CycleGAN-Based Data Augmentation with CNN and Vision Transformers (ViT) Models for Improved Maize Leaf Disease Classification

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***Abstract*—Crop losses pose a serious danger to global food security, and this problem also affects maize crops. To successfully address this issue, precise disease detection techniques are required. However, a major hurdle to developing reliable models to address this issue is the dearth of datasets. In response, we present a novel approach that uses synthetic images created by CycleGAN to supplement constrained datasets. We thoroughly assessed deep learning models, such as ResNet50V2, DenseNet169, VGG16, VGG19, Xception, MobileNetV2, and emerging vision transformer models, such as ViT-B/16 and ViT-B/32, with a focus on the two critical classes of maize leaf diseases, blight and common rust. Notably, DenseNet169 performed better than other models with an accuracy of 98.48%, especially when trained on the CycleGAN-enhanced dataset. CycleGAN-augmented data outperformed the performance of the models trained solely on the original dataset, demonstrating the effectiveness of the augmentation approach in performance enhancement. By utilizing CycleGAN's synthetic images, this study expands the field of maize leaf disease diagnosis and establishes DenseNet169 as a viable model for precise disease identification. The findings of the study have the potential to significantly revolutionize agricultural operations using advanced maize disease detection techniques.**

***Index Terms*—maize crops, disease detection techniques, synthetic images, augmentation, CycleGAN, deep learning models, vision transformers, accuracy.**

I. Introduction

Maize, scientifically known as Zea mays, is of critical importance in agriculture due to its numerous contributions to global food security, economic prosperity, and human well-being. Maize, being one of the world's most frequently farmed crops, is a major food source for billions of people worldwide, particularly in Africa, Latin America, and Asia. Because of its adaptability, it is used to feed cattle in addition to humans, making it an important part of animal husbandry and the livestock business. In terms of annual production, maize is consistently one of the world's highest-yielding crops. According to the Food and Agriculture Organization (FAO), global maize production has just surpassed 1.1 billion metric tons, making it one of the primary contributors to global grain production [1]. This massive production reflects the crop's tolerance to a wide range of climates and growing circumstances, making it a staple crop in both industrialized and developing countries. Notably, regions such as the United States, China, Brazil, and Argentina stand out as big maize producers, accounting for a sizable proportion of overall annual output.

The worldwide maize production environment is not without difficulties, with one of the most significant setbacks being the impact of diseases on crop output and quality. Maize plants are susceptible to a variety of diseases, which can severely limit output levels, resulting in large economic losses for farmers and a negative impact on food security. Fungi, bacteria, and viruses, among others, contribute to these losses by creating diseases that impede plant growth, development, and overall production. The fungal disease "Maize Lethal Necrosis" (MLN), for example, has received attention due to its destructive impact on maize output. The virus that causes MLN is a mix of two viruses: Maize chlorotic mottle virus and Sugarcane mosaic virus. This disease spreads quickly through infected planting materials and insect vectors, causing severe stunting, leaf yellowing, and necrosis. According to studies conducted by the International Maize and Wheat Improvement Center (CIMMYT), MLN can cause yield losses ranging from 30% to 100%, hurting maize production in East and Central Africa severely [2]. Another well-known disease is "Maize Rust," which is caused by the fungus Puccinia sorghi. This disease damages maize leaves, causing rust-colored lesions that limit photosynthesis and impede nutrient absorption. Maize rust outbreaks have caused output losses of up to 50% in regions such as Asia, Africa, and the Americas, according to researchers [3].

