



Performance Comparison of VGG16 and VGG19 Architectures for Corn Leaf Disease Classification

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Abstract

Corn (*Zea Mays L.*) faces challenges from leaf diseases, which become severe when farmers lack the expertise to recognize and manage them. This study presents a comparative analysis of VGG16 and VGG19 architectures for detecting corn leaf diseases, highlighting their performance under standardized conditions using transfer learning. The novelty of this study lies in the direct benchmarking of both models across multiple image resolutions and training epochs, which has not been comprehensively explored in previous studies. The system categorizes diseases based on images, thereby helping farmers manage corn leaf diseases more effectively. The VGG16 architecture was chosen for its balance of depth and computational efficiency, while VGG19 offers higher accuracy due to its increased layer depth and complexity. This system is expected to assist farmers in detecting corn leaf diseases more efficiently and accurately than previously possible. The dataset used in this study consists of 4198 images, divided into four categories: Healthy, Blight, Common Rust, and Gray Leaf Spot. The dataset was split into 80% for training and 20% for testing purposes. The classification results using 2 architectures, VGG16 and VGG19, with the use of the SGD optimiser, show that VGG19 outperforms VGG16. The VGG19 model demonstrated a performance level of 92.74% accuracy, alongside 91% for precision, recall, and F1-score. In comparison, VGG16 achieved a slightly lower accuracy of 92.62%, with precision at 91%, recall at 89%, and an F1-score of 90%. This performance variance is attributed to the architectural depth, as VGG19 utilizes 19 layers while VGG16 is limited to 16. Ultimately, this tool aims to provide farmers with a more precise and streamlined method for identifying corn foliage conditions.

Keywords: CNN; corn; leaf image; VGG16; VGG19

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1. Introduction

Globally, maize (*Zea Mays L.*) represents a cornerstone of food stability, ranking just behind wheat and rice in terms of its critical role in feeding the world's population. Together, these staple foods account for more than half of the daily calorie intake of the global population [1]. According to FAO projections in 2016, global demand for corn is expected to increase continuously, reaching approximately 3.3 billion tons by 2050 [2]. As it develops, the maize plant remains vulnerable to numerous pathogens, especially those targeting the foliage. Because the leaves are the primary site for photosynthesis, any infection can obstruct the plant's metabolic processes, leading to stunted growth and diminished agricultural output [3].

Detecting leaf diseases early is essential for minimizing crop damage. Traditionally, farmers rely on visual

inspection to identify signs of disease, such as color changes or patterns on the leaves [4]. Nevertheless, this conventional manual approach is hindered by significant drawbacks, including extensive time requirements and a high propensity for error. Furthermore, the results are frequently compromised by the subjective nature of human judgment, which lacks the consistency of automated tools [5]. Moreover, farmers in rural areas may lack the expertise to recognize specific disease symptoms, leading to delays in diagnosis and treatment. As a result, developing a streamlined and high-precision automated framework has become essential for supporting agricultural workers in the swift detection and mitigation of crop ailments.

Convolutional Neural Networks (CNNs) have emerged as a transformative paradigm for addressing agricultural challenges, consistently delivering high-precision

results in image classification tasks across multiple sectors [6] - [8]. Architectures based on CNNs possess the capacity to analyze extensive image datasets, identifying intricate and latent features that typically elude manual observation. In recent years, various CNN architectures have been applied to classify crop diseases, including AlexNet, ResNet, and custom CNNs, each with varying levels of accuracy and computational efficiency [9] - [12].

However, existing studies on corn leaf disease classification present several gaps. Notably, many previous investigations have centered on isolated CNN models, frequently lacking comparative assessments conducted under uniform experimental conditions. Furthermore, there is a distinct shortage of literature that evaluates the delicate balance between structural complexity and processing efficiency—a factor that remains vital for deploying real-time diagnostic tools in the agricultural sector. For example, studies utilizing AlexNet or custom CNNs demonstrate decent accuracy but lack depth analysis when compared to deeper networks such as VGG16 and VGG19 [11], [13].

