A Hybrid Deep Learning Framework for Wheat Yellow Rust Detection and Severity Assessment Using STARGAN and Convolutional Neural Networks

Robin Singh[1,*], Raghuvinder[2]

[1,*]Programmer, Jagat Guru Nanak Dev Punjab State Open University, Patiala-147001, Punjab, India

[2]Department of Computer Science and Engineering, Chaudhary Devi Lal University, Sirsa, Haryana, India

Email: robinsingh1275@gmail.com, raghuvinder.bhardwaj@gmail.com

Abstract

Wheat is one of the most important cereal crops worldwide and plays a critical role in ensuring food security. However, wheat production is significantly affected by fungal diseases, particularly yellow rust (stripe rust), which causes severe yield losses and quality degradation. Traditional disease diagnosis methods rely on manual inspection by agricultural experts, making large-scale monitoring difficult and time-consuming. This paper proposes a hybrid deep learning framework for automatic wheat yellow rust detection and severity assessment using image-based analysis. The proposed approach integrates Star Generative Adversarial Networks (STARGAN) for data augmentation and Convolutional Neural Networks (CNN) for disease classification and severity prediction. A customized dataset comprising images collected from primary and secondary sources was utilized. Images were preprocessed through resizing and normalization before model training. Experimental results demonstrate that the proposed framework achieves a classification accuracy of 95.24% for wheat yellow rust detection and 94.8% accuracy for disease severity assessment. The findings indicate that GAN-based augmentation significantly enhances CNN performance and provides a practical solution for precision agriculture applications.

Keywords: Wheat Yellow Rust, Deep Learning, CNN, STARGAN, Disease Severity, Plant Disease Detection, Precision Agriculture.

1. Introduction

Agriculture plays a crucial role in the economic development of many countries and serves as the primary source of livelihood for a significant portion of the population. Wheat is among the most widely cultivated cereal crops globally and contributes substantially to food security. However, wheat productivity is often affected by fungal diseases, among which yellow rust (stripe rust) is considered one of the most destructive.

Yellow rust is caused by *Puccinia striiformis* and spreads rapidly under favorable environmental conditions. Severe infections can result in substantial yield reduction and economic losses. Traditional disease detection methods primarily depend on field inspections conducted by experienced agronomists. Such methods are labor-intensive, time-consuming, and unsuitable for large-scale agricultural monitoring.

Recent developments in artificial intelligence, computer vision, and deep learning have provided new opportunities for automated crop disease detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks and are increasingly being adopted in precision agriculture applications. However, deep learning models require large volumes of labeled data for effective training. Agricultural datasets are often limited due to the cost and complexity of data collection.

To address this challenge, this study employs Star Generative Adversarial Networks (STARGAN) to generate synthetic wheat disease images and improve dataset diversity. The generated images are subsequently used to train a CNN model for wheat yellow rust classification and disease severity estimation.

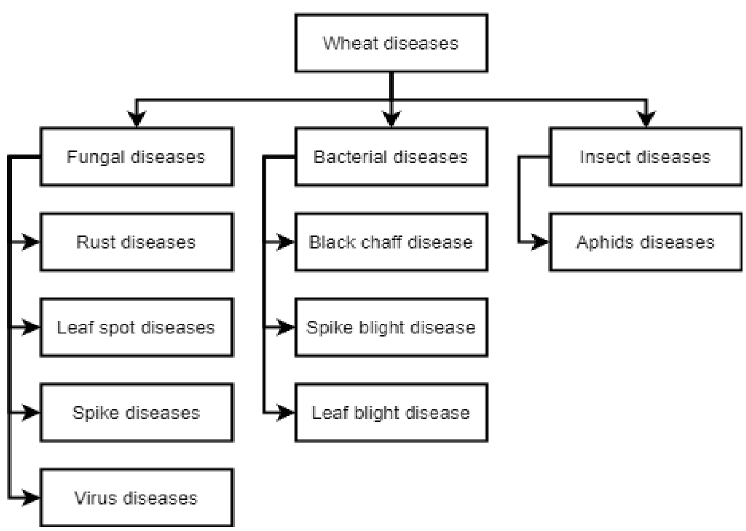

Figure 1: Categorization of Wheat Diseases.