Historically, plant disease detection methods relied on visual inspection by experienced professionals to identify signs and symptoms of plant diseases. This procedure entails manually inspecting plant leaves, stems, fruits, and other parts for distinctive patterns, discolorations, lesions, deformities, and other signs of disease presence. This procedure, however, is time-consuming, labor-intensive, and frequently prone to human mistake. Furthermore, the knowledge required to correctly identify a wide range of plant diseases may be confined to experienced specialists. The landscape of plant disease detection has changed due to technological breakthroughs and the rise of machine learning. Machine learning approaches have transformed the accuracy, speed, and scalability of disease detection systems. These methods make use of algorithms and computational models to assess enormous quantities of plant pictures and other pertinent data. One advantage of machine learning-based disease detection systems is their capacity to interpret large amounts of visual data fast and reliably. These algorithms can learn to recognize elaborate patterns and small variations that the human eye may miss. Machine learning models are trained on broad datasets that comprise photos of both healthy and unhealthy plants, allowing them to generalize and diagnose diseases across plant species and growth phases.

GANs (Generative Adversarial Networks) have emerged as an advanced technology with impressive potential in disease identification. GANs are a type of deep learning model comprised of two neural networks, a generator and a discriminator, competing to produce extremely realistic and contextually appropriate data. GANs have been used to improve disease detection systems in a variety of fields, including the medical and agricultural sectors, in recent years. The application of Vision Transformers (ViTs) in plant disease detection has resulted in significant advances in computer vision and agricultural technology. ViTs are a sort of deep learning architecture that was originally intended for image classification tasks, and their application to plant disease detection demonstrates their adaptability and usefulness in handling complicated real-world problems. Convolutional Neural Networks (CNNs) have traditionally been the go-to solution for image-based tasks such as illness diagnosis. ViTs, on the other hand, have emerged as a promising alternative that challenges the traditional paradigm. Unlike CNNs, which use convolutional layers to extract local features, ViTs take a different approach, transforming 2D picture data into sequences of flattened patches that are subsequently processed using a succession of self-attention methods.

This study's novelty is as follows:

1) This study explores the application of GAN, in particular CycleGAN, to address the challenges posed by a limited dataset in maize leaf disease analysis and it includes synthetic image generation and dataset augmentation.
2) The evaluation phase encompasses the utilization of CNN and ViT models to assess performance. A comparison of datasets with and without CycleGAN augmentation is conducted in this analysis. The objective of this method is to pinpoint superior models and to measure the influence of GAN's performance.
3) The assessment's thoroughness is demonstrated by the wide range of metrics it takes into account, including accuracy, loss, precision, recall, and f1-score. This all-encompassing strategy guarantees a thorough comprehension and understanding of the significance served by GAN and model performance.

II. Literature Review

Recent advancements in the field of maize leaf disease detection have witnessed the integration of machine learning techniques, particularly Convolutional Neural Networks (CNNs), to enhance accuracy and efficiency. Ramar Ahila Priyadharshini et al. [4] presented a deep convolutional neural network (CNN)-based architecture for maize leaf disease classification (modified LeNet). The suggested CNNs were trained using maize leaf pictures from the PlantVillage dataset, with the goal of identifying four separate classes, three illnesses and one healthy class. In diagnosing maize leaf diseases, the learned model had a remarkable accuracy of 97.89%. Abdul Waheed et al. [5]developed a dense convolutional neural network (CNN) architecture (DenseNet) for detecting and classifying corn leaf diseases. The study addresses the problem of recognizing early-stage leaf diseases in maize crops, with the goal of improving crop health monitoring and output quality. The suggested optimized DenseNet model outperformed existing CNN designs such as EfficientNet, VGG19Net, NASNet, and Xception Net while requiring fewer parameters and computation time. Kshyanaprava Panda Panigrahi et al. [6] introduced a CNN-based method for detecting maize leaf diseases, emphasizing the importance of precise and early disease detection in enabling digital agricultural systems. To improve detection accuracy, the suggested CNN model included corrected linear unit activation functions, an Adam optimizer, and parameter tweaks. The model demonstrated quicker training convergence durations while achieving an exceptional average detection accuracy of 98.78% for three major maize leaf diseases, including Cercospora leaf spot, common rust, and northern leaf blight. IHAI ZHANG et al. [7] presented an improved method for automatically detecting maize leaf diseases using deep convolutional neural networks. The study offered improved GoogLeNet and Cifar10 models for leaf disease recognition, with an emphasis on parameter modifications, pooling combinations, dropout operations, and the use of rectified linear unit (Relu) functions. For recognizing eight forms of maize leaf diseases, the GoogLeNet model scored an amazing top-1 average identification accuracy of 98.9%, while the Cifar10 model achieved an average accuracy of 98.8%.