In an effort to overcome these challenges, the present research conducts a head-to-head performance analysis of the VGG16 and VGG19 frameworks specifically for identifying corn leaf pathogens. To ensure a fair comparison, both models are evaluated under identical conditions, including uniform training datasets, optimization settings, and image preprocessing techniques. The goal is to identify the most effective architecture by balancing predictive metrics—such as precision and accuracy—with operational efficiency, ultimately fostering the creation of more robust agricultural diagnostic tools.

The primary contribution of this work lies in providing a systematic and replicable evaluation of the VGG16 and VGG19 frameworks. By maintaining strict uniformity across the experimental design—specifically in preprocessing techniques, optimizer selection, and data partitioning—this study ensures a fair and transparent performance benchmark. Such a comprehensive evaluation provides new insights into the trade-offs between model complexity and performance in plant disease classification, which have been underexplored in previous literature.

The implementation of deep learning frameworks, specifically Convolutional Neural Networks (CNNs), has become a focal point in the literature for identifying plant pathogens. This investigation leverages a pre-trained CNN architecture to distinguish between various maize foliar conditions. The experimental dataset encompasses five distinct classifications, covering healthy specimens alongside four specific ailments: downy mildew, leaf spot, blight, and rust. Integrating a transfer learning approach led to a marked enhancement in both processing speed and predictive performance. Specifically, the model achieved a training accuracy of 85% and a validation accuracy of

88%, while keeping error rates notably low at 0.45% and 0.54%, respectively [9].

Another research diseases [10] highlighted the significance of corn as a primary food source in Indonesia, second only to rice. The study addressed the challenge of manually detecting corn leaf diseases and proposed a CNN-based digital image processing system. The AlexNet architecture was implemented to analyze a comprehensive collection of 4,198 images, categorized into Healthy, Gray Leaf Spot, Common Rust, and Blight groups. This model demonstrated strong diagnostic capabilities, reaching a 90% classification accuracy and proving its reliability for automated corn leaf assessment. In another study [11], researchers explored the diagnostic capabilities of CNNs in identifying maize foliage ailments. Their experimental work utilized a collection of 3,846 images, specifically focusing on three common pathologies: rust, leaf spot, and blight.

The implementation of their CNN architecture yielded a success rate of over 90%. Such results highlight the significant role that deep learning methodologies play in the precise identification of various corn leaf conditions.

Research conducted in [12] explored corn leaf disease classification via a custom CNN framework. The architecture was designed with a sequence of four convolutional and two pooling layers, integrated with three dropout layers and a flattening stage before reaching two dense layers using ReLU activation. Evaluated on a 900-image dataset, the system recorded accuracies of 89% for training and 84% for testing. The authors concluded that employing the Adam optimizer in conjunction with a 3x3 kernel size provided the most effective results. Given the successful application of various CNN architectures in previous studies and their demonstrated high accuracy in corn leaf disease classification, this study employs VGG16 and VGG19 architectures. VGG16 is chosen for its balance of depth and computational efficiency, while VGG19 is selected for its higher accuracy due to its increased layer depth and complexity. The specific attributes of VGG16 and VGG19 render them highly effective for building a reliable framework for maize disease diagnosis. Although various CNN models have been utilized for agricultural monitoring, their effectiveness is often contingent upon their architectural depth, total parameters, and the resulting computational demands. For example, AlexNet, as used in [11], offers relatively fast training and a smaller number of parameters but tends to underperform in fine-grained classification tasks due to its shallower depth. In contrast, custom CNN models like the one proposed in [13] often suffer from lower generalization capabilities and are highly dependent on dataset-specific tuning. ResNet, another widely used architecture, introduces residual connections to prevent vanishing gradients in deeper networks, making it suitable for very deep models [Ref]. However, ResNet often requires more

computational resources and longer training times than VGG architectures. Compared to these models, VGG16 and VGG19 strike a balance between accuracy and architectural simplicity. Although they are deeper than AlexNet and most custom CNNs, their uniform layer structure and compatibility with transfer learning frameworks make them easier to implement and optimize. Moreover, their superior performance in this study demonstrates their robustness in handling multi-class plant disease datasets. The key trade-off lies in VGG19's higher accuracy at the cost of slightly more computational demand than VGG16, making it preferable when precision is prioritized, and resources are sufficient. This comparative analysis highlights that while lightweight models like AlexNet are sufficient for quick deployment, deeper models like VGG and ResNet offer better feature extraction capabilities—especially for tasks involving subtle visual distinctions such as corn leaf disease classification.

