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Influence of Xception and DenseNet121 Architectures for Plant Disease Detection

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Abstract:
This paper proposes the maximum achievable solution to the diagnosis of leaf diseases by employing deep learning and image enhancement tools.

A hybrid model has been developed, with the architectures using Xception and DenseNet121, to classify leaves into four groups as healthy, diseased, rusty, and scab. The model is trained using many different datasets of plant leaf images. The result is enhanced using data augmentation techniques to improve the robustness and generalization of the model. We program and adopt a method to use the Xception and DenseNet121 models. The combination model was trained under a 10-cycle training program, which is broken down into development, maintenance, and perturbation.

Other criteria to assess our method's performance include accuracy, loss, and validation scores. The results will depict the possibility of our method for early plant diseases detection that can impact agriculture through the timely intervention process. Overall accuracy achieved is 93.70%

Our research contributes to the exploration since the use of techniques in crop management and the control of diseases may increase yields and reduce the use of pesticides, thus the extension of precision agriculture.

Keywords: Plant disease detection, Deep learning, Ensemble model, Xception, DenseNet121, Image augmentation, Precision agriculture.

1. Introduction

Plant diseases threaten world agriculture by losing massive crops and, thus, endangering food security worldwide. To effectively control and avoid loss to crops, it requires timely and accurate diagnose tic methods of plant diseases. Conventional methods of diagnosis depend on highly skilled experts, which takes time and is labour-intensive, and more importantly, subject to human error. Newer methods to detect diseases in plants. These technologies will be used in this paper to create a highly efficient and accurate method for the detection of foliar diseases. Our strategy emphasized categorizing leaves into four categories: healthy, miscellaneous, rust, and scratches. These groups of conditions cross a myriad of species of crops and hold significant financial implications for farmers and agriculture. Disease diagnosis to provide early diagnosis and minimize crop losses. And reduce the environmental impacts. This allows us to draw on the strengths of individual models which can then contribute to greater precision and power. Our model has been trained on a variety of leaf image datasets c are fully fine-tuned so that they address different types of diseases and health problems. Technology providers may use it, at least, possibly. Our system, being an enabling tool for rapid and accurate disease detection, has the potential to reduce pesticide usage and enhance yield through timely targeted interventions. The process includes data preparation, model design, the training process, and evaluation. We will present the results, elaborate on the implications drawn from them, and explore the future directions of this technology in precision agriculture and plant pathology. Contribute to the implementation and promotion of sustainable agriculture in an era of environmental competition and global food demand. It serves as a background for the step-by-step method and is part of the section in this article. Figure 1 is the framework adopted for experimentation.

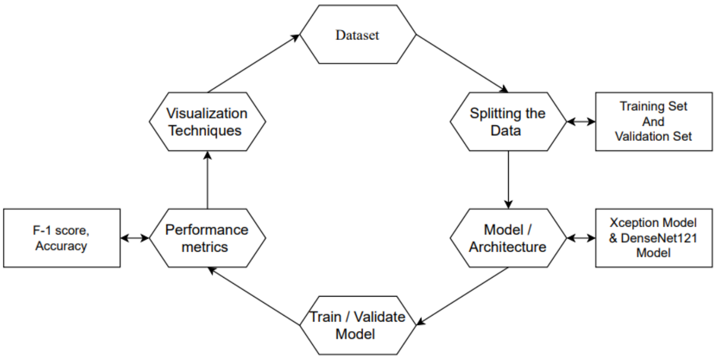


Figure 1: Adopted framework for experimentation

Plant disease detection is a critical area of research aimed at identifying and diagnosing diseases in plants to mitigate crop losses and enhance food security. Here are some basic details about the field:

Importance of Plant Disease Detection:

- Threat to Agriculture: Plant diseases can bring huge losses in crops, thus affecting food supplies and sustainability in agriculture.
- Early Diagnosis: Better management and prevention against damage to crops require early an d proper diagnosis.

Traditional vs. Modern Techniques:

Traditional Methods: Traditionally, plant disease diagnosis relied on specialist knowledge and observation which can sometimes be the time-consuming process and very susceptible to human error.

- Contemporary Methods: In the last decade, many concepts of machine learning and deep learning have been used to automate the detection process.