The major contributions of this work are:

1. Development of a hybrid STARGAN-CNN framework for wheat yellow rust detection.
2. Construction of a wheat disease image dataset from multiple sources.
3. Automatic classification of disease severity levels.
4. Comparative evaluation against existing approaches.
5. Demonstration of the effectiveness of GAN-based data augmentation in agricultural image analysis.

2. Related Work

The application of machine learning and deep learning techniques for crop disease diagnosis has attracted significant attention in recent years. Earlier studies employed traditional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees (DT), Artificial Neural Networks (ANN), and Random Forests (RF) for disease classification.

Neural network-based approaches achieved encouraging performance in wheat rust detection, reporting accuracies exceeding 90%. SVM-based methods were also widely adopted due to their strong classification capabilities when combined with handcrafted image features. However, the performance of these methods depended heavily on manual feature engineering.

The emergence of deep learning has transformed plant disease recognition systems. CNN architectures such as AlexNet, VGG16, ResNet, DenseNet, and EfficientNet have achieved state-of-the-art results in various agricultural applications. Researchers have reported classification accuracies ranging from 93% to 98% for wheat rust disease identification using deep learning models.

Although CNN-based approaches have demonstrated superior performance, their effectiveness is constrained by the availability of large annotated datasets. Most existing studies rely on conventional augmentation methods including image rotation, flipping, translation, and scaling. Advanced generative techniques such as GANs remain relatively underexplored in wheat disease diagnosis.

This research addresses this gap by integrating STARGAN-based augmentation with CNN-based classification to improve disease detection and severity estimation performance.

3. Proposed Methodology

The proposed framework consists of four major stages:

1. Dataset Collection
2. Image Preprocessing
3. Data Augmentation using STARGAN
4. Disease Detection and Severity Classification using CNN

3.1. Dataset Collection

A customized wheat yellow rust dataset was developed using both primary and secondary data sources.

Primary data were collected directly from agricultural fields using a Canon camera under expert supervision. Secondary data were obtained from publicly available agricultural image repositories, websites, and research databases.

The collected dataset consisted of healthy wheat plants and wheat plants infected with yellow rust disease.

Figure 2: Dataset Samples.

3.2. Image Preprocessing

Image preprocessing was performed to standardize the dataset and improve training efficiency.

The following operations were applied:

- Image resizing to 224 × 224 pixels
- RGB color normalization
- Removal of inconsistent image dimensions
- Dataset standardization

Preprocessing reduced computational complexity and facilitated efficient feature extraction.

3.3. Data Augmentation Using STARGAN

To overcome the challenge of limited training samples, STARGAN was employed for synthetic image generation.

STARGAN consists of two major components:

(1) Generator

The generator learns image distributions and produces realistic synthetic wheat leaf images.

(2) Discriminator

The discriminator evaluates whether generated images are real or artificial and continuously improves image quality through adversarial learning.

The generated images were merged with the original dataset to create a larger and more diverse training set.

3.4. CNN-Based Disease Classification

A Convolutional Neural Network was utilized for disease classification and severity estimation.

The CNN architecture consisted of:

• Convolution Layers
• Pooling Layers
• ReLU Activation Functions
• Fully Connected Layers
• Softmax Classification Layer

The network automatically extracted disease-specific features such as lesion patterns, rust spots, and texture variations.

4. Experimental Setup

4.1. Hardware Configuration

The experiments were performed on a Lenovo notebook with the following specifications:

• Intel Core i5-1135G7 Processor
• 8 GB RAM
• Windows 10 Pro

4.2. Software Environment

Implementation was carried out using Python with the following libraries:

• TensorFlow
• Keras
• OpenCV
• Scikit-Learn
• NumPy
• Matplotlib

4.3. Training Parameters

Table 1: Parameters Values.