2. Methods

2.1 Corn Leaf Disease Dataset

Diseases in corn plants result from the interaction of three main factors: pathogens, hosts, and the environment. The spread of diseases, both in terms of increased intensity and extent, is greatly influenced by significant contributions from these three factors, ultimately leading to a decrease in yield [13]. In corn, there are three distinct leaf diseases: Blight, Common Rust, and Gray leaf spot. This study employed a dataset containing three categories of corn plant diseases and one category representing healthy corn plants. The dataset comprised 4,198 images and was sourced from the website kaggle.com [14]. The images obtained from the dataset are shown in Figure 1.

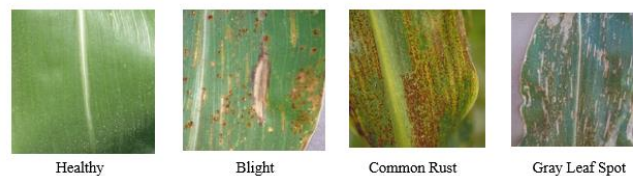


Figure 1. Corn Leaf Disease Dataset [15]

2.2 CNN

A CNN, a neural network type frequently employed in image data processing, is one of the most widely recognised and favoured methods within the neural network domain [16]. A CNN can handle high-dimensional data, including videos and images. Within

the CNN, kernels merge spatial features with spatial shapes kinematic of the input media [17].

A typical CNN architecture is built from a sequence of specialized layers, starting with convolutional and activation function layers, followed by pooling and dense (fully connected) layers to process the data [18]. An illustration of the CNN is shown in Figure 2.

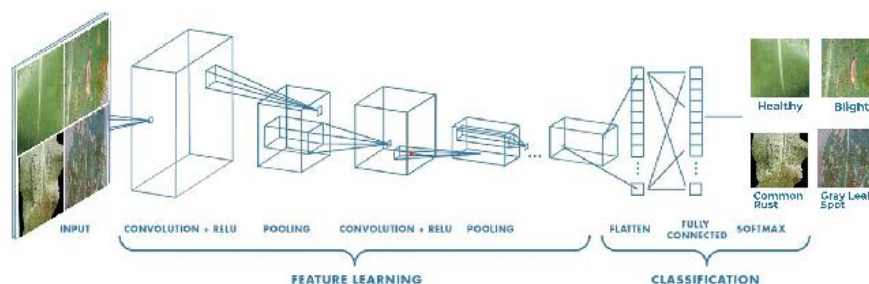


Figure 2. Convolutional Neural Network [19]

2.3 VGG16 and VGG19 architectures

The VGG architecture, a creation of Simonyan and Zisserman, serves as a cornerstone for image recognition within convolutional neural networks. Its 16-layer version, VGG16, integrates 13 convolutional layers alongside 3 dense (fully connected) layers to process visual data efficiently [20]. VGG19 operates on the premise that adding more layers can boost a model's predictive power. Its structure, which includes 16 convolutional and 3 dense layers, enables the network to generate highly detailed image descriptors. Consequently, this depth reduces the probability of misclassification when compared to shallower CNN

frameworks [21]. The selection of VGG16 and VGG19 for this study is justified by their proven performance in image classification tasks [22]. We selected the VGG16 model due to its optimal trade-off between architectural complexity and processing speed. This characteristic makes it highly effective for time-sensitive tasks that demand a high degree of precision without excessive computational overhead [23]. On the other hand, VGG19 is selected for its higher accuracy due to its increased layer depth and complexity, which allows for more detailed and nuanced image recognition[24]. These characteristics make VGG16 and VGG19 ideal candidates for developing a robust system for

classifying corn leaf diseases. The architectures of VGG16 and VGG19 are shown in Figure 3.