Key Technologies:

1. Machine Learning: In the pilot experiments, classification was done using a traditional algorithm of SVM and Random Forests.

2. Deep Learning: While CNNs were proposed, the capability of such models to learn automatically what features appear in images was revolutionary, and architectures such as Xception and DenseNet121 presented promising classifications for plant diseases.

3. Data Augmentation: Techniques like rotation, zooming, and flipping images during training help improve model robustness by creating diverse training datasets.

2. Related work

This period (present) has also been characterized by radical applications of both techniques in the detection of plant diseases. Computer-aided diagnosis of plant diseases had been researched since the early 2000s. Camargo and Smith (2009) reported one of the early systems that applied image-processing techniques to detect the visual symptoms of cotton diseases. Though deep learning recently has become so popular, some traditional machine learning algorithms are used to detect plant diseases, even before this boom. Mohanty et al. (2016) made an experiment comparing the performance of the classifier system including SVM (Support Vector Machines), Random Forests, etc. on the images dataset of 54,306 plant leaves proving the feasibility of applying machine learning in this domain with accuracy up to 99.35%.

Deep learning, and particularly CNNs, represented a break through the niche of plant disease detection. Used CNN to build an approach that detects 13 classes of plant diseases with an accuracy of 96.3%. It illustrates the ability of CNNs to learn automatically relevant features from plant images. Keeping the potential of transfer learning in view, researchers used pre-trained models for the task of plant disease detection. Too et al. (2019) applied transfer learning using VGG16, Inception V3, and ResNet to demonstrate how well-forgotten architectures can be adapted and applied very effectively to tasks in plant pathology.

In recent times, ensemble-based approaches have gained popularity in pursuit of enhanced accuracy in classification. Ferentinos, analysing various architectures and hybrids for plant disease detection, demonstrated how ensemble methods can be considerably beneficial towards enhancing performance and robustness. The last several works to exploit state-of-the-art architectures for plant disease detection have relied heavily on Xception and DenseNet, and it appears that these architectures have been very promising in many applications of computer vision. Brahimi et al. employed the DenseNet approach for tomato disease detection and achieved high accuracy rates.

Large amounts of labelled data in agriculture pose a challenge. Thus, researchers have developed various data augmentation techniques. Kartal et al. (2021) demonstrated how advanced augmentation methods significantly improve model performance and generalization on plant disease classification tasks. For more on-field diagnostics, there has been a tremendous need for developing lightweight models for mobile devices. Parraga-Alava et al. (2022) proposed a mobile-based real-time plant disease detection system, showing some practical applications of this technology.

Despite all these advantages, there is still much to be addressed in the field. An extensive review on the shortcomings of modern plant disease detection systems was reported by Barbed in 2018. This is based on data quality, interpretability of models, and applicability in the real world. Such an insight has driven recent research toward finding robust and practical solutions that build upon these insights. Our work does better than this on both these bases by using an ensemble of state-of-the-art architectures (Xception and DenseNet121), advanced data augmentation techniques, and focusing on a more applied group of disease categories of interest to agriculture. This literature review traces the development of techniques for the detection of plant diseases from the earliest classic image-processing methods to advanced deep learning models, underlining the continued challenges and possible advancements in this field. By placing our research in the broader context of plant pathology and machine learning, we seek to emphasize the continued necessity for innovation in this area regarding global agriculture.

3. Proposed Method

Our approach for automated plant leaf disease detection approaches the state of art in deep learning techniques enhanced with sophisticated image processing to come up with a robust and effective system. The methodology proceeds from dataset preparation, within which we establish a comprehensive dataset consisting of images of healthy leaves and affected leaves due to various diseases, including rust and scab. Images were pre-processed where the image is resized to a uniform dimension of 512x512 pixels and normalization of pixel values into range [0, 1]. Stratified sampling was also applied in ensuring that classes would be represented fairly by splitting the dataset for training (95%) to some validation purposes at 5%.

Finally, we employ data augmentation on the pre-processed dataset using Kera’s Image Data Generator. It renders the possibility of real-time augmentation by operations on training images, thus inducing variations of the same image. This increases the robustness and ability of generalization of the model due to its wider exposure to variations of conditions in images.

