Fostering Crop Health - Investigating state-of-art CNNs for Corn and Maize leaf disease Analysis

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Abstract. The fast detection and sorting of plant diseases are really important to make sure we have enough food and keep farming productive. In this study, we're using the latest technology called Convolutional Neural Networks (CNNs) to figure out what's wrong with maize leaves. We're using five different CNN models to do this and making them work better for identifying maize leaf diseases. Our main goals are to compare how well these models perform, see how accurate they are, and find the best one for identifying maize leaf diseases. We're looking at a big collection of pictures of maize leaves, some healthy and some sick, for our study. We're using popular models like VGG, ResNet, Inception, EfficientNet, and MobileNet which are really good at understanding pictures. We're making these models better at finding diseases on maize leaves by adjusting their settings. Our study shows that these modern models are really good at spotting plant diseases. We're checking how accurate each model is and comparing them to find the one that's the best at knowing which disease is on a maize leaf. We're using different ways to measure their performance, like how well they remember things, how exact they are, and other factors. Among all the models we studied, VGG is the most accurate and promising for identifying maize leaf diseases. This model could be really helpful in real farms because it's really good at finding problems in the pictures. It's especially good to see small details that show which disease is on the leaf. To sum it up, our study shows that using advanced CNN models is really important for finding plant diseases. The results make it clear that picking the right model is key to knowing what disease is there. These models could also make farming better in the future.

Keywords: VGG, ResNet, Inception, EfficientNet and MobileNet

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1 Introduction

One of the most widely grown and economically important crops, is prone to a number of diseases that can have a major negative influence on quality and output. Agronomists must manually evaluate crops as part of traditional disease identification techniques, which can be laborious and error-prone. Advances in technology, especially deep learning and Convolutional Neural Networks (CNNs), have opened up new approaches to solving this problem in recent years. The discipline of image classification—including the identification of plant diseases—has been completely transformed by CNNs' capacity to automatically learn and extract complicated information from photos. CNNs have shown remarkably effective across a range of areas, attaining cutting-edge outcomes on benchmarks such as the ImageNet dataset.

The difficulty of employing sophisticated CNN architectures for disease detection in corn leaves is the main focus of this work. The goal is to precisely determine if corn leaves are disease-free or healthy by using these potent computer models. We are experimenting with five popular implementations of these models: VGG, ResNet, Inception, DenseNet, and MobileNet. By utilizing a carefully selected collection of images of maize leaves that illustrate various plant growth patterns and disease types, we are improving these techniques.

The primary objective of this study is to evaluate the classification accuracy of these CNN models, compare their performances, and identify the CNN architecture that excels in accurately identifying corn leaf diseases. By doing so, we aim to provide insights into the effectiveness of state-of-the-art CNNs for plant disease detection, with specific implications for the agricultural sector. The outcomes of this research have the potential to revolutionize disease management strategies, leading to improved crop yield, reduced economic losses, and enhanced food security.

2 Related Work

A variety of factors, such as fungi, nematodes, bacteria, viruses, and environmental factors, make it difficult to identify diseases in maize leaves. Farmers, for example, struggle to diagnose diseases based purely on symptoms due to its intricacy, which forces them to rely on expensive expert advice [1]. Unfortunately, there aren't many Convolutional Neural Networks (CNNs) designed for plant disease recognition that are also user-friendly, especially when working with raw photos that have feature extraction tools built in [2]. There is a rising need to use intelligent algorithms into Artificial Neural Network (ANN) frameworks to address this issue and effectively manage plant diseases while preserving crop health [3]. Since it automatically detects pertinent features without the need for complex setup processes, deep learning, notably through CNNs, has emerged as a promising solution in agriculture [4]. Automating the accurate disease detection in unhealthy leaves is a key goal [5]. This research investigates the integration of the pre-trained VGG16 network, strengthening the architecture inherited from AlexNet by adding more convolutional layers [6], in order to improve disease identification skills. Transfer learning is essential for allowing the model to use