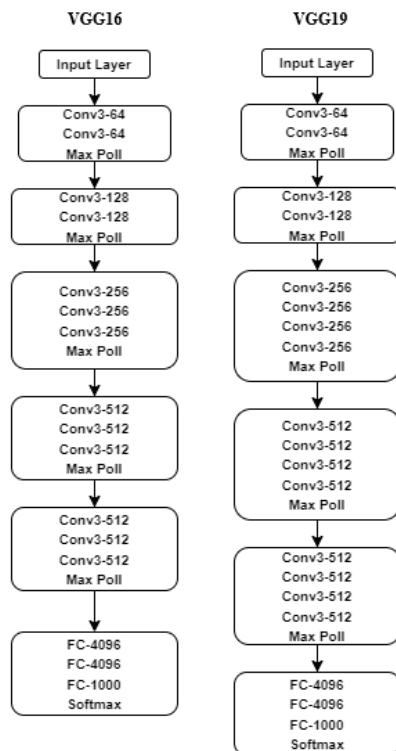


Figure 3. VGG-16 and VGG-19 architectures [22]

2.4 Confusion Matrix

To evaluate the effectiveness of the classification stage, a confusion matrix is employed as a primary assessment tool. As shown in Table 1, the False Positive (FP) and False Negative (FN) values are identified for each of the three specific categories. These variables, along with True Positives (TP) and True Negatives (TN), are highlighted using distinct color coding to ensure clarity during analysis. These fundamental values serve as the basis for calculating secondary performance metrics for every individual class [25].

Table 1. Different performance measures from the Confusion Matrix [23]

Confusion Matrix		Predicted			False Negative (FN)	Recall
		Class 1	Class 2	Class 3		
Actual	Class 1	A	B	C	B+C	$A / (A+B+C)$
	Class 2	D	E	F	D+F	$E / (D+E+F)$
	Class 3	G	H	I	G+H	$I / (G+H+I)$
	False Positive (FP)	D+G	B+H	C+F	Overall Accuracy = $A+E+I / (\text{Sum of red and green squares})$	
	Precision	$A / (A+D+G)$	$E / (B+E+H)$	$I / (C+F+I)$		
Legend:	True positives	True Negatives	Misclassified cases	False Positives	False Negatives	

Following the image input phase, preprocessing is performed to refine image quality and augment the system's object classification ability. The preprocessing phase comprises adjustments to image dimensions. Data preprocessing involves resizing and augmenting the data. The research dataset was divided into 80% training data and 20% testing data.

2.5 System Model

In this study, a design is presented regarding a system to implement the CNN method in classification as shown in Figure 4.

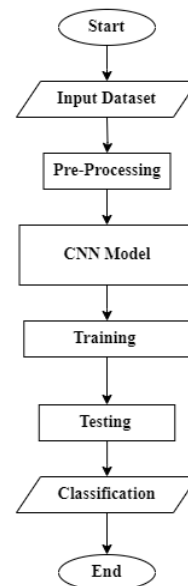


Figure 4. System model

The initial phase of the system design involves acquiring the necessary dataset to fulfill the project's technical specifications. Sourced from the Kaggle repository, the data consists of leaf imagery categorized into four distinct groups: Common Rust, Healthy, Gray Leaf Spot, and Blight.

A total of 4,198 maize leaf images were utilized in this research, distributed across four specific categories: 1,306 for Common Rust, 1,172 for Healthy, 1,146 for Blight, and 574 for Gray Leaf Spot. The experimental framework utilized a standard distribution strategy, where 80% of the dataset was dedicated to the training phase, while the remaining 20% served as the evaluation set to verify model performance.

The framework of this research utilizes the pre-trained VGG16 and VGG19 architectures to develop a Convolutional Neural Network (CNN). By applying a transfer learning approach, both models were fine-tuned using updated datasets and parameters. Once the preprocessing phase was finished, the architectures were tasked with identifying four distinct classes: Blight, Gray Leaf Spot, Healthy, and Common Rust.

The design of the specific CNN training model follows the initialization of these pre-trained structures.

For the CNN model design, a sequential architecture was employed using the TensorFlow and Keras built-in libraries. The layers from the pretrained model obtained via transfer learning are integrated into this model. The input images are sized at 224x224 pixels. Within this model's structure, the fully connected layers are presented as multidimensional arrays resulting from the feature maps generated by the convolutional and pooling layers. Thus, a flattening process is employed to convert them into inputs for the fully connected layers. Subsequently, a dense layer (512) with ReLU activation is implemented. Finally, the output layer uses a dense layer (4) with the softmax activation function.

