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Research Article

A Novel Wheat Leaf Disease Classifier Leveraging Generative Adversarial Networks

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Abstract: Automatic diagnosis and control of wheat plant disease are highly desired by agricultural experts. Accurate diagnosis of wheat leaf diseases is important for effective crop management. This study introduces a Wheat Leaf Convolutional (WLC) model, an enhancement of the VGG16 architecture, designed to detect and classify six distinct types of wheat leaf diseases using deep learning techniques. The model is trained using wheat leaf images dataset, augmented by Generative Adversarial Networks (GANs) to improve generalization. The WLC model got an accuracy of 94.88%, outperforming classical CNN models such as ResNet-50, AlexNet, and MobileNet by significant margins. Key metrics, including recall, precesion and F1-score, were evaluated across six disease categories: Leaf Rust, Black Chaff, Powdery Mildew, Wheat Streak, Septoria, and Healthy plants. Experimental results show that the WLC model accurately and efficiently identifies diseases, making it a useful tool for real-time applications in precision agriculture. This work contributes to improving wheat disease diagnosis, enabling timely interventions and better crop management practices.

Keywords: Wheat diseases, Image classification, Deep learning, Precision agriculture, Convolutional neural networks, Generative Adversial Networks, Data Augmentation

1. Introduction

Wheat is a key cereal crop widely cultivated in temperate climates around the world, providing essential nutrients like carbohydrates, protein, and fiber to a large global population. As a vital agricultural product, wheat plays an important role in food security and economic stability. However, wheat production is frequently threatened by a several kind of diseases, such as Leaf Rust, Septoria, Powdery Mildew, and Wheat Streak, which can significantly reduce yield quality and quantity. The early detection of these diseases is necessary to prevent large-scale crop losses, maintain stable food supplies, and support farmers' livelihoods.

Traditional methods of disease identification in wheat crops typically rely on manual inspection by agricultural experts, which is labor-intensive, time-consuming, and prone to human error. To overcome these limitations, there is a need for automated solutions that can reliably and efficiently detect wheat diseases in real-time. With the advancement of image processing and machine learning technologies has enabled the development of deep learning models, offering an approach to automate plant disease detection and classification.

2. Related Work

Several studies have explored the application of deep learning in identifying wheat diseases. Jouini et al.[1] proposed an approach for detecting wheat leaf diseases with a focus on efficiency and real-world usability. The CropNet, blended transfer learning with shallow CNN-based feature refinement to create a lightweight solution. Using RGB images from real-world conditions, they fine-tuned popular models like EfficientNet and ResNet50, enhancing the shallow CNN layers to optimize performance. Their approach achieved an accuracy in classification of 99.80%.

Goyal et al. [2] tackled the problem of classifying the wheat disease in leaves and spikes by creating a custom deep learning model. Their model achieved a testing accuracy of 97.88%, outperforming widely used architectures like VGG16 and ResNet50. They used a dataset of over 12,000 images, representing 10 disease classes such as Fusarium head blight, black chaff, and leaf rust. The study highlighted the role of image preprocessing and data augmentation. This approach also enhanced accuracy but also emphasized the potential for real-world applications in crop health management.

Hossen et al.[3] approached the challenge of wheat disease detection with a CNN-based model that achieved an impressive accuracy of 98.84%. Their study utilized a dataset of 4,800 images, encompassing 12 classes of wheat diseases, including healthy crops. To overcome the limitations of smaller datasets, the team employed data augmentation techniques like flipping and rotating images to create more robust training data. Their Keras-based sequential model successfully distinguished diseased crops from healthy ones, presenting a tool for early detection and prevention.

Mikhail A. Genaev et al., [5]in their study, used the Wheat Fungi Diseases (WFD2020) dataset comprising 2,414 images to classify wheat diseases like leaf rust, powdery mildew, yellow rust, stem rust, and septoria. They employed the EfficientNet-B0 neural network and style-based data augmentation, achieving an accuracy of 94.2%.

Similarly, Deepak Kumar and Vinay Kukreja[6] conducted a systematic review titled "Deep Learning in Wheat Diseases Classification" that analyzed 74 studies from 1997 to 2021, finding that Artificial Neural Networks (ANN) were the most common techniques used for disease prediction, achieving an average accuracy of 67%.

Furthermore, using a dataset of 2,700 images of powdery mildew, stripe rust, and healthy wheat leaves, Xiaojie Wen et al. [7] evaluated CNN models like MobileNetV3, ShuffleNetV2, GhostNet, MnasNet, and EfficientNetV2. Using a lightweight parameter size of 19.09M and a mix of data augmentation, transfer learning, and optimal training procedures, the MnasNet model obtained the maximum recognition accuracy of 98.65%, making it ideal for deployment on mobile devices.

