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Employing Deep Learning Approaches for the Automated Diagnosis and Management of Wheat Plant Diseases

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***Abstract* - Precise identification of foliar diseases in wheat is crucial for the development of effective crop management strategies. This study presents the Wheat Leaf Convolutional (WLC) model, which enhances the VGG16 architecture, with the objective of detecting and classifying six different types of foliar diseases using deep learning techniques. The model is trained on a dataset comprising images of wheat leaves, which has been augmented through the use of generative adversarial networks (GANs) to improve its generalization capabilities. The WLC model attained an impressive accuracy of 94.88%, significantly exceeding that of traditional CNN models such as ResNet-50, AlexNet, and MobileNet. Performance metrics, including recall, precision, and F1 score, were evaluated across six disease categories: leaf rust, black scale, powdery mildew, wheat streak, Septoria, and healthy plants. The experimental results demonstrate that the WLC model effectively and accurately identifies diseases, establishing it as a valuable tool for real-time applications in precision agriculture. This research contributes to the advancement of wheat disease diagnosis, enabling timely interventions and enhanced agricultural practices.**

Keywords: Image classification, Image processing, Agriculture research, WLC, Precision agriculture, Convolutional neural networks, Deep learning, Generative Adversial Networks, Wheat Leaf Convolutional, Data Augmentation, Wheat diseases.

I. INTRODUCTION

Wheat is a fundamental food source cultivated in temperate regions across the globe, supplying vital nutrients such as carbohydrates, protein, and fiber to a significant portion of the world's population. As an essential agricultural product, wheat is integral to ensuring food security and supporting economic stability. Nonetheless, its production is often jeopardized by various diseases, including leaf rust, Septoria, powdery mildew, and wheat streak, which can severely impact both the quality and yield of the crop. Timely identification of these diseases is crucial to avert substantial crop losses, ensure a consistent food supply, and protect the livelihoods of farmers.

Traditional methods for detecting wheat diseases typically depend on manual assessments conducted by agricultural specialists, a process that is labor-intensive, time-consuming, and susceptible to human error. To address these challenges, there is a pressing need for automated solutions capable of accurately and efficiently identifying wheat diseases in real time. Recent advancements in image processing and machine learning technologies have facilitated the creation of deep learning models that offer a promising approach to the automation of plant disease detection and classification.

II. SYSTEM THEORY

Despite notable advancements, challenges related to model accuracy, generalization, and computational efficiency persist in practical applications. This research introduces a new deep learning framework, the Wheat Leaf Convolutional (WLC) model, which is built upon the VGG16 architecture. The model aims to identify six prevalent wheat diseases from leaf images: leaf rust, black scale, powdery mildew, wheat streak, Septoria, and healthy leaves. Yellow rust is caused by the basidiomycete fungus Puccinia striiformis f. sp. tritici (Pst), while Septoria leaf spot is attributed to Mycosphaerella graminicola. Additionally, Puccinia triticina leads to brown lesions on wheat leaves, and Blumeria graminis is responsible for powdery mildew. The WLC model undergoes thorough evaluation against established CNN architectures, including ResNet-50, AlexNet, and MobileNet, showcasing superior performance in precision, accuracy, and recall. Achieving an accuracy rate of 94.88%, the WLC model proves to be a valuable asset for detecting diseases in wheat crops. This technology equips farmers and agricultural experts with actionable insights, facilitating timely interventions that reduce crop losses and enhance overall farm management.

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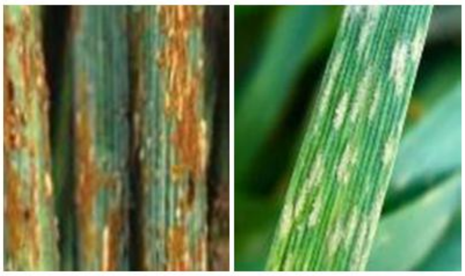
The primary objective is to automate the detection and classification of wheat leaf diseases through deep learning methodologies. The system utilizes the Large Wheat Disease Classification Dataset (LWDCD) 2020 and the Plant Village Dataset as foundational data, which comprise labeled images of wheat exhibiting various diseases, including leaf rust, Septoria, leaf smut, wheat streak, powdery mildew, and healthy leaves. Figure 1 illustrates images from the LWDCD dataset, while Table 1 provides the total number of images per class. In total, 8,926 wheat leaf image samples were gathered. A training-to-testing ratio of 70:30 is implemented, with 70% allocated for training and 30% for testing. To enhance the diversity of the sample data, this study employs a Generative Adversarial Network (GAN) model for dataset augmentation, thereby improving the model's generalization capabilities.



(a) (b)

Figure.1: Images of wheat leaf diseases: (a) Leaf Rust (b) powdery mildew

III. LITERATURE REVIEW

Numerous studies have explored the use of deep learning for detecting diseases in wheat. Jouini et al. [1] introduced a method aimed at identifying leaf diseases in wheat, emphasizing its practical effectiveness and user-friendliness. CropNet integrated transfer learning with shallow CNN-based feature refinement to develop a streamlined solution. By utilizing real-world RGB images, they fine-tuned established models like EfficientNet and ResNet50, enhancing shallow CNN layers to boost performance. Their method achieved an impressive classification accuracy of 99.80%.