information from related issue domains [7]. With the introduction of INC-VGGN, a new deep learning architecture that places a strong emphasis on transfer learning, state-of-the-art performance is demonstrated, with potential applications in mobile-based monitoring and more thorough plant disease identification [8] Additionally, this study uses deep learning to solve the problem of quickly identifying plant diseases, avoiding the difficulties involved in putting up large annotated datasets. When dealing with smaller datasets, Few-Shot Learning (FSL) algorithms that use Siamese networks and triplet loss outperform conventional learning approaches, demonstrating their ability to learn about new plant leaf and disease kinds with little to no training data [9].
Convolutional Neural Networks (CNNs) are a potent technique for classifying insects for crop protection. The study successfully uses CNNs to classify insects that seriously damage crops, a process that is sometimes made difficult by their identical outward looks [10]. Only a little amount of study on the computerized classification of illnesses affecting rice plants has been done in India. To categorize diseases affecting rice plants, deep CNN transfer learning was initially investigated. The experiments also included dividing the entire dataset into various training-to-testing set ratios [11]. In addition, this study uses segmentation models and Efficient Net to recognize tomato plant diseases in 18,161 leaf images. The results demonstrate that disease categorization can be significantly enhanced by deeper neural networks trained on segmented images, outperforming earlier studies in terms of accuracy and performance [12][13].

3 Proposed Methodology

We explore the methodology, dataset, experimental design, and findings of our investigation in the sections that follow. The importance of choosing the most accurate CNN architecture and its consequences for improving agricultural practices are also emphasized.

A. Models Used

State-of-Art CNN Models:

In this study, we harness the power of several well-established Convolutional Neural Network (CNN) architectures to address the task of corn leaf disease classification. Each architecture brings its unique strengths in feature extraction and representation, which makes them suitable candidates for image-based classification tasks.

1. VGG16 (Visual Geometry Group 16): VGG16 is a seminal CNN architecture known for its simple yet effective structure. It comprises 16 weight layers, including 13 convolutional layers and three fully connected layers. The consistent use of 3x3 convolutional filters throughout the architecture leads to a homogeneous and deep network, making it an insightful choice for our study [14] .

2. ResNet (**Residual Network**): ResNet introduces the concept of residual blocks, allowing for the training of exceptionally deep networks. The residual blocks enable the propagation of gradients abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable. and help prevent the vanishing gradient problem. Deeper versions of ResNet, such as ResNet-50 and ResNet-101, have shown remarkable performance improvements over shallower architectures.

3. MobileNet: MobileNet is designed for efficiency, particularly in terms of computational resources and model size. It employs depthwise separable convolutions to drastically reduce the number of parameters and computational complexity while maintaining competitive accuracy. This architecture is particularly suited for resource-constrained environments.

4. EfficientNet: EfficientNet represents a family of CNN architectures that achieve exceptional performance by scaling the depth, width, and resolution simultaneously.[18] The architecture balances these dimensions using a compound scaling method, resulting in networks that are both efficient and accurate across various tasks.

5. Inception: The Inception architecture, also known as Google Net, features the innovative use of multiple filter sizes within a single layer, capturing features at different scales.[16][17] This approach aids in capturing both fine-grained and high-level information from the images, leading to improved feature representations.

Fine-Tuning and Transfer Learning

For each of these CNN architectures, we initialize the model with pre-trained weights obtained from training on the ImageNet dataset. This process, known as transfer learning, leverages the pre-trained model's learned features, which are highly effective in capturing general image patterns. We replace the final classification layers with our custom layers that suit the corn leaf disease classification task [14].

Fine-tuning is then performed on the corn leaf dataset, allowing the models to adapt to the specific features and characteristics of the dataset. We employ techniques such as learning rate scheduling and data augmentation to enhance the models' convergence and generalization capabilities during the fine-tuning process.

Activation functions:

ReLU :

The ReLU function is a simple but powerful activation function that introduces non-linearity to neural networks. It's widely used in hidden layers to enable networks to learn complex relationships in the data.