In the data preparation phase, the dataset is bifurcated into training and testing components. These distinctive groups are subsequently fed into the classification algorithm, facilitating the development and validation of the proposed predictive model.

The final step involved classifying the image data into the 4 classes of corn leaf diseases.

3. Results and Discussions

The testing phase involves evaluating the classification of corn leaf diseases into four categories: Healthy, Blight, Common Rust, and Gray Leaf Spot. This section elaborates on the simulation process and programming setup for classifying corn leaf diseases using the CNN method with two architectures: VGG16 and VGG19. The dataset used in this study comprised a total of 4198 images, distributed as follows: 1172 images for the Healthy class, 1146 images for the Blight class, 1306 images for the Common Rust class, and 574 images for the Gray Leaf Spot class.

Testing was conducted under 2 scenarios involving the training of two architecture models using a transfer learning system. In both scenarios, the test data comprised 20% of the total images, and the remaining 80% served as training data. The optimiser employed in this study is SGD. The testing aim was to observe the impact of the model on image resizing and epoch values. Scenario A employs the VGG16 architecture, while scenario B utilises the VGG19 architecture with several resize dimensions, namely 64x64, 128x128, and 224x224. The number of epoch values tested was 10, 20, 30, 40, and 50. Other parameters such as the learning rate was set to 0.001, decay step was set to 900, decay rate was set to 0.9, and the batch size was 32.

3.1 VGG16

In this testing, simulations were conducted for the classification of corn leaf diseases using the CNN method with the VGG16 architecture and SGD optimiser. Testing is divided into two parts, namely resize testing and epoch testing. The following are the results of the confusion matrix for epoch 50 with the VGG16 architecture, as shown in Figure 5.

		Predicted			
		Healthy	Blight	Common Rust	Gray Leaf Spot
Actual	Healthy	258	1	0	0
	Blight	2	199	3	11
	Common Rust	1	8	247	3
	Gray Leaf Spot	3	28	2	74

Figure 5. VGG16 Confusion Matrix

Based on Figure 5, this represents the outcome of the confusion matrix at epoch 50, employing the VGG16 architecture and SGD optimiser. It can be concluded that most images were correctly classified by the proposed system. In total, 778 of 840 images were classified correctly. However, there were 62 classification errors out of the 840 images. These errors occurred in the Healthy class (1 image), Blight class (16 images), Common Rust class (12 images), and Gray Leaf Spot class (33 images). The first test was performed by resize testing. This test used various resize sizes, namely 64x64, 128x128, and 224x224.

Based on Table 2, the results of the tests reveal that when employing the SGD optimiser and epoch 30, the highest accuracy rate was obtained with an image resize of 224x224, resulting in accuracy of 92.14%, precision of 91%, recall of 88%, and an F1-score of 89%. The subsequent experiment will explore epoch values 10, 20, 30, 40, and 50. While maintaining the VGG16 architecture and a resize of 224x224.

Table 2. VGG16 Resize Test Results

Resize	Parameter Accuracy	Precision	Recall	F1-Score
64 x 64	86.90%	83%	81%	82%
128 x 128	90.83%	89%	87%	88%
224 x 224	92.14%	91%	88%	89%

Table 3. Epoch VGG16 Test Results

Epoch	Parameter Accuracy	Precision	Recall	F1-Score
10	89.40%	90%	84%	85%
20	91.19%	90%	87%	88%
30	92.14%	91%	88%	89%
40	92.74%	92%	89%	90%
50	92.62%	91%	89%	90%

From the test results in Table 3, with the SGD optimiser and an image size of 224x224, the peak accuracy was achieved at epoch 50, recording an accuracy of 92.62%, precision of 91%, recall of 89%, and an F1-score of 90%.

3.2 VGG19

In this testing, simulations were conducted to classify corn leaf diseases using the CNN method with the VGG19 architecture and SGD optimiser. Testing

VGG19 involves 2 parts: resize testing and epoch testing. Below are the outcomes of the confusion matrix for epoch 50 utilising the VGG19 architecture, illustrated in Figure 6.

