International Journal of Electrical, Electronics and Computer Engineering **14**(1&2): 48-50(2025)
ISSN No. (Online): 2277-2626

A Comprehensive Literature Review on Real time wheat leaf disease detection using Convolutional Neural Network (CNN)

Harpreet Bharwal* and Arpan Choudhary
School of Computer Science Engineering and Technology,
Government College Dharamshala (H.P.), India.

(Corresponding author: Harpreet Bharwal)*
(Received: 27 February 2025, Accepted: 03 April 2025)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: Wheat is a really important food crop worldwide, but diseases from things like fungi, bacteria, and viruses often mess with how much we can grow. Spotting these diseases early is super important so we don't lose a ton of wheat and mess up the food supply. Usually, people check for diseases by hand, which takes forever, needs a lot of work, and people make mistakes. But lately, machine learning, especially with CNNs, has gotten good at automatically finding diseases in plants. This paper is all about using CNNs to spot wheat diseases right away. It's about sorting and naming wheat diseases by looking at pictures of leaves and stems that are infected. The goal is to give farmers a quick, correct, and easy-to-use way to figure out what's wrong, so they can fix it fast and grow better crops. The results are looking good, and CNNs could really help with finding wheat diseases and protecting how much wheat we can grow.

Keywords: CNN, Real time analysis, Disease detection, Wheat leaf.

INTRODUCTION

Agriculture is the cornerstone of world food security, and wheat, as one of the most farmed crops, is responsible for feeding millions of people around the globe. Wheat production, however, has many challenges, one of the most pressing ones being disease. Wheat diseases, caused by infections with a variety of pathogens such as fungi, bacteria, and viruses, can severely weaken yield, quality, and in other cases lead to complete loss of crops (Mishra *et al*., 2024). Proper and timely disease diagnosis is necessary to mitigate losses and wheat farming sustainability. Conventionally, wheat disease detection was dependent on visual observation by farmers or field experts, which is usually a time-consuming, variable, and human-error-prone process. s technology in this area, such as computer vision and machine learning, continues to develop, our method of being able to identify this disease in wheat, will need to adapt (Sharma *et al.*, 2021). Class of deep learning software is known as Convolutional Neural Networks (CNNs) and these works great for image-based operations such as object recognition, classification, segmentation. These models can offer real-time, accurate systems for identifying disease that can be used directly by farmers in the field, enabling timely and effective fighting of crop disease. In addition, the use of CNNs with mobile devices and cloud systems has made it possible to develop easy-to-use applications that farmers with minimal technical knowledge can operate. Such tools can be applied to improve precision agriculture through rapid on-site diagnosis of diseases and treatment recommendations, thereby enhancing overall crop management. This work delves into the possibility of employing CNNs to detect wheat disease in real time, with the focus on the creation of an automated system to recognize and categorize wheat disease from leaf and stem images. Utilizing deep learning approaches, this work aims to narrow down the disparity between conventional agriculture methods and new technologies, providing an efficient and scalable solution for safeguarding wheat crops.

RELATED WORK

Sharma *et al.* (2020), focused on the detection of wheat diseases using CNNs in real-time. It proved that if CNNs are trained with a very large image dataset of Wheat crops the max accuracy that MTV were able to diagnose wheat rust, powdery mildew and blight. But they faced difficulties in deploying the model under real-world situations since environmental factors such as light and ambient noise impacted its functionality. They concluded that more development of strong models for real-time field-based disease detection was required.

The authors (Sharma *et al.*, 2021) utilized transfer learning with pretrained models such as VGG16 and ResNet for detecting wheat diseases in 2021. Their model performed well after fine-tuning on a wheat disease dataset, especially for diseases such as wheat rust and yellow rust. Although they succeeded, they were unable to detect early-stage diseases with faint symptoms. They suggested increasing the dataset to include early-stage symptoms in order to enhance model accuracy for real-time disease detection.

This work (Kumar *et al.*, 2022) focused on mobile applications for real-time wheat disease detection. They developed an application that uses deep learning models (CNN and RNN) to identify wheat plant images taken using smartphones. The app was developed to identify diseases like leaf rust, powdery mildew, and fusarium head blight. But the app had issues with false positives, especially with images of plant stressors that was similar to diseases were fed in. Kumar *et al.* (2022) recommended incorporating more data such as weather data and improving the image preprocessing methods for improved accuracy.

The authors (Kumar *et al*., 2023) also investigated incorporating multilingual data for wheat disease detection in 2023. They trained one model on English and local Indian language datasets to enhance the system's usability for Indian farmers. The researchers were challenged by the unavailability of labelled data in many dialects, an impact which affected the performance of the model across different linguistic areas. They highlighted the significance of domain-specific model training and multilingual datasets for precise detection across languages.

In this paper authors (Joshi *et al.*, 2023) suggested implementing attention mechanisms within deep learning frameworks for improving fine-grained detection of wheat diseases. The use of the attention mechanism enabled the model to zoom into particular plant parts, thus making it distinguish among diseases sharing analogous visual appearance. The model's performance on developed disease conditions such as wheat rust and powdery mildew was strong but poor against initial-stage diseases.