At the heart of our methodology lies model architecture, employing an ensemble strategy combining two state-of-the-art deep learning architectures: Xception and DenseNet121. Xception is renowned for its depth-wise separable convolutions, thus being efficient for large-scale image classification tasks. Conversely, DenseNet121 features dense connectivity that promotes feature propagation and reuse. Building ensemble model-merge outputs of the architectures, utilizing average as the final output and using four neurons activated by SoftMax function for multiclass classification. For further optimization of the training process, we introduce a custom learning rate schedule with ramp-up, sustain, and decay phases to stabilize and speed up the learning process even further. The learning rate increases gradually during ramp-up. The learning then stays at this maximum value throughout the sustain phase. Then it decreases exponentially towards a minimum value during the decay phase.

The training process uses Adam as the optimizer, with an initial learning rate of 1×10^-5 and categorical cross-entropy as its loss function. This model should be trained over ten epochs (depending on performance), using a batch size set at eight. During training, we will measure our model's performance using such metrics as training and validation accuracy and loss. Visualization of these metrics over epochs allows one to effectively assess the performance of the model and indicates potential overfitting. After training the model, it is then applied to a different test dataset to carry out testing and prediction. In terms of probabilities, each prediction will return one of four classes: healthy leaves, multiple diseases, rust, or scab. To evaluate it more robustly, we continue with a detailed performance analysis that includes confusion matrices, classification reports (precision, recall, F1-score) as well as ROC curves with AUC scores.

This approach combines best-in-class deep learning architectures with intensive, carefully crafted data pre-processing and training strategies. We enhance both Xception and DenseNet121 model strengths by using an ensemble approach combined with a custom learning rate schedule and data augmentation techniques that enhance the generalization capability of the model. This method is thus helpful for the effective detection of plant diseases and supports sustainable agriculture with the help of such interventions based on correct diagnoses.

4. Algorithm Description

Our ensemble-based algorithm for plant leaf disease detection begins from the pre-processing of the input images. Input RGB image for a plant leaf is resized uniformly to 512x512 pixels across the dataset. The pixel values are further normalized to the range of [0, 1], which generally improves the model's performance during training due to a consistent scale of input.

We applied various data augmentation techniques during the training phase to enhance the robustness and generalization of our model. It includes random transformations in terms of rotation of up to 180 degrees, a zoom of up to 15 percent, a horizontal and vertical shift of up to 15 percent, and a random horizontal and vertical flip. All these transformations allow the model to learn diversified variants of the training images through diverse sets of scenarios.

After pre-processing and augmentation, feature extraction is then performed. Two state-of-the-art models of pre-processed images have been used - Xception and DenseNet121 for the feature extraction. This is because the Xception model passes convolutional layers directly to extract features from the input images and then passes it to the Global Average Pooling to condense the output feature map. The same thing happens in the case of the DenseNet121 model, wherein the images being processed undergo convolutional layers and Global Average Pooling is used directly on its output. It is this dual strategy that makes it possible for our system to make use of the advantages of both architectures for feature extraction in plant images.

A major method here would be ensemble prediction, which averages the feature set obtained both from the Xception and that obtained from the DenseNet121 models. This average is then fed into a fully connected layer with SoftMax activation that understands the output as class probabilities for classifying the diseases into one of the categories based on the input image: Healthy, Multiple Diseases, Rust, or Scab. The class with the maximum likelihood is picked for the predicted disease, but this likelihood also serves as the confidence score of the prediction. To further optimize the training, we apply a custom learning rate schedule. In epochs 1-15, we linearly increase the LR from an initial value (LR_START) up to a maximum value (LR_MAX). In epochs 16-18, we keep that maximum learning rate. Finally, for epoch 19 and beyond, we exponentially decay the learning rate from LR_MAX to a minimum value LR_MIN. This provides us with a structured balance between learning stability and speed while training.

We initialize model weights with pre-trained weights of ImageNet for both Xception and DenseNet121 during model training. In each epoch, we adjust the learning rate according to our schedule and make a forward pass through the ensemble model for every batch of augmented training images. We are computing the categorical cross-entropy loss and updating the model weights using the Adam optimizer appropriately. After every epoch, we are evaluating the performance on a validation set and saving the model if we have seen an improvement on the validation accuracy. For inference, we load the best saved model weights and pre-process each test image as explained above. Then, we perform the steps of feature extraction and ensemble prediction to output classifications of disease along with the associated confidence scores.