		Predicted			
		Confusion Matrix			
Actual	Healthy	259	0	0	0
	Blight	6	187	3	19
	Common Rust	3	7	245	4
	Gray Leaf Spot	1	18	0	88
		Healthy	Blight	Common Rust	Gray Leaf Spot

Figure 6. Confusion Matrix VGG19

Figure 6 depicts the outcomes portrayed in the confusion matrix for epoch 50, employing the VGG19 architecture alongside the SGD optimiser. It can be concluded that most images were correctly classified by the proposed system. Out of the 840 images, 779 were classified correctly. There were 62 classification errors out of the 840 images. These errors were divided into 28 Blight images, 14 Common Rust images, and 19 Gray Leaf Spot images.

The first test was performed by resize testing. This test used various resize sizes, namely 64x64, 128x128, and 224x224. In this test, the VGG19 architecture, epoch 30, and SGD optimiser were used.

Based on the testing data provided in Table 4, employing the SGD optimiser and epoch 30, the peak accuracy level was reached with an image resize of 224x224 pixels. This configuration yielded an accuracy of 90.57%, precision of 89%, recall of 89%, and an F1 score of 89%.

Table 4. VGG19 Resize Test Results

Resize	Parameter			
	Accuracy	Precision	Recall	F1-Score
64 x 64	82.34%	79%	79%	79%
128 x 128	88.42%	87%	85%	86%
224 x 224	90.57%	89%	89%	89%

The next research involves testing with variations in epoch values (10, 20, 30, 40, and 50). In this test, a resize of 224x224 is used, which was the result of testing with the highest accuracy value.

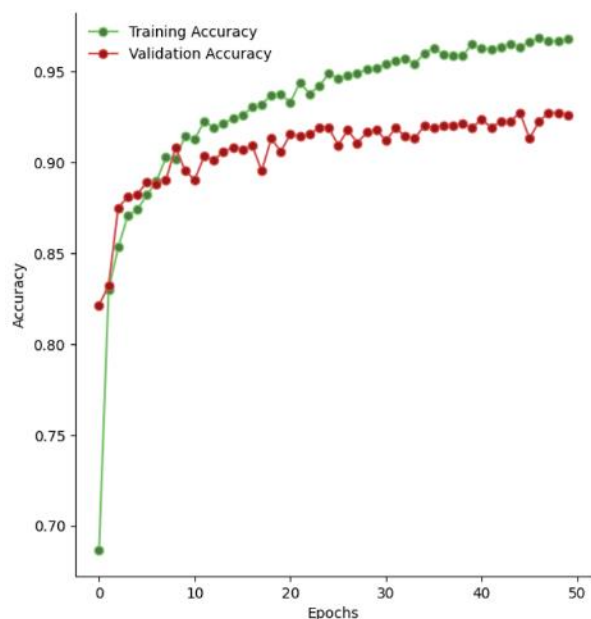
Table 5. Epoch VGG19 Test Results

Epoch	Parameter			
	Accuracy	Precision	Recall	F1-Score
10	87.23%	85%	86%	85%
20	87.95%	88%	83%	84%
30	90.57%	89%	89%	89%
40	92.50%	91%	90%	90%
50	92.74%	91%	91%	91%

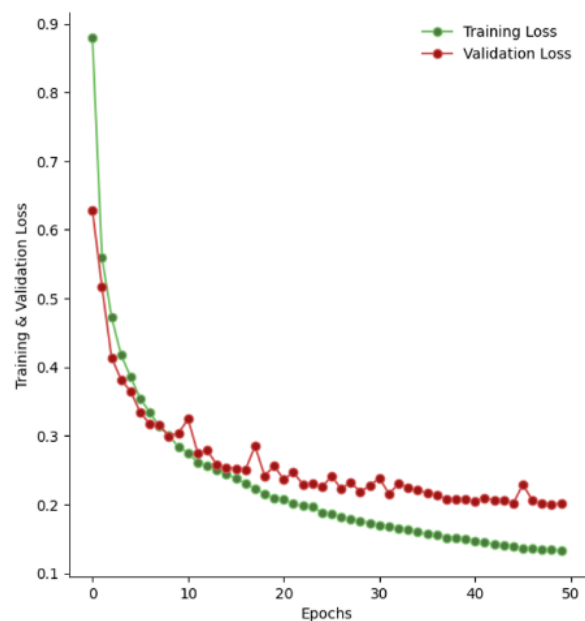
From the test results in Table 5, with the SGD optimiser and an image size of 224x224, the peak accuracy was attained at epoch 50, recording an accuracy of 92.74%, precision of 91%, recall of 91%, and an F1-score of 91%.