Sumita Mishra et al. [8] used a deep convolutional neural network (CNN) to construct a real-time maize plant disease recognition system. The project aimed to reduce crop losses caused by corn diseases in India by employing smart devices for autonomous disease detection. The deep CNN model was adjusted by adjusting hyperparameters and pooling combinations. The model recognized maize leaf illnesses with an accuracy of 88.46%, making it suitable for real-time inference. Mohammad Syarief et al. [9] used convolutional neural networks (CNNs) to classify images of maize leaf disease. They used 200 photos and divided them into four categories: healthy, cercospora, common rust, and northern leaf blight. Seven CNN models (AlexNet, VGG16, VGG19, ResNet50, ResNet101, GoogleNet, and Inception-V3) and machine learning algorithms (SVM, kNN, Decision Tree) were used for feature extraction and categorization. AlexNet with SVM produced the best classification results, with an accuracy of 93.5%, sensitivity of 95.08%, and specificity of 93%. Dionis A. Padilla et al. [10] used a Convolutional Neural Network (CNN) with OpenMP implementation to detect corn leaf illnesses. The study used CNN and OpenMP to identify and classify illnesses in corn leaves. The study's accuracy in detecting Leaf Blight, Leaf Rust, and Leaf Spot was 93%, 89%, and 89%, respectively. Yan Zhang et al. [11] suggested a method for detecting maize leaf disease using a Convolutional Neural Network (CNN) optimized by a Multi-Activation Function (MAF) module. The goal of the study was to improve the accuracy of traditional AI algorithms for disease identification. Due to the limited dataset, image pre-processing procedures were applied to extend and supplement the disease samples. To expedite training, transfer learning and warm-up procedures were used. The suggested MAF module enhanced the accuracy of mainstream CNNs, with MAF-ResNet50 achieving 97.41% accuracy.

In recent years, the field of plant disease detection has witnessed innovative approaches that leverage Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) for enhanced accuracy and robustness in disease identification [12]. Yan Zhang et al. [13] suggested a method for detecting maize leaf disease using a Convolutional Neural Network (CNN) optimized by a Multi-Activation Function (MAF) module. The goal of the study was to improve the accuracy of traditional AI algorithms for disease identification. Due to the limited dataset, image pre-processing procedures were applied to extend and supplement the illness samples. To expedite training, transfer learning, and warm-up procedures were used. The suggested MAF module enhanced the accuracy of mainstream CNNs, with MAF-ResNet50 achieving 97.41% accuracy. Yasamin Borhani et al. [14] proposed using Vision Transformer (ViT) a deep learning approach for automated plant disease classification.

Regarding the classification of maize leaf disease using CNN-based models, Vision Transformer (ViT), and CycleGAN as data augmentation. Through a review of the literature, we found a number of gaps and research limitations. A brief overview of these difficulties is given below:

1) Limited investigation of GAN approaches, notably CycleGAN, as efficient data augmentation methods for overcoming the difficulties of maize leaf disease analysis.
2) There is a paucity of studies looking at the potential of Vision Transformer (ViT) and Convolutional Neural Network (CNN) based models working with CycleGAN-augmented datasets to identify maize leaf diseases.

III. Methodology

The proposed methodology for detecting maize leaf disease is based on a systematic approach that integrates several methodologies to improve accuracy. It all starts with gathering a dataset of maize leaf images [15]. This dataset is then pre-processed to ensure consistency and quality. The methodology relies on CycleGAN, a generative model, to alter and generate synthetic images. This synthetic image production step takes advantage of CycleGAN's strengths to generate enhanced data with disease characteristics, increasing the dataset's diversity and size.