Goyal et al. [2] tackled the classification of wheat diseases affecting both leaves and ears by creating a customized deep learning model. This model reached a test accuracy of 97.88%, surpassing well-known architectures such as VGG16 and ResNet50. They employed a dataset comprising over 12,000 images across 10 disease categories, including ear blight, black smut, and leaf rust. The research underscored the significance of image preprocessing and data augmentation, which not only enhanced accuracy but also showcased the model's potential for practical use in managing crop health.

Hossen et al. [3] confronted the issue of wheat disease detection with a CNN-based model that achieved a remarkable accuracy of 98.84%. Their study utilized a dataset of 4,800 images representing 12 classes of wheat diseases, including healthy specimens. To address the challenges posed by smaller datasets, the team implemented data augmentation techniques such as image flipping and rotation to generate more robust training data. Their Keras-based sequential model effectively differentiated between diseased and healthy plants, offering a valuable tool for early detection and prevention.

Mikhail A. Genaev et al. [5] used the 2414-image "Wheat Fungi Diseases" (WFD2020) dataset in their study to classify wheat diseases such as leaf rust, powdery mildew, stripe rust, stem rust, and Septoria. They used the EfficientNet-B0 neural network and style-based data augmentation and achieved an accuracy of 94.2%. Similarly, Deepak Kumar and Vinay Kukreja[6] conducted a systematic review titled "Deep Learning in Wheat Disease Classification," analyzing 74 studies from 1997 to 2021. They found that artificial neural networks (ANNs) were the most commonly used disease prediction technique, with an average accuracy of 67%.

In addition, Xiaojie Wen et al. a dataset containing 2,700 images of powdery mildew, yellow rust, and healthy wheat leaves. [7] evaluated CNN models such as MobileNetV3, ShuffleNetV2, GhostNet, MnasNet, and EfficientNetV2. By using a small parameter size of 19.09 M and a combination of data augmentation, transfer learning, and optimal training techniques, the MnasNet model achieved a maximum detection accuracy of 98.65%, making it ideal for use on mobile devices.

IV. PROPOSED SYSTEM DESIGN

The overview of WLDC is shown in Figure 2. It begins with the LWDCD dataset, which consists of annotated images of wheat leaves, ensuring that each image is correctly labeled for training. Data augmentation techniques are applied to improve the model's performance and generalization. The core of the classification system is the WLC model, which is based on the improved VGG16 model. Batch normalization and dropout layers are integrated into the network. These additions help stabilize training and improve model capacity. Finally, the trained model is used for image identification and classification, where it analyzes new images of wheat leaves and detects the presence of diseases.

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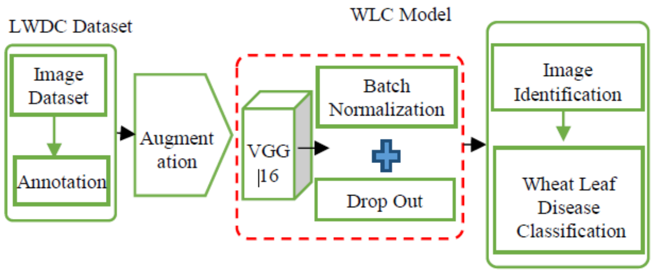

Figure 2: Overview of the Wheat Leaf Convolution (WLC) model

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- to high-level abstractions. Each main block consists of two or three convolutional layers, followed by batch normalization. To ensure that the model captures both local and global features, pooling layers are applied after each block, reducing the spatial dimensions and expanding the receptive field.

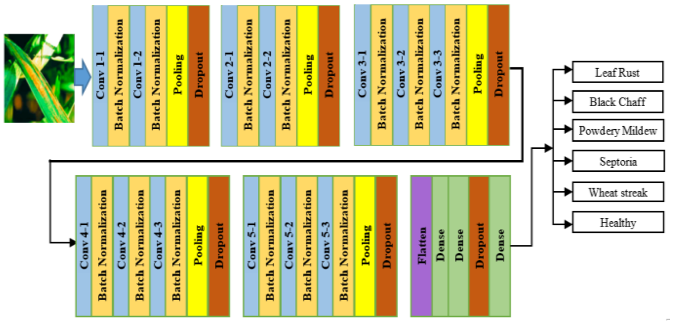

Figure 3: Flow diagram of proposed wheat leaf Convolution (WLC) model

To improve the model's generalization ability and avoid overfitting, dropout layers are added. As the network progresses, fully connected (dense) layers are formed. Batch normalization is used after each convolutional layer to improve performance on different datasets.

With a deep architecture consisting of five main blocks, the model can extract a wide range of features, making it ideal for wheat leaf disease classification. Using dropout layers improves the model's ability to efficiently process unrecognized data.