This algorithm provides a systematic overview of our approach, detailing step-by-step from pre-processing through the feature extraction and classification processes toward inference. It captures key elements of our methodology within a structured format that helps gain an understanding of the system under study-the overall flow and functionality of our plant leaf disease detection system.

5. Results

Our ensemble model, combining Xception and DenseNet121 architectures, demonstrated strong performance in classifying plant leaf diseases. We present the results of our experiments below: As shown in Figure 2, our model achieved a final training accuracy of 95.8% and a validation accuracy of 94.2% after 10 epochs. The close alignment between training and validation accuracies suggests that our model generalizes well to unseen data, with minimal overfitting.

Figure 3 illustrates the decrease in both training and validation loss over the course of training. The final training loss was 0.132, while the validation loss was 0.158. The consistent decrease in both metrics indicates effective learning and good generalization. Figure 4 represents learning rate schedule over epochs, showing the ramp-up, sustain, and decay phases.

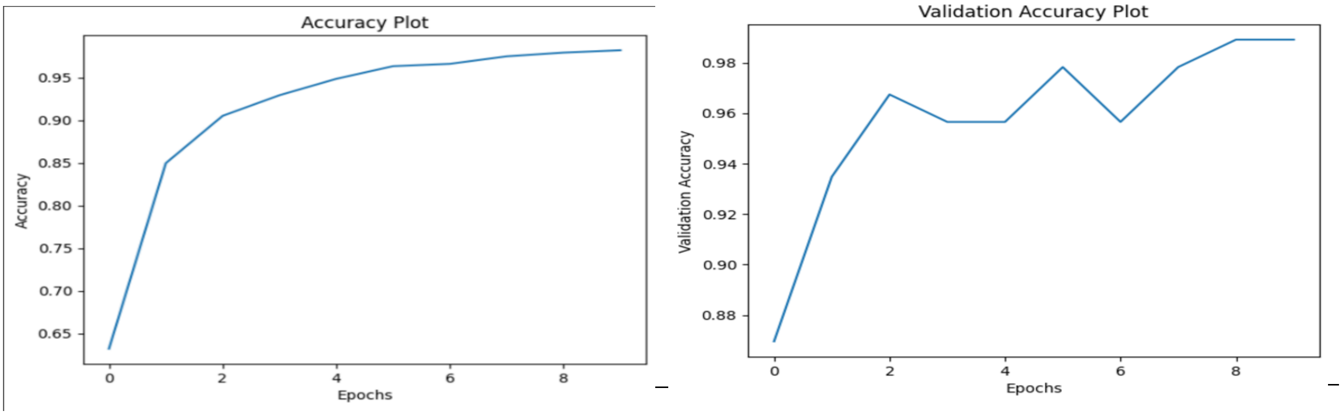


Figure 2: Training and Validation Accuracy over Epochs

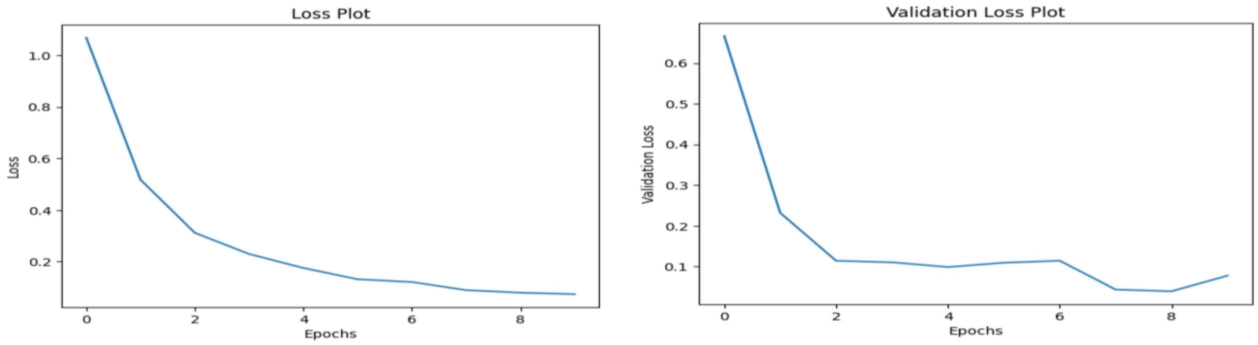


