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Wheat Rust Detection and Control through Precision Framing Using RCNN Model

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ABSTRACT

Wheat (*Triticum* spp.) stands as one of the most critical staple crops in the global agricultural landscape. Wheat cultivation is consistently threatened by various biotic and abiotic factors. Among these, rust diseases, caused by the fungal pathogen, poses a significant threat to wheat yields globally. In recent years, advances in artificial intelligence (AI) and machine learning (ML), particularly through the application of convolutional neural networks (CNNs), have begun to revolutionize the detection and management of disease in crop plants. Recent progress in in-depth remote sensing and learning technologies have considerably improved the capacity of convolutional neural networks (RCNN) based on the region in the detection and control of wheat rust, a critical threat to global food security. Machine learning based detection techniques, emphasizing the importance of integrating advanced methodologies such as RCNN have shown promise to improve precision in the identification of wheat rust diseases. Studies have demonstrated the effectiveness of hybrid models that combine the extraction of regions with automatic learning algorithms to classify rust diseases, resulting in better diagnostic precision. In addition, the merger of multiple techniques has shown an improvement in the performance of the classification of diseases. This convergence of technologies, including the analysis of ground imaging contributes to the development of more robust agricultural practices, ultimately supporting sustainable agriculture initiatives and furthering wheat improvement.

Introduction

Wheat (*Triticum spp.*) stands as one of the most critical staple crops in the global agricultural landscape, providing a fundamental source of carbohydrates, proteins, and essential nutrients for billions of people worldwide. According to the Food and Agriculture Organization (FAO), wheat accounts for approximately 20% of the calories consumed by humans, thereby playing an indispensable role in food security and nutrition. In India, wheat is the second most important crop grown over an area of more than 30mha (Trethowan *et al.,* 2018). Wheat cultivation is consistently threatened by various biotic and abiotic factors.

Among these, yellow rust disease, caused by the fungal pathogen *Puccinia striiformis f. sp. tritici*, poses a significant threat to wheat yields globally (Kumar *et al.,* 2019; Kamboj *et al.,* 2020). The disease is characterized by the formation of yellowish-orange pustules on the leaves and stems of infected plants, which ultimately leads to chlorosis, necrosis, and significant reductions in grain yield if left uncontrolled. Stripe rust epidemics have been reported to cause yield losses to reach 40 % and up to 100 % under severe infections. It has been frequently reported in all continents, with the most severe occurrences in the Pacific Northwest (the United States), East Asia (Northwest and Southwest China), South Asia (Nepal), Oceania (Eastern Australia) and East Africa (Kenya) (Chen, 2020). The spread of *Pst* has increased significantly over the last few decades, with 88 % of wheat varieties being susceptible to it. Although research has been done on breeding new wheat varieties and identifying rust resistance genes, the rapid loss of rust resistance in the newly developed cultivars makes the prevention and treatment of the disease very difficult (Hungilo *et al.,* 2019; Jadhav *et al.,* 2020; LeChun *et al.,* 2015). Hence, accurate and timely detection of stripe rust infestation are critical for implementing crop management strategies and ensuring food security.

In recent years, advances in artificial intelligence (AI) and machine learning (ML), particularly through the application of convolutional neural networks (CNNs), have begun to revolutionize the detection and management of disease in crop plants (Bashish *et al.,* 2010; DeChant *et al.,* 2017; Kamilaris and Boldu, 2018; Khalid, 2024; Nigam *et al.,* 2024). Most disease detection and recognition efforts rely on digital images of symptoms that are either visibly apparent or detectable through spectrum-based sensors. A major challenge in this context is the wide variety of plant disorders, many of which produce similar physiological and visual alterations. Ideally, a dataset should include examples of all relevant disorders to enable accurate discrimination. However, despite significant strides made by some studies to achieve this goal, attaining truly comprehensive coverage remains virtually unfeasible. As a result, most studies are limited to a narrow subset of disorders, often ignoring other potential causes of the observed symptoms. This leads to models that are constrained to select from the known classes, even when the input belongs to an unseen or unrelated category, potentially yielding inaccurate predictions (Kumar and Kukreja, 2024; Adem *et al.,* 2024; Kumar *et al.,* 2024; Vimla *et al.,* 2024).