Parameter	Value
Image Size	224 × 224
Optimizer	Adam
Learning Rate	0.001
Epochs	10–100
Dropout Rate	0.5
Train-Test Split	70:30

5. Results and Discussion

5.1. Wheat Yellow Rust Classification

The CNN model achieved excellent classification performance on the testing dataset.

Table 2: Classification Results.

Metric	Value
Precision	94.94%
Recall	96.77%
F1-Score	95.85%
Accuracy	95.24%

The results indicate that the proposed model can effectively distinguish healthy wheat plants from yellow-rust-infected plants.

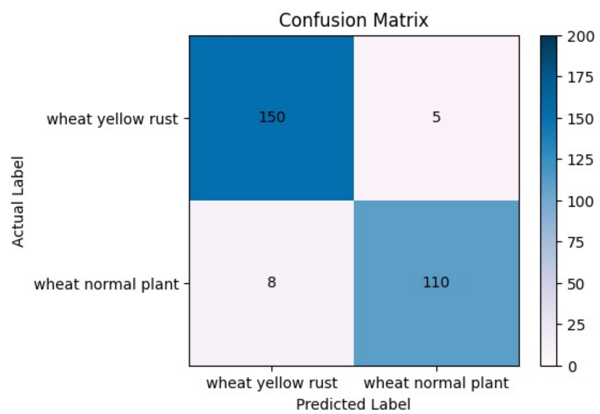

Figure 3: Confusion Matrix for classification.

5.2. Disease Severity Classification

Disease severity was categorized into five classes:

1. Very Low (0–20%)
2. Low (21–40%)
3. Medium (41–60%)
4. High (61–80%)
5. Very High (81–100%)

The CNN model achieved a maximum severity classification accuracy of 94.8%.

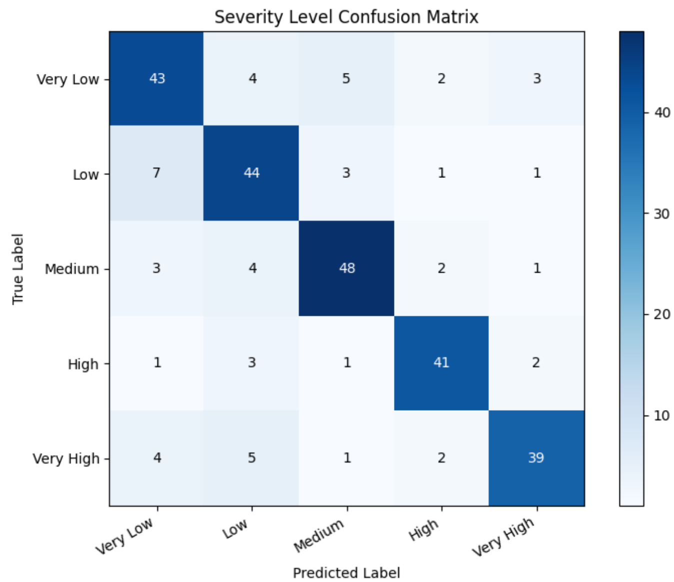

Figure 4: Confusion matrix for severity level.

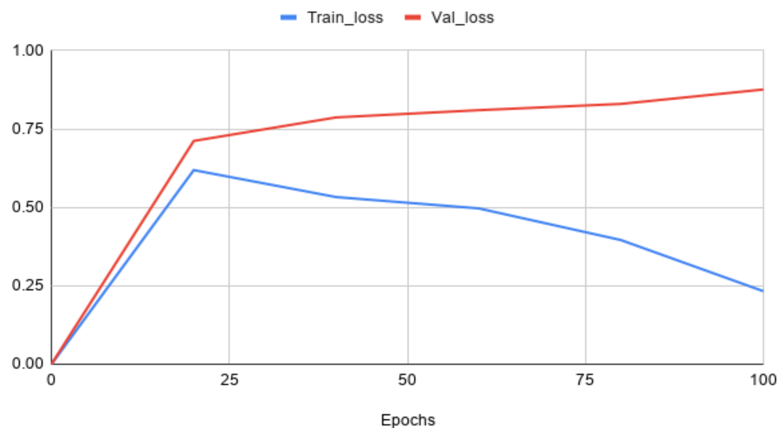

Figure 5: Loss graph of training vs. validation with different epochs.