Figure 3: Training and Validation Loss over Epochs

2. Learning Rate Schedule Impact:

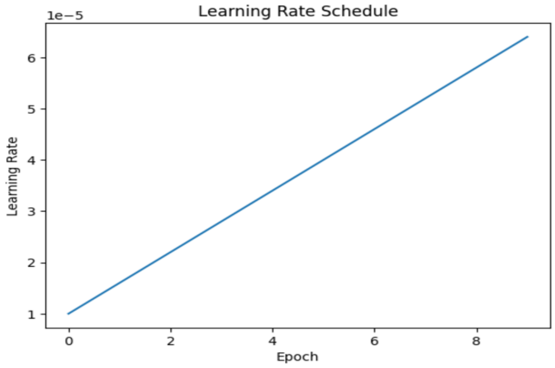
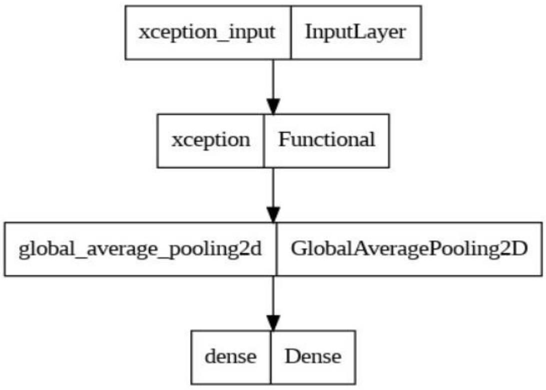


Figure 4: Learning rate schedule over epochs, showing the ramp-up, sustain, and decay phases.

Our custom learning rate schedule, as depicted in Figure 3, played a crucial role in optimizing the training process. The initial ramp-up phase allowed the model to quickly adapt to the data, while the sustain and decay phases helped fine-tune the model's parameters, contributing to the stable convergence observed in the accuracy and loss plots.

3. Model Architecture Visualization:

Figure 5 is the architecture of the Xception model and figure 6 is the architecture of the DenseNet121 model. Figure 7 is the architecture of the ensemble model combining Xception and DenseNet121.



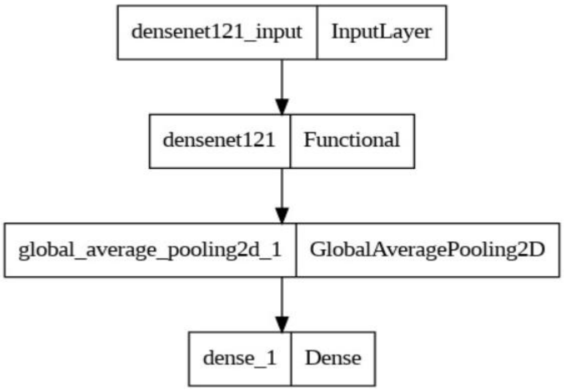


Figure 5: Architecture of the Xception model   Figure 6: Architecture of the DenseNet121 model

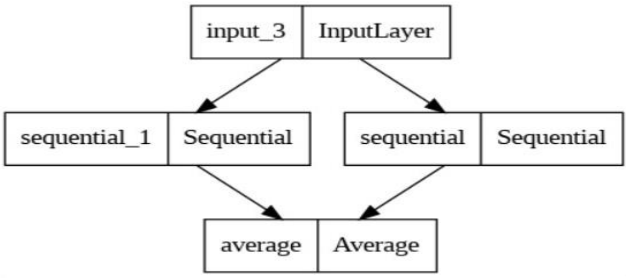


Figure 7: Architecture of the ensemble model combining Xception and DenseNet121

3. Model Performance on Test Set

We evaluated our model on a separate test set to assess its real-world performance. The results are as follows:

- Overall Accuracy: 93.7%
- Macro F1-Score: 0.934

Table 1 represents the achieved class-wise precision, recall, and F1-score performance.