These innovations provide new avenues for early disease detection, allowing for more timely interventions and thereby lessening the economic and food security impacts associated with yellow rust outbreaks in wheat. The advent of artificial intelligence (AI) and machine learning algorithms, specifically convolutional neural networks (CNNs), represents a potentially transformative approach in the field of plant pathology. These AI-based applications can analyze vast amounts of data, including remote sensing imagery and field-level observations, to accurately diagnose yellow rust outbreaks in a fraction of the time previously required. With the advent of AI and machine learning, particularly deep learning models like RCNN, there is a promising opportunity to automate the detection process (Mishra and Kaur, 2024; Mandava *et al.,* 2024; He *et al.,* 2016). RCNNs are highly effective in object detection tasks, and in this case, they could help accurately identify symptoms of yellow rust (e.g., pustules on leaves) from images, thereby enabling early intervention. An RCNN is a type of Convolutional Neural Network (CNN) designed to perform object detection by first generating potential regions of interest (RoIs) in an image (i.e., where the disease may be present) and then classifying these regions. RCNNs have been proven effective in various agricultural applications like plant disease identification, pest detection, and crop counting (Barbedo, 2018; Boulent *et al.,* 2019; Ferentinos, 2018; Jain *et al.,* 2009). This study focuses on the application of RCNN to identify yellow rust symptoms in wheat crops. With the advancement of consumer-grade UAVs, ultra-high resolution RGB data can be acquired more easily at a much-reduced cost, which has greatly increased the user base. In this study, RGB-based high-resolution images from UAVs were explored for detecting diseased transmission centers of wheat stripe rust under complex field conditions.

Semantic segmentation CNNs were used to map the diseased areas in wheat fields where sections of the fields were naturally infected by wheat stripe rust in Xiangyang, Hubei, China (Lu *et al.,* 2017; Lee *et al.,* 2015). The primary objectives of the research were to find whether RGB imagery is efficient for accurately detecting stripe rust disease transmission centers in a heterogeneous wheat field. The research will utilize images from various wheat fields to train and validate the AI model. Additionally, the study will explore how integrating AI-driven disease detection systems can enhance the overall management of wheat diseases, leading to better decision-making in pest and disease control (Zhang *et al.,* 2021). By focusing on early detection, this research seeks to contribute to the development of integrated pest and disease management (IPDM) strategies that combine AI with traditional crop management practices.

Key Components of RCNN

Region Proposals: First, a set of candidate regions is proposed from the image, which could potentially contain the object of interest (in this case, yellow rust lesions).
Feature Extraction: Once potential regions are identified, the RCNN applies CNNs to extract features from these regions.
Classification and Localization: After feature extraction, a classifier (like an SVM) is used to identify whether the region contains yellow rust and where it is located within the image.

Materials and Methods

Collection and Creation of Datasets

For conducting the research, a dataset of 2000 images consisting of wheat plant leaves images to develop AI based model for wheat diseases classification. After created a dataset of 2000 images that consist of healthy leaves (1000 images), yellow rust infected leaves (1000 images). The dataset is further divided into training (1600 images), testing (200 images) and validation set (200 images). This dataset was created by capturing real field images using a smartphone. All of the images were taken in different weather situations in agricultural fields.

Description of Wheat Plant Diseases Classes used in Dataset

The dataset consists of images of healthy wheat leaves as well as images belonging to diseased leaves. The diseased classes are quite commonly observed in Karnal area; hence we focused on collecting images of these diseased rust leaves. Their identification criteria are described as below.

Early leaf spot: The early leaf spot disease is seen to arise after around a month of sowing. Initially tiny near to circular chlorotic marks develop on upper surface of leaf. The spots are seen to develop brownish color with a yellow boarder around.

Late leaf spot: Late Leaf spot disease signs are normally observed around one months later than the sowing period and remain till the time of harvesting.

Rust and Late Rust: Rust disease may be early or may be late. It is observed to have chlorotic spots in the starting phases which arise on the upper surface of the leaf.

Early signs: Small, yellowish spots (chlorotic flecks) on the leaf surface.

Progression: Narrow, yellow-orange pustules aligned in stripes along veins (unlike leaf rust, which appears scattered).

Touch test: Spores are powdery and easily rub off on fingers or clothes.

Symptoms

It will develop in the form of narrow, yellow, linear stripes mainly on leaves and spikelets. When ear heads are infected, the uredia appear on the inner surface of the glumes and lemmas, occasionally invading the developing grains. Mainly occur on leaves than the leaf sheaths and stem. Bright yellow pustules (Uredia) appear on leaves at early stage of crop and pustules are arranged in linear rows as stripes. The stripes are yellow to orange yellow.

The teliospores are also arranged in long stripes and are dull black in colour. The pustules of stripe rust, which contain yellow to orange-yellow uredospore's, usually form narrow stripes on the leaves. Pustules also can be found on leaf sheaths, necks, and glumes. Since rust affects the photosynthetic ability of the infected plant, the quantification of chlorophyll content plays a crucial role in phenotyping at early stages.

Since yellow rust can occur whenever the wheat plants in green and the environmental condition conducive for the spore infection, yellow rust is a severe problem in the wheat-producing regions worldwide. Temperatures during the time of winter wheat emergence and the coldest period of the year are crucial for epidemic development in winter-habit wheat crops. The disease can infect all stages of wheat growth but is most damaging during the early stages of plant growth.