4.1 Configuring the Model Training Environment Parameters

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 and Python version 3.8 were used as the programming language. The datasets were trained for 30 epochs using the Adam optimizer, with 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 Equations 1–6, the model's accuracy, precision, recall, and specificity (F1) were used. Positive (P) represents the total number of image examples in the dataset that contain positive instances. Negative (N) represents the total number of samples in the negative class. The number of true positive instances, or true positives (TPs), is the number of instances that the model correctly predicts as positive.

True Negative (TN) is the number of true negative instances, which represents the number of instances that the model correctly predicted as negative. False Positives (FP) represent false positives and indicate the number of samples that the model incorrectly predicted as positive. False Negatives (FN) represent false negatives and indicate the number of samples that the model incorrectly predicted as negative.

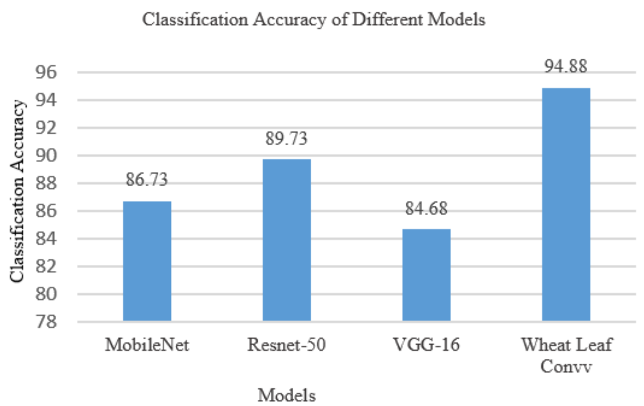

Figure 4: Classification of accuracies of all the selected models

4.2 Model Performance

The training accuracy of the WLC model is 94.88%, and the validation accuracy is 87.04%. Table 2 shows the comparison of the results between the WLC model and several classical models. In comparison, it can be seen that the proposed WLC model outperformed the classical models. For example, in terms of accuracy, the WLC model outperforms ResNet-50 by 5.15%, AlexNet by 9.19%, VGG-16 by 10.2%, and MobileNet by 8.15%. Improvements have also been made in metrics such as precision and recall.

V. RESULTS AND DISCUSSION

The WLC model has been optimized to align with the generated image dataset, further enhancing its performance. Figure 5 presents the training and validation efficiency curves for the WLC model. The model achieved peak training and validation efficiencies of 94.88% and 87.04%, respectively,

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across 30 epochs. Figure 6 displays the confusion matrix for unseen data processed by the WLC model.

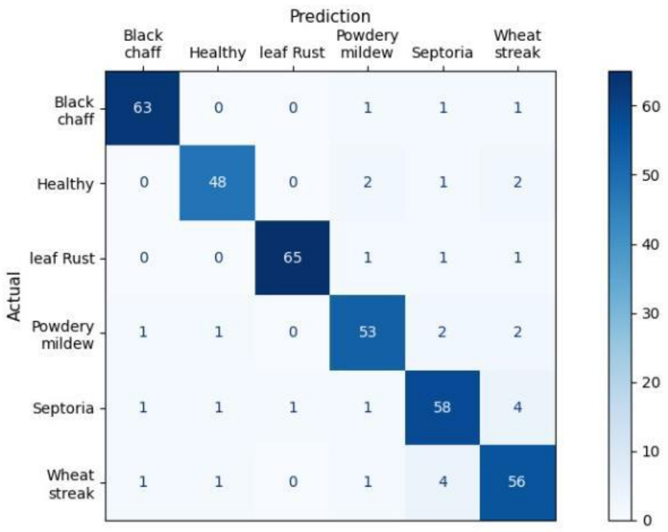

Figure 5: Confusion matrix for wheat leaf classification using WLC model

Table 1: F1-score, precision, recall, and support using WLC

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

The proposed WLC model surpasses traditional CNN models in terms of both convergence speed and final accuracy. It demonstrates a quicker convergence rate and superior accuracy, accompanied by a relatively stable training process.

VI. CONCLUSION

6.1 Conclusion

This research introduces an innovative model for sorting wheat leaves, highlighting its effectiveness in diagnosing leaf diseases with accuracy and efficiency. The incorporation of Generative Adversarial Networks (GAN) for data augmentation significantly enhanced the model's training process, leading to improved generalization and resilience against variations in image quality and disease representation.

The experimental findings indicate that the WLC model outperforms ResNet-50 by 5.15%, AlexNet by 9.19%, VGG-16 by 10.2%, and MobileNet by 8.15%. A comparative analysis with four established CNN frameworks further validates the superiority of the proposed model.

The WLC model's performance exceeds that of existing convolutional neural network architectures, showcasing its exceptional capability to identify intricate patterns and features associated with various leaf diseases. This progress holds promise for swift and precise disease detection, thereby enhancing disease management strategies in wheat farming.

6.2 Future Scope

While the current model is tailored for diagnosing leaf diseases in wheat, its underlying architecture and approach have significant potential for adaptation to other crops, including rice, maize, and potatoes. Expanding the model to encompass a broader spectrum of diseases across different crops could enhance its versatility and effectiveness in precision agriculture, ultimately benefiting farmers and improving agricultural practices in various farming systems.

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