The resulting expanded dataset is then used to train both Convolutional Neural Network (CNN) models and Vision Transformers (ViTs). CNN-based models excel at detecting localized features and patterns, but ViTs detect global context inside images. The maize leaf disease detection model achieves complete image analysis, allowing accurate identification of diverse diseases by combining the capabilities of both CNNs and ViTs. In order to identify the optimal model, assessment metrics including accuracy, loss, precision, recall, and f1-score were examined both with and without the Cyclegan augmentation dataset. The overall procedure has been demonstrated in figure 1.

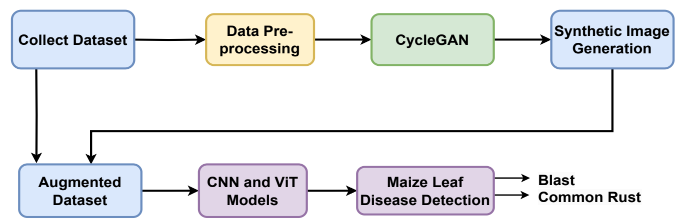

Fig. 1. Overall Workflow of The Study

A. CycleGAN-Enhanced Synthetic Image Generation

CycleGAN, a variant of Generative Adversarial Networks (GANs), plays a crucial part in enhancing images by translating one image into another. CycleGAN, in contrast to conventional augmentation methods, permits the creation of artificial pictures in a domain without the necessity for paired training data. Within the CycleGAN architecture, this novel method uses the dynamic interaction of two generators and two discriminators.

Generator A ($G_{A\to B}$) transforms images from domain A to domain B. Given an image x_A from domain A, the generator aims to produce a corresponding image $x_{A\to B}$ in domain B:

$$x_{A\to B} = G_{A\to B}(x_A)$$

Similarly, Generator B ($G_{B\to A}$) converts images from domain B to domain A:

$$x_{B\to A} = G_{B\to A}(x_B)$$

The discriminators, D_A and D_B, distinguish between real images from their respective domains and generated (fake) images. D_A assesses the realism of images from domain A, while D_B evaluates images from domain B.

$$D_A(x_A) \text{ measures the realism of } x_A$$

$$D_B(x_B) \text{ measures the realism of } x_B$$

The goal of the CycleGAN is to achieve image translation in a way that preserves the underlying content of the images. To accomplish this, it introduces cycle-consistency loss, ensuring that an image translated and then translated back remains similar to the original. Equation 1 is the cycle-consistency loss of the model.

$$\mathcal{L}_{\text{cyc}}(G_{A\to B}, G_{B\to A}) = \mathbb{E}_{x_A}\left[\|x_A - G_{B\to A}(G_{A\to B}(x_A))\|_1\right] \quad (1)$$

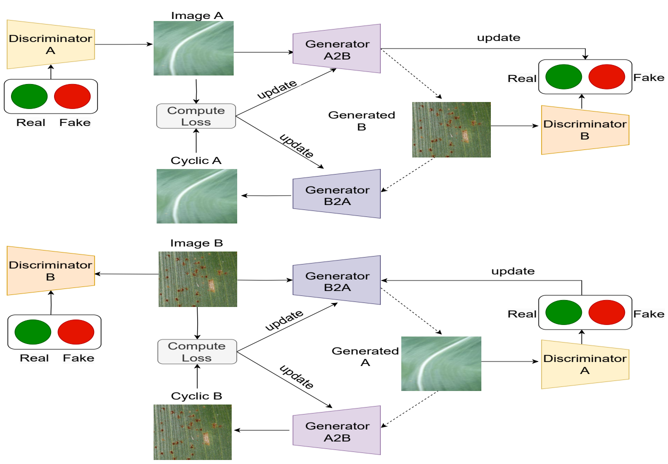

Fig. 2. CycleGAN architecture

In this instance, the capability of CycleGAN is utilized to convert images of healthy maize leaves into simulated counterparts showing the signs of blight and common rust maize disease images. The Generator A to B, which learns to change pristine leaf pictures into artificially diseased ones, facilitates this transformation. In contrast, Generator B to A produces pictures of maize leaves that appear to be in good condition from diseased inputs. Discriminator A compares the veracity of produced diseased images to real diseased ones, whereas Discriminator B examines the veracity of produced images of healthy leaves. The architecture of CycleGAN is illustrated in figure 2.