3.3 Training Curve

The training curve outcomes in CNN modelling are presented in two scenarios: Scenario A employing the VGG16 architecture, and Scenario B employing the VGG19 architecture. The parameters applied to the curve comprise SGD optimisation, resizing to 224x224, and running for 50 epochs. These can be observed in Figure 7 for the training curve of Scenario A and Figure 8 for the training curve of Scenario B.

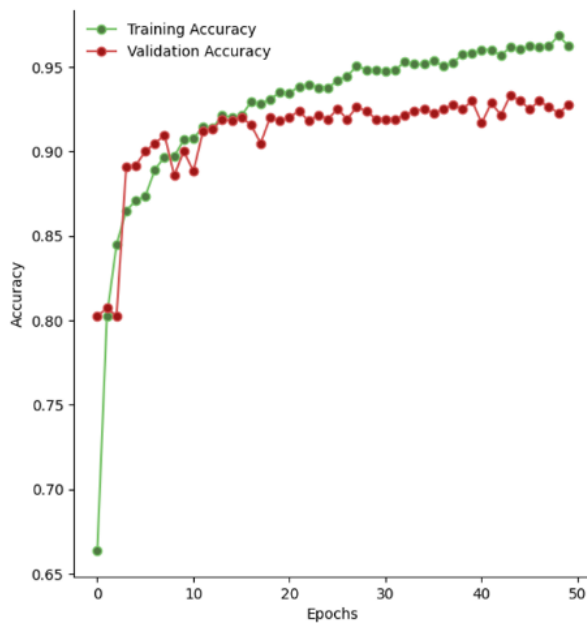


(a)

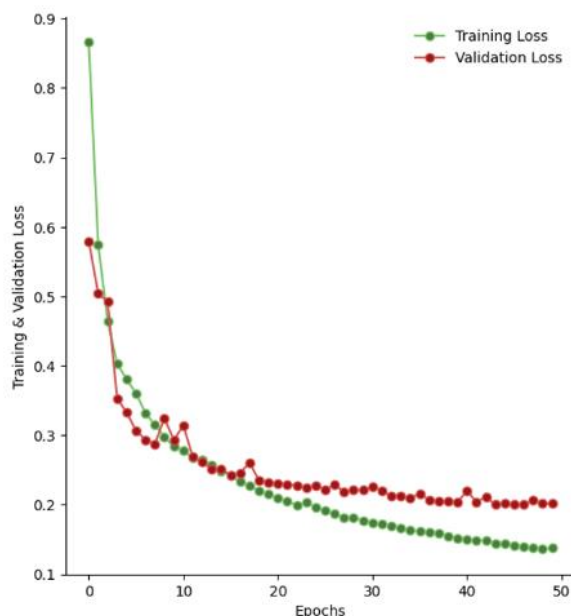


(b)

Figure 7. VGG16 (a) Curve Accuracy, (b) Curve Loss



(a)



(b)

Figure 8. VGG19 (a) Curve Accuracy, (b) Curve Loss

Unlike previous studies that focused solely on the application of single CNN models, this work introduces a novel comparative perspective by systematically evaluating VGG16 and VGG19 under matched experimental conditions. This structured approach not only ensures fairness in performance comparison but also provides practical recommendations for selecting CNN architectures in agricultural disease detection tasks.

The performance of the system when testing corn leaf disease images using the VGG16 and VGG19 architectures achieved an accuracy level above 90%. This indicates that the system developed in this study is effective in classifying various types of corn leaf

diseases based on their classes. The use of the VGG16 and VGG19 architectures was selected because both are capable of handling the classification of large amounts of data and achieving high accuracy in classifying corn leaf diseases. Table 6 presents the comparison of testing outcomes between VGG16 and VGG19.

From the data provided in Table 6, which details the comparison of testing outcomes between VGG-16 and VGG-19, various metrics were collected, including accuracy, precision, recall, and F1-score. The highest accuracy was achieved by the VGG19 architecture with an accuracy of 92.74%, while the VGG16 architecture obtained an accuracy of 92.62%. Furthermore, the precision values for both the VGG16 and VGG19 architectures were 91%. Subsequently, the recall value obtained from the VGG16 architecture was 89%, whereas the VGG19 architecture obtained a recall value of 91%. Finally, the F1-score obtained from the VGG16 architecture was 90%, whereas that of the VGG19 architecture was 91%.