Author, publisher and Year	Technique Used	Objective	Performance Metrics	Dataset	Simulator Outcomes
Sharma *et al.* (2020)	Convolutional neural networks (CNN)	To detect wheat diseases (rust, blight, mildew) using deep learning	Accuracy, precision, recall, F1-score	Wheat plant image dataset (diseased leaves)	High accuracy in controlled conditions; struggles in real time field conditions
Sharma *et al*. (2021)	Transfer learning with pretrained models	To improve wheat disease detection by fine tuning pretrained CNN models	Accuracy, precision, recall, F1-score	Wheat disease dataset (rust, mildew, yellow rust)	Improved performance on large dataset; challenges with early- stage disease detection
Kumar *et al.* (2022)	CNN and RNN-based Mobile Application	To develop a mobile app for real-time wheat disease detection	Accuracy, Response Time	Mobile images captured by farmers in the field	Real-time detection with 90% accuracy; fast response time (under 3 seconds)
Kumar *et al.* (2023)	Multilingual Data Integration for ML	To integrate multilingual data for improved accessibility of disease detection	Accuracy, Multi-lingual Classification Score	English and regional Indian language datasets for wheat diseases	The model showed accuracy in multilingual settings but struggled with regional dialects.
Joshi *et al.* (2023)	Attention Mechanism with CNNs	To improve the precision of wheat disease detection by focusing on key features	Accuracy, Precision, Recall	Wheat leaf images (rust, blight, healthy)	Attention mechanism improved precision by 6%; overall accuracy 92%.

RESEARCH GAP

Although the work on wheat leaf disease diagnosis with CNNs has advanced considerably, some critical gaps need to be filled. These involve increasing dataset diversity, enhancing mobile device real-time processing, robustness against environmental noise, real-world applicability, multi-disease detection capability, model interpretability, and addressing scalability and cost-effectiveness for farmers. Filling these gaps will be instrumental in the general adoption of CNN-based systems into agricultural operations, ultimately leading to more accurate, timely, and accessible disease management for farmers globally. By enhancing the accessibility and performance of the technology, we can ensure more sustainable and resilient wheat production for the future. There is limited diverse dataset, inadequate Real-World Applicability and Deployment, Real-Time Processing and Computational Efficiency.

FINDING SUGGESTIONS

CNN-based Wheat Disease Detection utilized CNNs for real-time detection of wheat diseases. It has been proven that the maximum accuracy was able to diagnose wheat rust, powdery mildew and blight using MTV if CNNs were trained using a very large image dataset of Wheat crops. The variety and quality of the datasets are the building blocks of any machine learning model's success, especially in agriculture where the environment can be extremely variable. The recommendation to increase the variety of datasets to encompass images taken from different geographical locations, under conditions of both favorable and adverse weather, and at different disease stages, is instrumental in making sure that CNN models are generalizable. The hurdle of executing CNN models on mobile devices in real-time is one of the primary challenges in deploying disease detection systems directly into the field. Smartphones, which most farmers, particularly in rural settings, have access to, prove to be an appropriate platform for disease detection programs. The hardware in most cases lacks the processing capacity to execute large CNN models efficiently. Efficient models can be created by applying methods such as pruning, quantization, and knowledge distillation in order to enable real-time disease detection.

CONCLUSIONS

The globe is under threat by agriculture, specifically fro m plant diseases which lowers the production. Wheat is one of the key crops of the world but it is beset by numerous diseases that lower its production and endanger food security. The application of CNNs presents a chance to detect such diseases early, allowing farmers to have the instruments to take preventive measures ad ultimately save the crops.

In the end creating a system to detect wheat leaf disease in real time with CNNs is not so much about technology its about assisting others and taking care of everyone. With ongoing research, collaboration and innovation, these systems can be developed to assist farmers all over the world. That will assist them in safeguarding their crops, experiencing better harvests, and building more resilient and sustainable future in agriculture.

REFERENCES

Joshi, A., Chakraborty, S. and Rani, P. (2023). Attention-Aware Fine-Grained Wheat Disease Detection. *Nigerian Journal of Artificial Intelligence and Machine Learning, 10*(4), 105-118.

Kumar, A., Gupta, R. and Patel D. (2022). Wheat Disease Detection Mobile Application for In-Situ Real Time Detection. 24th International Conference on Mobile Computing and Networking (MOBILECOM).

Kumar, S., Singh, P. and Joshi, S. (2023) Multilingual Data Integration for Wheat Disease Detection. *International Journal of Agricultural AI and Robotics 18*(7), 123–136.

Mishra, R., Singh, V. and Yadav, H. (2024). Generative adversarial networks for detection of mild symptoms of wheat disease. Symposium on AI in Agriculture IPC-G-3cX, *International Conference on —AI in Agriculture, 21*(2), 33-46.

Sharma, A., Gupta P. and Verma R (2020) Wheat Disease Detection using Convolutional Neural Networks. *Proceeding of the International Conference on Agriculture Technology and Machine Learning, 12*(3), 89-104.

Sharma, A., Kumar, S. and Singh, V. (2021). Wheat Disease Detection using Transfer Learning on ResNet50. *Journal of Agricultural Research and AI Applications, 9*(2), 156-170.