B. Vision Transformers (ViT) model

With the use of self-attention mechanisms and transformer architectures, the concept of Vision Transformers (ViT) has become a paradigm shift in image classification. ViT adopts a patch-based methodology in place of conventional Convolutional Neural Networks (CNNs), turning pictures into sequences of patches. Each patch is hierarchically encoded and attentively interconnected, enabling the model to grasp intricate contextual relationships and patterns across the image. The "Transformer Encoder" design, which enables the integration of self-attention techniques across patches, is a critical invention of ViT. This allows the model to incorporate global context information, which is required for recognizing complex patterns and relationships in images.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

where Q, K, and V are query, key, and value matrices, respectively, and d_k is the dimension of the key matrix.

ViT-B/16 improves classification accuracy by including wider patches, allowing for a stronger contextual knowledge that is necessary for differentiating between cases of blight and common rust maize leaf. The "/16" stands for the patch size that was used to separate the input image into smaller, more manageable portions for processing.

ViT-B/32 enhances classification performance even further by enlarging patches, allowing for greater resolution analysis and enhancing the difference between blight and common rust categories in maize leaf images. The "/32" indicates the size of the provided image patch.

Figure 3 depicts the Vision Transformer (ViT) model's architecture. ViT can capture long-range dependencies and contextual subtleties naturally due to this feature, which is essential for precise image classification.

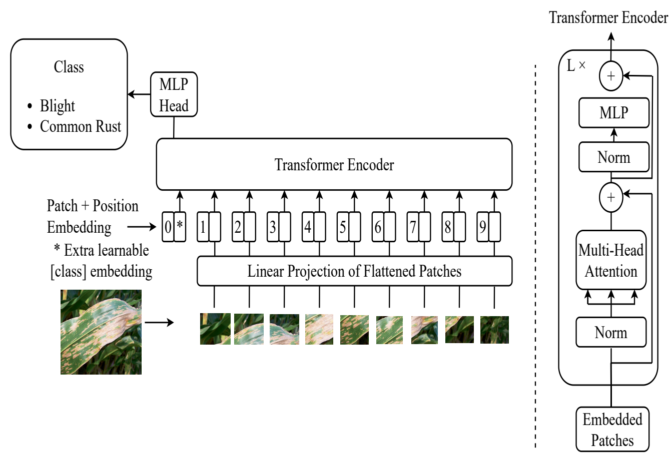

Fig. 3. Vision Transformers (ViT) architecture

C. CNN-based Model

Convolutional neural networks, also known as CNNs, which architectures collect and interpret features using convolutional layers, pooling layers, and fully connected layers, which enables them to handle complex visual patterns. For the purpose of detecting maize leaf disease in this study, a variety of deep-learning models were used. These models include VGG16, ResNet50V2, Xception, MobileNetV2, DenseNet169, and VGG19. These models each provide distinctive architectural characteristics that enhance their performance in picture categorization tasks.

DenseNet169 is known for its dense connection patterns, where each layer is linked to all succeeding layers, enabling rich feature reuse and boosting gradient flow. On the other hand, VGG16 is a frequently used architecture in the area since it consists of a series of convolutional and pooling layers, comprising 16 layers. VGG19 adheres to the same architectural principles as VGG16 but has 19 layers. ResNet50V2 uses residual connections to address the vanishing gradient issue and makes it possible to train tremendously deep networks. Xception's architecture aims to capture fine-grained features through a hierarchy of transformations. MobileNetV2, which stresses efficiency through lightweight separable convolutions, is targeted for mobile and embedded devices.

The table I provides key factors for CNN-based and ViT models training, with 50 epochs and a learning rate of 0.001 determining training duration and weight updates. By highlighting robust optimization and a multi-class classification focus, the AdamW optimizer and Categorical Cross-entropy loss function improve transparency and reproducibility.

