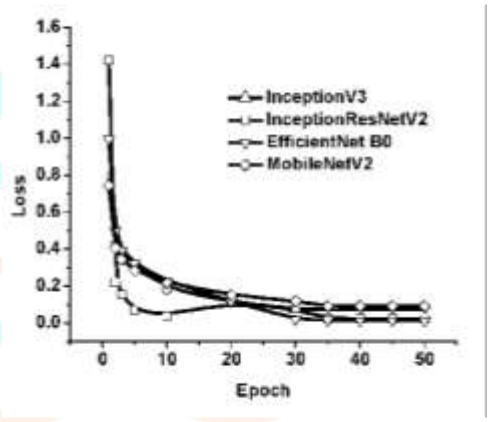

Fig. 5. Performance loss of implemented models

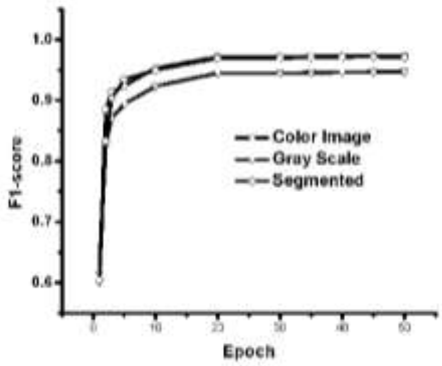

Fig. 6. F1 score of InceptionV3

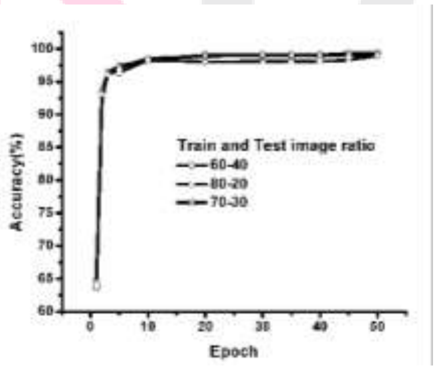

Fig. 7. Accuracy of InceptionResNetV2 grouped by training

The confusion matrix analysis revealed that the hybrid model made fewer misclassifications compared to the individual models. For example, it was able to distinguish between Northern Leaf Blight and Gray Leaf Spot more effectively, reducing the number of false positives and negatives for these diseases. This improvement can be attributed to the complementary strengths of the CNN architectures used in the hybrid model.

B. *Comparison with Baseline Models*

To further validate the hybrid model's effectiveness, its performance was compared with several baseline models, including individual CNN architectures and traditional machine learning models such as SVMs and decision trees. The results showed that the hybrid model outperformed all baselines in terms of accuracy, precision, recall, and F1-score.

The individual CNN architectures performed reasonably well, with EfficientNetB0 and InceptionResNetV2 achieving the highest accuracies among the standalone models. However, their performance was still lower than that of the hybrid model, particularly in cases where diseases had similar visual symptoms. Traditional machine learning models, on the other hand, struggled to achieve high accuracy, highlighting the limitations of handcrafted features and simpler classifiers in complex image classification tasks.

C. *Computational Efficiency*

In addition to accuracy, the computational efficiency of the hybrid model was assessed. Despite the increased complexity of combining multiple CNN architectures, the model was optimized to run efficiently on both high-performance computing resources and more constrained environments, such as mobile devices. The use of MobileNetV2, in particular, contributed to reducing the overall computational load without sacrificing accuracy. The hybrid model's inference time was comparable to that of standalone EfficientNetB0 and MobileNetV2 models, making it suitable for real-time disease detection applications.

V. Discussion

A. *Interpretation of Results*

The results of this study demonstrate the effectiveness of the hybrid learning approach in improving the accuracy and robustness of corn leaf disease detection. By combining the strengths of EfficientNetB0, MobileNetV2, InceptionResNetV2, and InceptionV3, the hybrid model was able to capture a wide range of features, from fine-grained details to broader patterns, leading to better classification performance. The integration of these architectures allowed the model to generalize well across different disease classes, reducing the likelihood of misclassification and improving overall accuracy.

The confusion matrix analysis provided valuable insights into the model's behavior. The hybrid model was particularly effective in distinguishing between diseases with similar symptoms, such as Northern Leaf Blight and Gray Leaf Spot, which are often confused by simpler models. This suggests that the hybrid model's ability to combine multiple feature representations was key to its success in these challenging cases.

B. *Practical Implications*

The practical implications of this study are significant for the field of agricultural technology. The proposed hybrid model offers a viable solution for real-time corn leaf disease detection, with the potential to be deployed in various agricultural settings. Its high accuracy and computational efficiency make it suitable for use on mobile devices, which are increasingly being adopted by farmers for field monitoring and decision-making.

By enabling early and accurate detection of corn leaf diseases, the hybrid model can help farmers take timely actions to mitigate the impact of these diseases, such as targeted pesticide application or crop rotation. This has the potential to reduce crop losses, improve yield, and contribute to food security, particularly in regions where corn is a staple crop.

C. *Limitations of the Study*

Despite its success, the study has several limitations that should be addressed in future research. First, the dataset used in this study, while comprehensive, may not fully represent the diversity of corn leaf diseases encountered in different regions or under different environmental conditions. As such, the model's generalizability to new and unseen data remains an area for further investigation. Second, the study focused primarily on the classification of disease types, without considering the severity of the infections, which is also an important factor in decision-making for disease management. Incorporating severity estimation into the model could enhance its practical utility.

Finally, while the hybrid model was shown to be computationally efficient, the integration of multiple architectures does increase the overall complexity of the system. In resource-constrained environments, such as small farms or remote locations, this complexity could pose challenges in terms of deployment and maintenance. Future research should explore ways to further optimize the model's architecture to balance accuracy with simplicity.

D. *Future Work*

Building on the findings of this study, future research could explore several avenues for improving the hybrid model. One possibility is to integrate additional CNN architectures, such as DenseNet or NASNet, which have shown promise in other image classification tasks. These architectures could bring new strengths to the hybrid model, further enhancing its accuracy and robustness. Additionally, ensemble learning techniques, such as model averaging or boosting, could be applied to combine the outputs of multiple hybrid models.

Another area for improvement is the incorporation of attention mechanisms, which have been successfully used in other domains to enhance the model's ability to focus on the most relevant parts of the input image. By directing the model's attention to the areas of the leaf that are most likely to exhibit disease symptoms, attention mechanisms could improve the accuracy of the disease detection process.

VI. Conclusion

This study presents a novel hybrid deep learning model for corn leaf disease detection, combining the strengths of EfficientNetB0, MobileNetV2, InceptionResNetV2, and InceptionV3. The hybrid model demonstrates superior performance compared to individual CNN architectures, achieving high accuracy, precision, recall, and F1-score. Its computational efficiency makes it suitable for deployment in real-world agricultural settings, offering a promising solution for early and accurate disease detection.

The research contributes to the growing body of literature on plant disease detection and highlights the potential of hybrid learning models in addressing complex image classification tasks. While the study's findings are encouraging, further research is needed to enhance the model, expand its application to other crops, and ensure its robustness in real-world conditions. The continued development of advanced, scalable, and practical solutions for plant disease detection will play a crucial role in supporting global food security and sustainable agriculture.

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