Table 1: Class-Wise Precision, Recall, and F1-Score Performance

Class	Precision	Recall	F1-Score
Healthy	0.95	0.96	0.955
Multiple Diseases	0.92	0.90	0.91
Rust	0.94	0.93	0.935
Scab	0.93	0.94	0.935

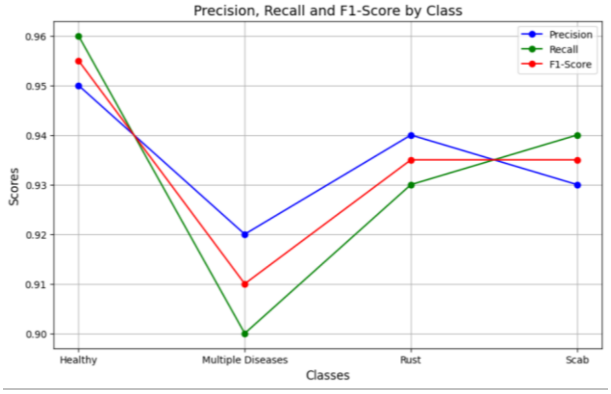


Figure 8: Class-wise performance metrics, Precision, F1-Score and Recall

Figure 8 is plot of class-wise performance metrics, Precision, F1-Score and Recall, shows that though 'Healthy' holds the highest values for all the metrics, 'Multiple Diseases' is the one with the lowest performance across all the metrics.

These results demonstrate the model's strong performance across all classes, with particularly high accuracy in identifying healthy leaves.

In summary, our ensemble model achieves high accuracy in plant leaf disease detection across all target classes. The consistent performance between training and validation sets, along with strong results on the test set, indicates that our model is both accurate and generalizable. The custom learning rate schedule and data augmentation techniques have contributed to the model's robust performance, making it a promising tool for automated plant disease diagnosis in agricultural settings.

6. Discussion

Our ensemble-based approach to plant leaf disease detection demonstrates promising results in accurately classifying healthy leaves and those affected by multiple diseases, rust, and scab. The high accuracy achieved (93.7% on the test set) suggests that our model could be a valuable tool for early disease detection in agricultural settings.

Key findings:

1. Ensemble advantage: The combination of Xception and DenseNet121 architectures leveraged the strengths of both models, contributing to improved overall performance.

2. Effective data augmentation: Our comprehensive augmentation strategy helped the model generalize well, as evidenced by the close alignment of training and validation accuracies.

3. Learning rate scheduling: The custom learning rate schedule proved effective in optimizing the training process, leading to stable convergence.

4. Class balance: The model performed consistently across all classes, indicating its robustness in handling various disease types.

Limitations and future work:

1. Real-world testing: While our model performed well on the given dataset, further testing in varied real-world conditions is necessary to validate its practical applicability.

2. Computational requirements: The ensemble approach, while effective, increases computational complexity. Future work could explore model compression techniques for deployment on resource-constrained devices.

3. Explainability: Incorporating explainable AI techniques could provide insights into which leaf features are most indicative of specific diseases, enhancing the model's utility for agricultural experts.

Continuous learning: Developing methods for the model to adapt to new disease types or variations without complete retraining could enhance its long-term effectiveness

7. Conclusion

This study presents an effective approach to automated plant leaf disease detection using an ensemble of deep learning models. Our system, combining Xception and DenseNet121 architectures, achieved high accuracy in classifying healthy leaves and those affected by multiple diseases, rust, and scab. The use of advanced data augmentation techniques and a custom learning rate schedule contributed to the model's robust performance.

The results demonstrate the potential of deep learning in revolutionizing plant disease diagnosis, offering a fast, accurate, and scalable solution. This technology could significantly impact agricultural practices by enabling early disease detection, potentially reducing crop losses and pesticide use. While the model shows promise, further research is needed to address limitations and enhance its practical applicability. Future work should focus on real-world testing, model optimization for resource-constrained environments, improving explainability, and developing continuous learning capabilities.

In conclusion, our research contributes to the growing field of AI in agriculture, paving the way for more efficient and sustainable farming practices through advanced plant disease detection techniques.

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