TABLE I
HYPERPARAMETERS FOR MODELS

Epochs	Learning Rate	Optimizer	Loss Function
50	0.001	AdamW	Categorical Crossentropy

IV. EXPERIMENTS AND RESULTS

The maize leaf disease dataset originally had 1306 samples for common rust and 1146 samples for blight. Original dataset samples have been shown in figure 4. The dataset was considerably enriched through CycleGAN augmentation, generating 1154 blight samples and 994 common rust samples. The dataset was adequately balanced as a consequence, yielding 2300 samples in total for each class. The state of the dataset after augmentation has been delineated in table II.

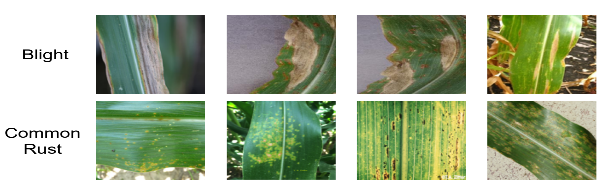

Fig. 4. Maize disease samples

Figure 5 demonstrated the blight and common rust disease classes' representative samples, were produced using CycleGAN. These illustrations demonstrate CycleGAN's capability to provide diverse and realistic disease-related variations.

Table III and figure 7 showcase the results obtained from various models in the context of detecting maize leaf diseases. The evaluation is based on multiple metrics, including accuracy, loss, precision, recall, and F1-score.

In the context of augmentation, the CycleGAN method was employed to augment the dataset, leading to improved model performance. Notably, the ViT-B/16 model achieved an

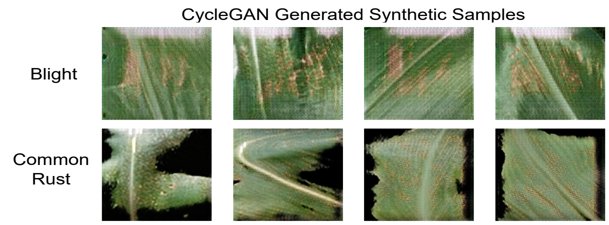

Fig. 5. CycleGAN generated synthetic samples

accuracy of 98.37% with a loss of 0.1146, while the ViT-B/32 and VGG16 models attained accuracies of 97.93% with loss values of 0.0970 and 0.1366, respectively. The CycleGAN augmented ResNet50V2 and Xception models demonstrated accuracies of 97.61% and 97.50%, respectively, indicating their robustness in disease detection. The MobileNetV2 model achieved an impressive accuracy of 98.37% with a notably low loss of 0.0684. However, the DenseNet169 model outperformed others with an accuracy of 98.48% and a significantly low loss of 0.0652, along with high precision, recall, and F1-score values.

On the other hand, the table also presents results without augmentation. In this scenario, the models exhibited slightly lower accuracy values. Among these, the MobileNetV2 model achieved an accuracy of 97.96% with a loss of 0.0798, while the DenseNet169 model demonstrated an accuracy of 97.76% and a loss of 0.0902. These results emphasize the importance of dataset augmentation, particularly through techniques like CycleGAN, in enhancing the performance of maize leaf disease detection models.

TABLE II
AUGMENTED DATASET

Disease	Initial Samples	CycleGAN Augmented Samples	Total Cumulative Samples
Blight	1146	1154	2300
Common Rust	1306	994	2300
Total	2452	2148	4600

The accuracy and confusion matrix of the best performing model, DenseNet169, are illustrated in Figure 6. The accuracy achieved by DenseNet169 was 98.48%, with a corresponding loss of 0.0652. The model demonstrated remarkable precision, recall, and F1-score values of 0.9848, 0.9848, and 0.9848, respectively. The confusion matrix further provides insights into the model's performance for each class, showing the true positive and true negative predictions as well as potential areas for improvement.