Table 6. Comparison of VGG16 and VGG19

Architec	Epoch	Parameter			
		Accuracy	Precision	Recall	F1-Score
VGG16	50	92.62%	91%	89%	90%
VGG19	50	92.74%	91%	91%	91%

The VGG19 architecture performs better due to its higher layer depth and complexity. VGG19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers, compared to VGG16's 16 layers. This additional depth allows VGG19 to capture more intricate features and patterns within the images, leading to improved classification accuracy and generalization. The increased complexity of VGG19 enables it to handle more detailed image representations, reducing the likelihood of misclassification.

In addition to VGG19, various studies have explored other CNN models for plant disease classification. Previous research using the AlexNet architecture achieved an accuracy of 90% in detecting corn leaf diseases via digital imaging [10]. While AlexNet showed good recognition capabilities, VGG19 demonstrated an advantage in learning finer features due to its greater layer depth, as reflected in improved accuracy and precision.

Another study employed a custom CNN model with 4 convolutional layers, 2 pooling layers, and multiple dense layers, achieving 84% test accuracy using a 3x3 kernel size and the Adaptive Moment (Adam) optimization algorithm [12]. Although this custom model produced promising results, its lower depth compared to VGG19 could limit its ability to detect the complex features present in various corn leaf diseases.

From these comparisons, it is evident that VGG19 excels in classifying corn leaf diseases due to its increased layer depth, enabling it to identify finer features. This makes VGG19 a highly suitable choice

for plant disease classification applications that require high accuracy and precision in distinguishing between disease types with similar characteristics.

In terms of computational efficiency, both VGG16 and VGG19 require significant processing power due to their deep architecture and large number of parameters—approximately 138 million for VGG19 and 134 million for VGG16. While this complexity contributes to high accuracy, it also increases training time and memory usage. For instance, training VGG19 with 50 epochs and 224×224 image resolution took longer and demanded more GPU resources compared to VGG16, making it less suitable for deployment on devices with limited computational capabilities.

Despite achieving promising results, this study has several limitations. First, the dataset used consists of only four classes of corn leaf conditions, which may not fully represent the variability encountered in real-world agricultural environments. Second, the use of static images without environmental context (e.g., lighting variation, leaf orientation) may affect generalizability. Furthermore, this study focuses solely on VGG-based architectures, leaving out lightweight or hybrid models that might offer better efficiency for real-time applications in the field.

Future improvements may include the integration of lightweight CNN models such as MobileNet, EfficientNet, or SqueezeNet, which are designed to operate efficiently on edge devices and mobile platforms. Additionally, incorporating data augmentation techniques or generative models to expand the dataset could improve model robustness. Finally, embedding the trained model into a mobile or IoT-based application could support real-time disease detection directly in the field, providing practical assistance to farmers.

4. Conclusions

This research develops and executes a corn leaf disease classification framework by utilizing Convolutional Neural Network (CNN) techniques with two architectures: VGG16 and VGG19. Two scenarios, Scenario A using VGG16 and Scenario B using VGG19, are explored. Test data comprised 20% of the total images, with the remaining 80% allocated to training. Testing employed the SGD optimiser, alongside additional parameters, such as a learning rate of 0.001, 900 decay steps, a decay rate of 0.9, and a batch size of 32. Different resizes and epoch values were applied to each architecture to optimise accuracy. In terms of performance, VGG19 outshone VGG16 by securing 92.74% accuracy, along with 91% for both recall and precision, and an F1-score of 91%. Meanwhile, VGG16 yielded slightly lower figures, specifically a 92.62% accuracy rate. While its precision matched VGG19 at 91%, its recall (89%) and F1-score (90%) were lower. This performance gap was attributed to the different numbers of layers in VGG16 (16 layers) and VGG19 (19 layers). The CNN method using

VGG16 and VGG19 architectures facilitates disease classification in corn leaves via transfer learning, providing a tool to aid farmers in detecting diseases affecting corn plants.

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