The ReLU function is defined as follows:

ReLU(x) = max (0, x)

Where

- x is the input to the function.
- ReLU(x) outputs the input x if it's positive, and outputs 0 if x is negative.
- ReLU(x) outputs the input x if it's positive, and outputs 0 if x is negative.
- ReLU effectively transforms negative values to zero, allowing positive values to pass through unchanged.

This non-linearity is essential for enabling neural networks to learn complex patterns and relationships in data.

SoftMax:

For multi-class classification problems, the SoftMax function is frequently utilised in the output layer of a neural network. It transforms a vector of raw scores, often known as logits, into a probability distribution across several classes.

The Softmax function is defined mathematically for each class i as follows:

For all classes j, softmax(x)$_i$ = exp(x_i) / sum(exp(x_j))

Where:

- Logit score for class 'i' is represented by x_i.
- The exponential of the raw score for class 'i' is denoted by exp(x_i).
- The exponentials of the raw scores for each class j are added up in the denominator.
- By converting the logits into probabilities using the SoftMax function, it is ensured that the output values fall between 0 and 1 and add up to 1. This is necessary in order to understand the output of the network as class probabilities, which is appropriate for tasks involving multi-class classification.
- To summarise, ReLU adds non-linearity to neural networks by permitting positive values to flow through unaltered, and for multi-class classification problems, the SoftMax function translates raw scores into class probabilities.

A. Training the CNN's

In this study, we undertake a comprehensive data preprocessing and model configuration approach for effective corn leaf disease detection. Initial steps involve resizing all input images to a standardized 224x224 pixel size, and maintaining aspect ratios. Multiple pre-trained CNN models—ResNet50, VGG16, EfficientNet, Inception, and MobileNet—are selected as base architectures, leveraging their weights pre-trained on the ImageNet dataset. Each model is enhanced with consistent classification layers, including global average pooling to preserve significant features, flattening for conversion to a 1D vector, and a fully connected layer with softmax activation for class probabilities. During training, the adaptive learning rate capabilities of the Adam optimizer contribute to efficient convergence, with a learning rate of 1e-3 (0.001) found suitable. The output layer employs SoftMax activation and Categorical Cross-Entropy loss for converting predictions into class probabilities and measuring dissimilarity. Model evaluation includes validation and testing on split datasets, employing metrics like accuracy, precision, recall, and F1-score. Hyperparameter tuning further optimizes learning rates, optimizer parameters, and model-specific parameters. Following training, models are deployable for real-world applications to predict unseen data, potentially revolutionizing disease identification processes.

B. Dataset

Corn/Maize Leaf Disease Dataset The Corn/Maize Leaf Disease Dataset was used in this study to train, validate, and test the classification models. This dataset comprises images of corn/maize leaves, categorized into four distinct classes: Blight, Common

Rust, Gray Leaf Spot, and Healthy. The dataset is used to assess the models' ability to accurately identify and classify different types of leaf diseases and healthy leaves.

Total Number of Images: 4188
The class Distribution is as follows

- Blight: 1146 images
- Rust: 1306 images
- Gray Leaf Spot: 574 images
- Healthy: 1162 images

The dataset's class distribution is relatively balanced, with each class containing a significant number of images for training and evaluation. This balance is important to ensure that the models are not biased toward any particular class during training. The dataset's diversity in terms of leaf disease types (Blight, Common Rust, Gray Leaf Spot) and healthy leaves allows the models to learn complex features associated with each class, contributing to their overall classification accuracy. These images were pre-processed by resizing them to a standardized resolution of 224x224 pixels to ensure uniformity and facilitate compatibility with the chosen pre-trained models.

C. Results and Discussion

The outcome of our study, as discussed in this section, reveals the performance of the corn leaf disease detection models. Among the five distinct CNN models—ResNet50, VGG16, EfficientNet, Inception, and MobileNet—the achieved accuracy rates offer valuable insights. Notably, ResNet50 and VGG16 stand out with the highest accuracies of 94.9% and 94.39%, respectively. This highlights their effectiveness in accurately identifying corn leaf diseases. EfficientNet follows closely with an accuracy of 92.24%, while Inception and MobileNet achieve accuracies of 91.28% and 91.05%, respectively. The variations in accuracies stem from the unique characteristics of each model's architecture. The superiority of ResNet50 and VGG16 underscores their suitability for this task, backed by their robust performance. EfficientNet's competitive accuracy demonstrates its capability, while Inception and MobileNet exhibit commendable results despite marginally lower accuracies. This analysis informs model selection for real-world application in corn leaf disease detection, taking into account each model's strengths and performance.