V. CONCLUSION AND FUTURE WORK

This work demonstrated the efficacy of CycleGAN-generated image augmentation in improving the preciseness of maize leaf disease classification using various CNN-based and Vision Transformer (ViT) models. The findings underscore

TABLE III
RESULT OBTAINED BY VARIOUS MODELS

Augmentation Method	Model	Accuracy (%)	Loss	Precision	Recall	F1-score
CycleGAN	ViT-B/16	98.37	0.1146	0.9837	0.9837	0.9837
	ViT-B/32	97.93	0.0970	0.9794	0.9793	0.9793
	VGG16	97.93	0.1366	0.9793	0.9793	0.9793
	ResNet50V2	97.61	0.1574	0.9762	0.9761	0.9761
	Xception	97.50	0.1291	0.9754	0.975	0.975
	MobileNetV2	98.37	0.0684	0.9837	0.9837	0.9837
	DenseNet169	**98.48**	**0.0652**	**0.9848**	**0.9848**	**0.9848**
	VGG19	97.72	0.1228	0.9772	0.9772	0.9772
Without Augmentation	ViT-B/16	96.95	0.1695	0.9695	0.9695	0.9695
	ViT-B/32	96.13	0.2120	0.9613	0.9613	0.9613
	VGG16	95.93	0.2187	0.9594	0.9593	0.9593
	ResNet50V2	94.91	0.2626	0.9498	0.9491	0.9491
	Xception	95.72	0.2950	0.9572	0.9572	0.9572
	MobileNetV2	97.96	0.0798	0.9799	0.9796	0.9796
	DenseNet169	97.76	0.0902	0.9778	0.9776	0.9776
	VGG19	96.54	0.1805	0.9654	0.9654	0.9654

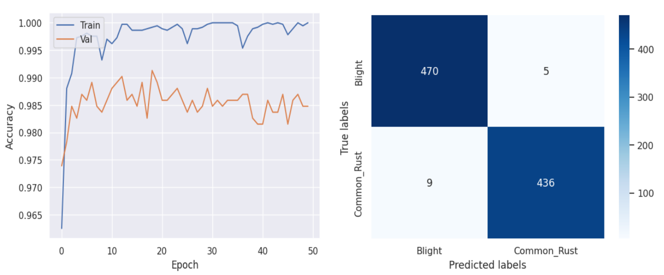

Fig. 6. Accuracy and confusion matrix of DenseNet169 on CycleGAN-augmented dataset

CycleGAN's potential to overcome the problems presented by limited datasets, leading to more accurate disease identification. Our test results demonstrated that the DenseNet169 outperformed the other models, obtaining a maximum accuracy of 98.48% in the CycleGAN expanded dataset. Furthermore, the study encompasses the integration of a Vision Transformer (ViT) model within the scope of maize leaf disease detection. Future research could focus on adjusting CycleGAN parameters for specific disease traits and investigating hybrid model architectures that include the advantages of CNNs and ViTs for even more reliable classification outcomes. The study might further broaden its focus to include other crop diseases, which would increase the usefulness of the suggested methodology in the field of managing agricultural diseases.

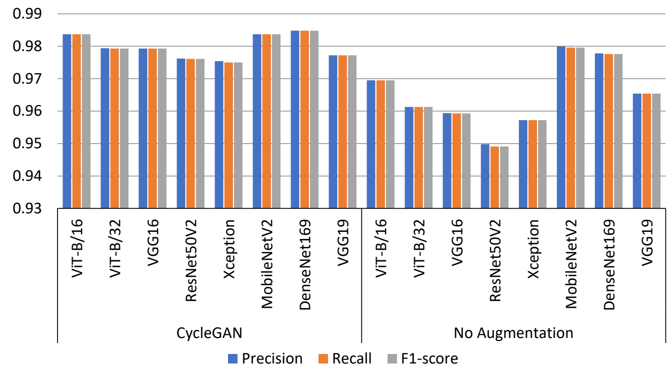

Fig. 7. Comparative analysis of evaluation metrics using CycleGAN augmented and non-augmented datasets for diverse models

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