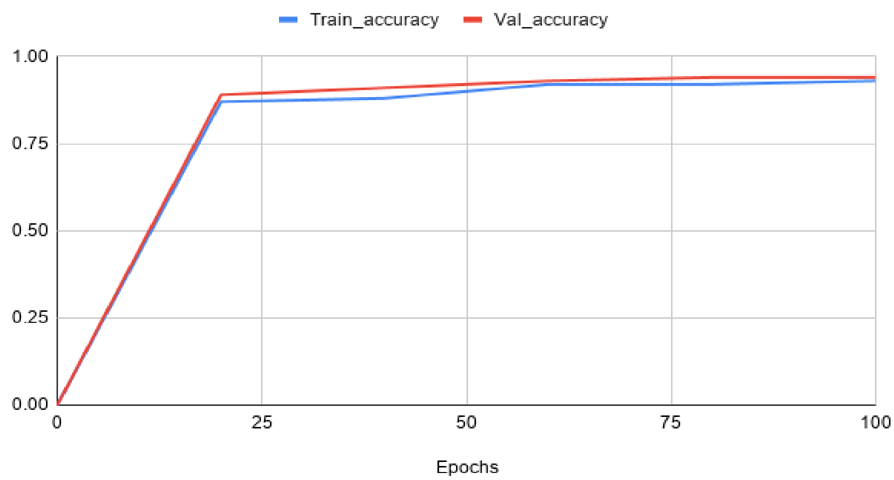

Figure 6: Accuracy graph for training vs. validation.

5.3. Comparative Analysis

The proposed hybrid framework was compared with previously reported approaches.

The results demonstrate that the integration of STARGAN with CNN improves classification performance and provides additional capability for disease severity assessment, which is absent in many existing systems.

Table 3: Comparative Results.

Referenced Study	Method	Dataset	Accuracy (%)	Disease Severity	Type of Disease
[18]	DACNN	8326 images	95.18	No	Wheat leaf rust
[20]	Naïve Bayes	53 plots	72.73	No	Powdery mildew
[23]	C-Densenet, Resnet	5,242	C-Densenet(92.53), Resnet(73.43)	No	Stripe rust
[24]	DCNN, RF	5 Plots	DCNN(0.85), RF(0.77)	No	Stripe rust

[53]	PSO-SVM	987 images	92	Yes	FHB
[54]	Mask-RCNN	55 images	98.8	No	FHB
[55]	DT, Alexnet, VGG-16, Resnet-50, and Sequential CNN	2324 images	Septoria leaf blotch(0.96), Stripe rust(0.94),FHB(0.96)	No	Septoria leaf blotch, Stripe rust, FHB
[63]	VGG-16, Alexnet, Resnet-18, Renet-34, Resnet-50	750 images	VGG-16(0.932),Alexnet(0.92), Resnet-18(0.939), Renet-34(0.936),	No	Leaf rust, Stem rust
[64]	CNN	1163 images	93	No	Stripe rust
Our proposed approach	GAN+CNN	900 images	CNN(95.24%) for binary classification, CNN(94.8%)for measuring severity at high level	Yes	Stripe rust and its severity levels

6. Conclusion and Future Work

This paper presented a hybrid deep learning framework for wheat yellow rust detection and severity assessment using STARGAN and CNN. The proposed methodology enhances dataset diversity through GAN-based augmentation and enables accurate disease classification using CNN. Experimental evaluation demonstrated classification accuracy of 95.24% and severity prediction accuracy of 94.8%.

Future work will focus on extending the framework to multiple wheat diseases, incorporating transfer learning models such as EfficientNet and Vision Transformers, and deploying the system on mobile and drone-based agricultural platforms.

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