AI methods for Wheat Plant Disease Identification

Initially, CNNs were employed primarily in image processing tasks due to their ability to hierarchically extract features from images. Traditional models, such as LeNet-5, were simplistic, with limited depth and capabilities. Most recent and advanced algorithm for yellow rust disease identification is Deep learning. The basic steps involved in yellow rust disease identification involves four phases namely image acquisition, image pre-processing, features extraction, and classification. Nowadays RCNN (Region-based Convolutional Neural Network) is a deep learning method commonly used for object detection and image segmentation. It can locate and classify specific disease regions in wheat images.

Deep CNN Models for Comparison

In this work, the VGG16, InceptionV3, VGG19, ResNet50, MobilenetV2, and ResNet152V2 pre-trained deep CNN models were examined and a detailed comparative analysis with proposed model is performed. Convolutional neural networks are a type of deep learning approach used for difficult pattern recognition and classification issues with large databases. The four primary layers of the model are convolution, max pooling, fully connected, and output, and they are constructed one on top of the other.

VGG16

VGG16 is a 16 layers CNN including convolutional and fully linked layers. The key feature of VGG16 is its uniformity in design, with small 3x3 convolutional filters and max pooling layers used throughout the network. In VGG16, each convolutional layer uses a 3x3 filter with a stride of 1 and a padding of 1 to preserve spatial dimensions.

VGG19

VGG19 was developed by the Visual Geometry Group at the University of Oxford. VGG19 is a CNN with 19 layers, an expansion of the VGG16 architecture. It starts with a set of convolutional layers, then moves on to layers with maximum pooling for down sampling, and finally layers with fully linked layers for classification.

MobilenetV2

MobileNetV2 is a convolutional neural network (CNN) architecture designed for efficient and lightweight image recognition on mobile and embedded devices. It is an evolution of the original MobileNet architecture, aiming to improve model accuracy while maintaining computational efficiency and small model size. MobileNetV2 utilizes depthwise separable convolutions as its fundamental building block.

InceptionV3

InceptionV3 is a convolutional neural network (CNN) architecture that was developed by Google. One key feature of InceptionV3 is the use of "Inception modules" that employ multiple filter sizes (1x1, 3x3, 5x5) within the same layer. This allows the network to capture information at different levels of abstraction and spatial resolutions.

ResNet152V2

ResNet152V2 refers to a specific variant of the ResNet (Residual Network) architecture that utilizes 152 layers. These models typically aim to enhance the model's performance, training efficiency, and generalization capabilities as compared to earlier RestNet CNN models. Below Table 3 summarizes the mentioned CNN model parameters with input shapes of images.

Rust Control Framework using RCNN Approach:

Region Proposals

R-CNNs begin by generating *region proposals*, which are smaller sections of the image that may contain the objects we are searching for. The algorithm employs a method called *selective search*, a greedy approach that generates approximately 2,000 region proposals per image. Selective search effectively balances the number of proposals while maintaining high object recall, ensuring efficient object detection. By limiting the number of regions for detailed analysis, this method enhances the overall performance of the R-CNN in detecting objects within images.

R-CNN represents a significant leap forward in the field of object detection, combining the strengths of deep learning and region-based methods. Its architecture and workflow have influenced numerous subsequent models, leading to faster and more efficient object detection systems. As research continues, R-CNN remains a cornerstone in the development of advanced computer vision applications, demonstrating the enduring impact of this groundbreaking model on the future of artificial intelligence. After generating the region proposals, these regions are warped into a uniform square shape to match the input dimensions required by the CNN model. R-CNN identifies and localizes objects in images by proposing R*egions of Interest (RoIs) and classifying them through the CNN*. The object detection framework starts with an input image containing potential objects and employs a *Region Proposal Network (RPN)*, like *Selective Search*, to generate bounding boxes likely to contain objects.

Each proposed region is resized and fed into a pre-trained CNN, such as *AlexNet or VGG16*, to extract feature representations. These features are then classified by the SVM into predefined categories or designated as background. To refine localization further, a bounding box regression model adjusts the coordinates of each box, aligning them more closely with the actual object boundaries. This systematic process effectively combines proposal generation, feature extraction, classification, and bounding box refinement, enabling accurate object detection.