3. Theory

In real-world applications, challenges still exist with model correctness, generalizability, and computing efficiency despite the significant progress. In this study, we propose a novel deep learning model, the Wheat Leaf Convolutional (WLC) model, which builds upon the VGG16 architecture. The model aims to classify six common wheat diseases bases of leaf images: Leaf Rust, Black Chaff, Powdery Mildew, Wheat Streak, Septoria, and Healthy. Basidiomycete fungus Puccinia striiformis f. sp. tritici (Pst) causes Yellow rust, Mycosphaerella graminicola fungus causes Septoria leaf blotch, Puccinia triticina produces brown lesions on the leaves of wheat plants, Blumeria graminis causes Powdery mildew.

The proposed WLC model is rigorously evaluated against several classical CNN architectures, including ResNet-50, AlexNet, and MobileNet, showing superior performance in accuracy, precision, and recall.By achieving an accuracy of 94.88%, the WLC model demonstrates its potential as a significant tool for on-field disease identification in wheat crops. This technology can provide actionable insights to farmers and agricultural professionals, allowing for timely interventions that minimize crop losses and improve overall farm management practices.

The aim is to automatically identify and classify wheat leaf disease using deep learning techniques. The system relies on the Large wheat disease classification dataset (LWDCD) 2020 and plant village dataset as raw data, which contains labeled wheat images representing some of the wheat diseases such as Leaf Rust, Septoria, leaf blight, Wheat Streak, Powdery Mildew and Healthy. Figure 1 shows the images from LWDCD dataset. The total number of images for each class is given in Table.1. Total 8926 image samples of wheat leaves are collected. A 70:30 ratios are used in training and testing, where training is 70% and testing is 30%. To diversify the sample data, this study utilized the Generative Adversarial Network (GAN) model to expand the dataset. This contributes to improving the model's generalization performance. Additionally, to facilitate model training and maintain consistent image input sizes, the images are cropped to dimensions of 224 × 224 × 3, streamlining the training process and enhancing the generalization of the model.

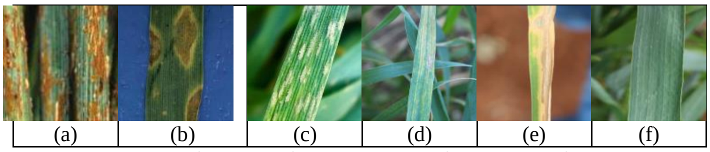

Figure.1: Images of wheat leaf diseases: (a) Leaf Rust (b) Leaf Blight (c) powdery mildew (d) Wheat streak (e) Septoria (f) Healthy

Table.1: Distribution of wheat leaf images

Classes	Original			Data Augmentation		
	Total	**Training**	**Testing**	**Total**	**Training**	**Testing**
Leaf Rust	2168	1667	501	9929	6950	2979
Leaf Blight	1095	842	253	5015	3510	1505
Wheat streak	1703	1310	393	8174	5722	2542
Septoria	1488	1144	344	7142	4999	2143
Healthy	1066	820	246	5116	3581	1535
Powdery Mildew	1406	1081	325	6748	4723	2025
Total	**8926**	**6864**	**2062**	**42124**	**29485**	**12729**

4. Proposed Model

The overview of WLDC shown in figure 2. It begins with the LWDCD dataset, which consists of annotated images of wheat leaves, ensuring that each image is properly labeled for training. To enhance the model's performance and generalization, data augmentation techniques are applied. At the core of the classification system is the WLC model is the enhancement of VGG16 model. Batch Normalization and Dropout layers are integrated into the network. These additions help stabilize training and enhance the model's ability. Finally, the trained model is used for image identification and classification, where it analyses new wheat leaf images and determines the presence of diseases.

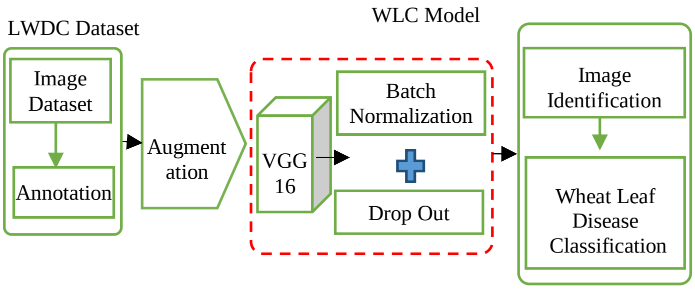

Figure 2: Overview of wheat leaf Convolution (WLC) model

The proposed network model shown in figure 3 uses multiple convolutional layers (Conv 1-1 to Conv 5-3) to learn hierarchical features from low-level to high-level abstractions. Each major block consists of two to three convolutional layers, followed by batch normalization. To ensure the model captures both local and global features, pooling layers are applied after each block, reducing spatial dimensions and expanding the receptive field.