TABLE I: Model Accuracies

CNN Model	Training Accuracy (%)	Testing Accuracy
ResNet50	**99.83%**	**94.98%**
VGG16	**99.46%**	**94.39%**
EfficientNet	**98.54%**	**92.24**
Inception	**97.08%**	**91.05**
MobileNet	**97.34%**	**91.28%**

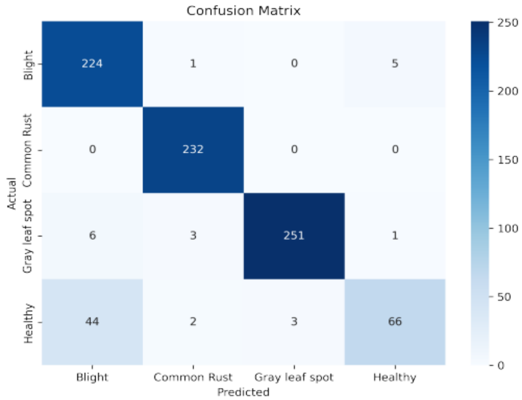

Fig. 1: EfficientNet

	precision	recall	f1-score	support
Blight	0.82	0.97	0.89	230
Common Rust	0.97	1.00	0.99	232
Gray leaf spot	0.99	0.96	0.97	261
Healthy	0.92	0.57	0.71	115
accuracy			0.92	838
macro avg	0.92	0.88	0.89	838
weighted avg	0.93	0.92	0.92	838

Fig. 2: Performance of EfficientNet Model

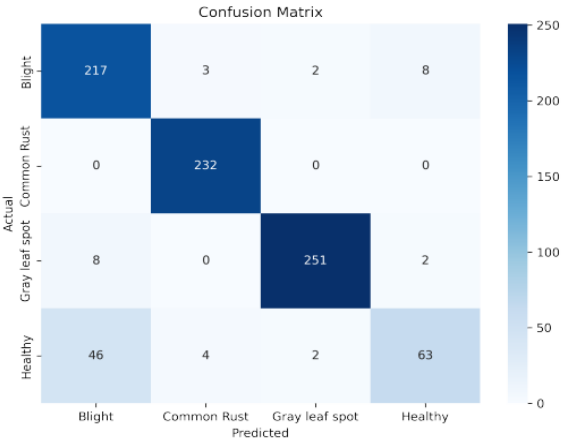

Fig 3: Confusion matrix

	precision	recall	f1-score	support
Blight	0.80	0.94	0.87	230
Common Rust	0.97	1.00	0.99	232
Gray leaf spot	0.98	0.96	0.97	261
Healthy	0.86	0.55	0.67	115
accuracy			0.91	838
macro avg	0.90	0.86	0.87	838
weighted avg	0.91	0.91	0.91	838

Fig. 4: Performance of InceptionNet Model

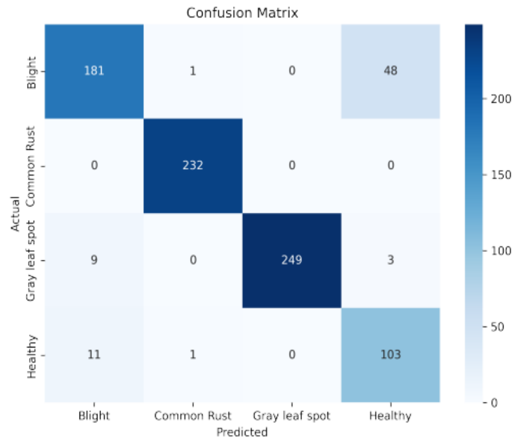

Fig. 5: MobileNet

	precision	recall	f1-score	support
Blight	0.90	0.79	0.84	230
Common Rust	0.99	1.00	1.00	232
Gray leaf spot	1.00	0.95	0.98	261
Healthy	0.67	0.90	0.77	115
accuracy			0.91	838
macro avg	0.89	0.91	0.89	838
weighted avg	0.92	0.91	0.92	838