Results and Discussion

The hyperparameters are empirically determined as per the multiple experiments conducted on the image dataset according to the best results obtained for wheat disease identification. the hardware setup and related operating environment used for implementation and comparative analysis. The distribution is as such that the testing set contains representative images from all classes. A RCNN is trained by making a prediction and assessing the results or errors while delivering training samples from the input layer to hidden layers and the output layer. Then, a proposed classification model based on many layers of convolutional neural networks is constructed to recognize and categorize wheat plant leaves. Each image from the normalized training dataset is fed into the multilayer convolutional neural network model to retrieve the features. For each training image, this model forecasts the class label. Below Table comparing the accuracy and loss of existing models on our wheat plant dataset. The complete dataset of wheat plant images is initially divided into a training dataset and a testing dataset with about 80% of the images are in the training set, while only 20% are in the testing set. The training and testing sets are randomly selected from the dataset to achieve this. Applications of neural networks frequently use this ratio distribution.

Large datasets with advanced model can motivate more researchers to experiment with deep learning, applying it for solving various agricultural problems involving classification or prediction, related to image processing. A sophisticated Artificial Intelligence based technique for image processing is needed for wheat plant disease identification. This study showed the feasibility of using RGB-based ultra-high-resolution imagery acquired by consumer-grade UAVs combined with CNN to accurately detect wheat stripe rust transmission centers under heterogeneous field conditions. We tested the CNNs with different frameworks, varying spatial resolutions, and different algorithms. In summary, our results showed that the CNN model works expertly in a large-scale dataset that is diverse location conditions, field types, flight altitudes and light characteristics. In particular, the data can be combined with the latest CNN algorithms enabling end-to-end image processing, eliminating the need for tedious and complex data pre-processing. The generalizability of the model across different regions and growing periods is a primary concern. In the future study, the model can benefit from continued training by collecting data from an even wider range of regions at different phenological stages of the crops to improve the robustness of the model. From an operation point of view, manual visual annotation of high-resolution UAV RGB images is a tedious and time-consuming task. Smaller rust transmission centers are likely to be missed by visual interpretation but the model will be able to detect them well, and an interactive annotation tool (Hao *et al.,* 2021) could be developed in the future to improve the annotation efficiency and accuracy. Furthermore, in addition to the CNN networks, popular deep learning networks such as Transformer (Xie *et al.,* 2021; Zheng *et al.,* 2021) could be drawn upon to potentially further improve the performance of wheat stripe rust segmentation. Finally, because of the outstanding performance at high resolution, UAV would be a particularly useful alternative to traditional field surveys in facilitating the generation of continuous and comprehensive reference data from remote sensing at large spatial scales (Carbonneau *et al.,* 2020; Gränzig *et al.,* 2021). It is still difficult to achieve large-scale automated real-time observation of plant diseases, and currently relies on manual observation, which severely affects the continuity, comprehensiveness and quantification of data, while satellite remote sensing can cover a large area but with limited accuracy and is too expensive. Our findings highlight that cooperation between high spatial resolution UAV imagery and CNN-based semantic segmentation algorithms is critical to detect wheat stripe rust efficiently and extensively. Given that high-resolution RGB imagery is now increasingly accessible and low-cost, consumer-grade UAVs can play a critical role in detecting wheat stripe rust.

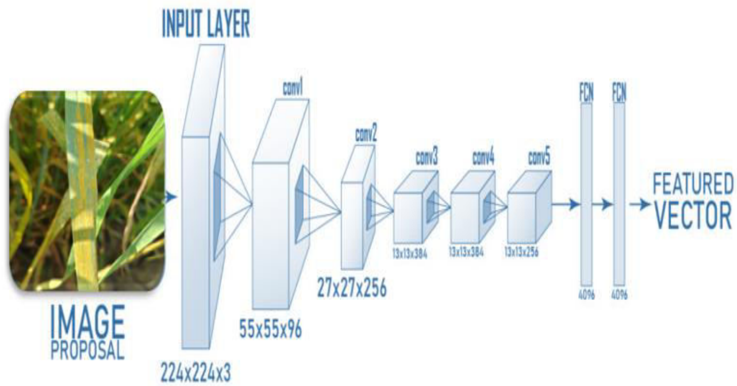
Table.1

Acquisition date	Training	Testing	Total
15.3.2025	1280	320	1600
22.3.2025	696	174	870
30.3.2025	505	127	632
7.4.2025	536	134	670
15.4.2025	788	197	985

Figure.1 Image of Yellow Rust Wheat Plant

Figure.2

Figure.3 Block Diagram of RCNN For Detection of Yellow Rust in Wheat



The research proposed an image-based classification model using Deep RCNN for classifying wheat plant leaf disease using transfer learning. A dataset of 2000 real wheat plant images were generated for the purposes. The categorization of leaf disease will require further work on data augmentation techniques to produce big datasets and train the deep RCNN model from scratch.

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Author Contributions

Priya Rani: Investigation, formal analysis, writing—original draft. Sanjeev Puri: Validation, methodology, writing—reviewing.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Conflict of Interest The authors declare no competing interests.

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