To improve the model's ability to generalize and prevent overfitting, dropout layers are added. As the network progresses, it transitions into fully connected (dense) layers. Batch normalization is used after each convolutional layer for improving performance across different datasets.

With a deep architecture consisting of five major blocks, the model can extract a rich set of features, making it well-suited for wheat leaf disease classification. The use of dropout layers reinforces the model's ability to handle unseen data effectively.

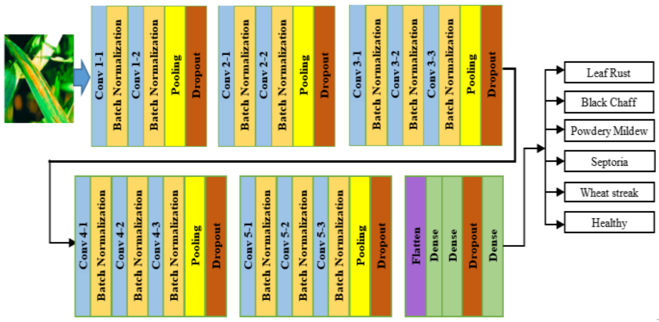

Figure 3: Architecture of proposed wheat leaf Convolution (WLC) model

4.1 Model training environment parameter configuration

The experiments in this paper were conducted on a google colab equipped with NVIDIA-SMI 535.104.05, Driver Version: 535.104.05 and CUDA Version: 12.2. The deep learning framework PyTorch version 1.1 is used, along with Python version 3.8 as the programming language. The datasets were trained over 30 epochs using the Adam optimizer, a batch size of 32, a learning rate of 0.0001, a uniform input image size of 224×224×3, and a momentum of 0.9.

As shown in equation 1 to 6, the model's accuracy, precision, recall, specificity, F1, were used. Positive(P) represents the total number of image samples in the dataset showing positive instances. The Negative (N) instances, or the total number of samples in the negative class. The number of true positive instances, or True Positive(TP), is the number of instances that the model properly predicts as positive.

True Negative(TN) are the number of true negative instances, representing the quantity of instances correctly predicted by the model as negative instance. False Positive(FP) represents false positive instances, indicating the number of samples incorrectly predicted as positive by the model. False Negative(FN) represents false negative instances that indicates the number of samples incorrectly predicted as negative by the model.

$$Accuracy = \frac{TP + TN}{P + N} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Rcall = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{FP + TN} \quad (4)$$

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

$$Kappa = \frac{P_0 - P_e}{1 - P_e} \quad (6)$$

4.2 Model Performance

The training accuracy for WLC model is 94.88 and validation accuracy of 87.04%. Table 2 shows the results are compared between the WLC model with several classical models. By comparison it shows that the WLC model proposed has outperformed the classical models. For instance, as per the accuracy, WLC model outperforms ResNet-50 by 5.15%, AlexNet by 9.19%, VGG-16 by 10.2%, and Mobilenet by 8.15%. There are also improvements in metrics such as precision and recall.

Table 2. Network models comparison table.

Model	Accuracy/%	Precision/%	Recall/%	FPS	F1 Score
AlexNet	85.69	86	85.50	365.4	0.857
MobileNet	86.73	87	86.50	370	0.868
ResNet-50	89.35	89.60	89	295.1	0.893
Vgg-16	84.68	84.90	84.50	320	0.847
Wheat Leaf Convv	94.88	94	93.80	280.6	0.939

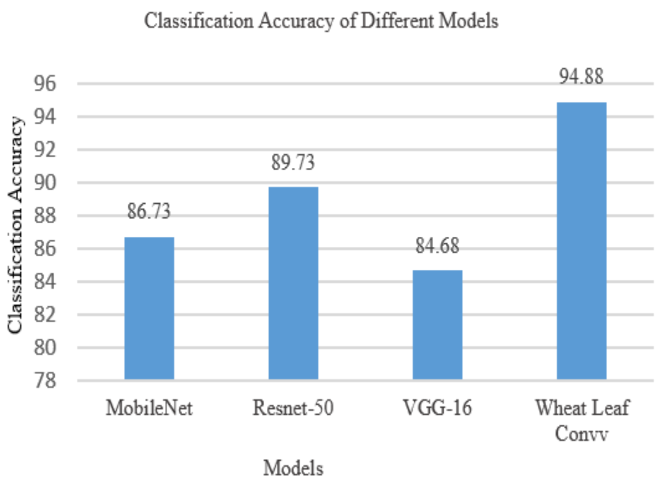

Figure 4. Classification accuracies of all the selected models

Figure 4, shows that, the WLC model proposed outperforms classical CNN models with both convergence speed and final accuracy. It exhibits faster convergence speed and higher accuracy, with a relatively stable training process.

5. Results and Discussion

The proposed WLC model is optimized to be consistent with the produced image dataset further improving the performance. Figure 5 depicts the WLC model's training and validation efficiency curves.