Fig. 6: Performance of MobileNet Model

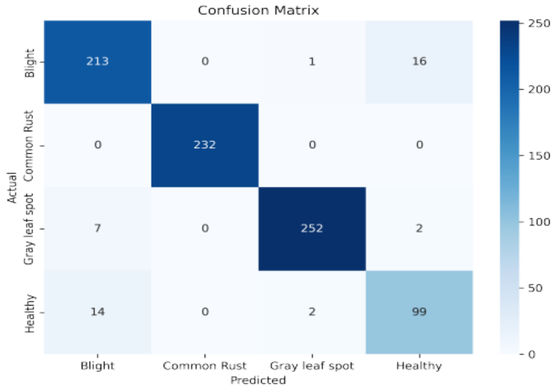

Fig. 7: ResNet

	precision	recall	f1-score	support
Blight	0.91	0.93	0.92	230
Common Rust	1.00	1.00	1.00	232
Gray leaf spot	0.99	0.97	0.98	261
Healthy	0.85	0.86	0.85	115
accuracy			0.95	838
macro avg	0.94	0.94	0.94	838
weighted avg	0.95	0.95	0.95	838

Fig. 8: Performance of ResNet Model

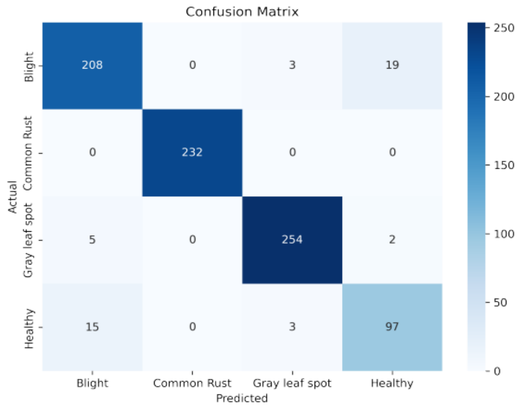

Fig. 9: VGGNet

	precision	recall	f1-score	support
Blight	0.91	0.90	0.91	230
Common Rust	1.00	1.00	1.00	232
Gray leaf spot	0.98	0.97	0.98	261
Healthy	0.82	0.84	0.83	115
accuracy			0.94	838
macro avg	0.93	0.93	0.93	838
weighted avg	0.94	0.94	0.94	838

Fig. 10: Performance of VGGNet

4 Conclusions

In summary, our research shows how well convolutional neural networks (CNNs), a cutting-edge technology, can identify illnesses in maize leaves. We can precisely determine if a leaf is healthy or diseased by carefully utilizing these potent computer models. With models like ResNet50 and VGG16 obtaining accuracies of roughly 94.9\% and 94.39\%, respectively, our results are encouraging. This indicates that they have a high level of problem recognition ability. The impact of this research is substantial. For us to have adequate food, it necessitates that farmers can identify and treat disease problems in their crops rapidly. We can save crops and lessen the need for dangerous herbicides by identifying issues early. This study also emphasizes the fascinating partnership between farming and technology. More intelligent methods of food production can result from fusing modern agricultural methods with more conventional ones. Finding methods to generate more food becomes crucial as the world's population rises. These developments in technology have the potential to revolutionize efficient and sustainable farming practices. Even though we're happy with our results, additional research needs to be done. We can adjust the model's parameters, put it to the test in various scenarios, and improve it still further. To make sure these models function successfully in real-world scenarios, more testing is required before using them on actual farms. Our research essentially demonstrates the significant impact that technology may have on agriculture. We are moving closer to a sustainable and safe food supply by utilizing smart computers to assist us comprehend plant health. We are getting closer to building a more intelligent and improved farming future as we continue along this route.

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