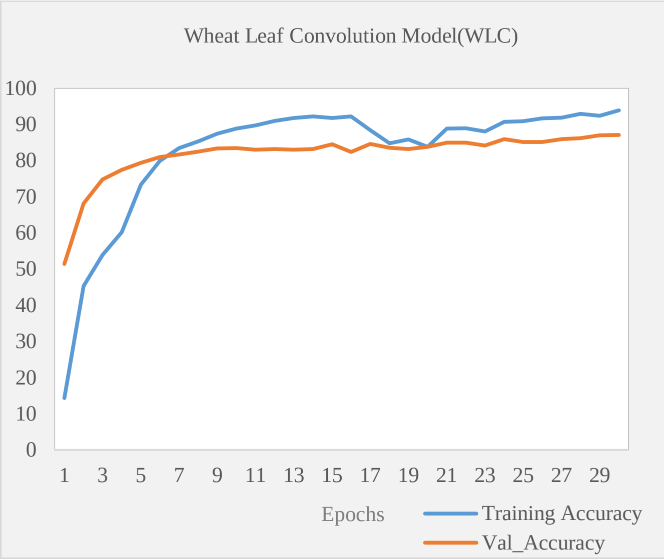

Figure 5: Curve of accuracy for Wheat leaf convolution(WLC) Model

WLC model had the maximum training and validation efficiency of 94.88% and 87.04%, respectively, over 30 epochs. Figure 6 show the confusion matrix for unseen data using WLC model.

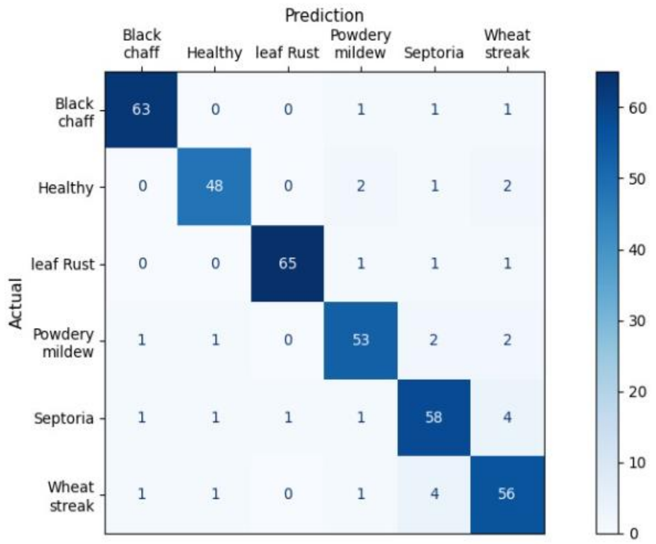

Figure 6. Confusion matrix for wheat leaf classification using WLC model

Table 3 shows f1-score, precision, recall, and support using WLC.

Table 3: recall, precision, f1-score and support for wheat leaf disease classification using WLC

Class	Precesion	Recall	F1-Score	Support
Black Chaff	0.92	0.99	0.95	66
Healthy	0.89	0.95	0.92	53
Leaf Rust	0.98	0.96	0.97	71
Powdery Mildew	0.91	0.94	0.93	59
Septoria	0.90	0.92	0.91	66
Wheat Streak	0.93	0.95	0.94	62

6. Conclusion and Future Scope

6.1 Conclusion

This study introduced a novel Wheat Leaf Classifier model, demonstrating its potential for accurate and efficient wheat leaf disease diagnosis. By incorporating GAN for data augmentation, the model's training process was significantly enhanced, leading to improved generalization capabilities and robustness against variations in image quality and disease presentation.

Experimental results demonstrate that the WLC model achieves improvements of ResNet-50 by 5.15%, AlexNet by 9.19%, VGG-16 by 10.2%, and Mobilenet by 8.15%. Comparison with four different classical CNN frameworks further confirms the superiority of the proposed model.

The WLC model's performance surpassed existing Convolutional Neural Network architectures, showcasing its superior ability to discern intricate patterns and features indicative of various wheat leaf diseases. This advancement holds promise for timely and precise disease detection, contributing to more effective disease management strategies in wheat cultivation.

6.2 Future Scope

While the current model is specifically designed for wheat leaf diseases, its architecture and methodology hold great potential for adaptation to other crops like rice, maize, or potatoes. By extending the model to classify a wider variety of diseases across different crops, it could become an even more versatile and impactful tool in precision agriculture, benefiting farmers and improving crop management practices across diverse agricultural systems.

Conflict of Interest

All Authors declare no conflict of interest.

Funding Source

none

Authors' Contributions

Dr. Girish: writing, Reviewing, Application Development,
Dr. Rajesh: Data Collection, methodology, Conceptualization
Dr. Ramesh: Data creation and Visualization
Mr. Shridhar: Software, Validation

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none

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