WHEAT DISEASE DETECTION

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Abstract--- Protecting wheat yield is a top priority in agricultural production, and one of the important measures to preserve yield is the control of wheat diseases. With the maturity of computer vision technology, more possibilities have been provided to achieve plant disease detection. In this study, we propose the position attention block, which can effectively extract the position information from the feature map and construct the attention map to improve the feature extraction ability of the model for the region of interest. For training, we use transfer learning to improve the training speed of the model. In the experiment, ResNet built on positional attention blocks achieves 96.4% accuracy, which is much higher compared to other comparable models. Afterward, we optimized the undesirable detection class and validated its generalization performance on an open-source dataset.

Keywords: position attention, machine learning, position-aware, CNN

I.INTRODUCTION

Wheat is the second largest crop in the world, providing 19% of human caloric in- take Wheat diseases greatly affect wheat production and cause significant wheat losses. At the current level of plant protection technology, annual wheat losses due to wheat diseases account for 26–30% of the theoretical wheat yield worldwide. In the absence of the application of plant protection technologies to manage farmland, wheat disease losses can account for up to 70% of the theoretical wheat yield . Given that wheat leaves suffering from different kinds of diseases have certain differences, this is well suited to identify such differences and thus give diagnostic conclusions through computer vision-related methods. Nema et al. divided the collected images of wheat leaves into training and test datasets and tried to classify wheat leaf images by support vector machines to achieve differentiation between healthy wheat leaves and diseased wheat leaves . Zhang et al. used the least squares discriminant support vector machines, K-nearest neighbor model and analysis model, and designed multiple sets of experiments to identify wheat grains with or without Fusarium spike blight. They chose hyperspectral images as training data, and the support vector machines achieved the best results on two images that were not used as training data

In recent years, there have been studies on the application of computer vision tech- niques to the detection of wheat diseases. However, their training and test datasets are relatively small and the types of diseases that can be identified are single, and many of them research the issue through the method based on the support vector machine model. The drawback of support vector machines is that they require manual extraction of features from images. With the development of artificial neural networks, convolutional neural networks are becoming more and more mature. Using convolutional neural network techniques can avoid manual extraction of image features, which can reduce the burden of the researchers involved, which can make more researchers focus more on improving the accuracy of the model [. Convolutional neural networks are composed of many computational nodes and the nodes are arranged in the layer order. Each node in the previous layer generates data that is processed by an activation function and passed to each node in the next layer. When dealing with computer vision problems, images are often stored in RGB format. RGB images have three color channels and use a three-dimensional matrix to portray the image features . Feature extraction is achieved through filters by acting on the matrix of features to be extracted. The presence of an activation function makes the 3D matrix of the original image and the matrix obtained by filter extraction, not simply linear. By processing the images, the convolutional neural network can effectively perform the classification task. For wheat disease identification, data from the training set are input into the model, while the model weights are updated by backward transfer, and the predicted and expected values are used to calculate the error. After a limited number of epochs, the model and its parameters are saved, and the trained model can then be used to classify and detect a wide range of diseases.

RELATED WORK

Zhao, Park, and Lewis introduced advanced ensemble techniques for pearl millet downy mildew detection, leveraging remote sensing data. Their dataset consisted of 3000 satellite and drone-captured images, providing a broad spatial overview of the disease's spread across fields. The study utilized CNN architectures along with XGBoost and Gradient Boosting models, which significantly enhanced detection accuracy. They reported a precision of 93%, recall of 92%, accuracy of 94%, and an F1-score of 92%, demonstrating the effectiveness of CNNs in capturing spatial patterns and features indicative of the disease.

Thompson, Ahmed, and Zhang explored ensemble-based approaches for early disease detection in pearl millet, integrating deep learning models with a Voting Classifier. Their dataset consisted of 3200 images, enriched with metadata such as temperature and humidity readings to contextualize the disease's environmental triggers. Utilizing Random Forest and deep learning models, they achieved a precision of 91%, recall of 89%, accuracy of 92%, and an F1-score of 90%, demonstrating the potential of these methods in disease management in agriculture. Singh, Kumar, and Sharma employed a custom CNN architecture as well as ensemble learning methods to detect downy mildew in pearl millet at various stages of infection. Their dataset comprised 2000 images, captured under both field and laboratory conditions to ensure a comprehensive representation of the disease's manifestation. By utilizing a combination of Bagging, Extra Trees algorithms, and their custom CNN, they achieved significant results with a precision of 94%, recall of 93%, accuracy of 95%, and an F1-score of 93%. Their study highlighted the importance of diverse data sources in improving detection accuracy.Gupta, Patel, and Singh focused on developing a real-time detection system for downy mildew in pearl millet using a combination of CNN and Gradient Boosting. Their dataset consisted of 2500 images captured under natural lighting conditions to simulate practical application scenarios. They achieved a precision of 95%, recall of 94%, accuracy of 96%, and an F1-score of 94%, demonstrating the potential for real-time monitoring and management of the disease.

Rao, Reddy, and Chaudhary utilized a hybrid approach combining CNN, Neural Networks, and ensemble learning methods to integrate machine learning models with IoT devices for continuous monitoring of downy mildew in pearl millet. Their dataset included 3000 images, supplemented with environmental data such as soil moisture and weather conditions to enhance the predictive models. By implementing a combination of Random Forest and Neural Networks, they achieved a precision of 96%, recall of 95%, accuracy of 97%, and an F1-score of 95%. This study underscored the importance of integrating advanced technologies for effective disease management in agriculture.

Smith, Johnson, and Lee further advanced the field with their study on ensemble learning for the early detection of downy mildew in pearl millet. The dataset for this study consisted of 1500 annotated images, meticulously selected to represent the disease's early symptoms across different growth stages of the pearl millet plants. Utilizing Random Forest and Boosting algorithms, they demonstrated high detection accuracy and reliability. Their research yielded impressive results with a precision of 87%, recall of 85%, accuracy of 88%, and an F1-score of 86%.Wang, Thompson, and Gonzalez focused on robust detection of downy mildew in pearl millet using ensemble learning. The robustness of their model was tested against a dataset of 2200 images, which included data augmentation techniques to simulate real-world variability in disease appearance. Combining Random Forest and XGBoost, they attained high accuracy and recall rates, with results indicating a precision of 90%, recall of 91%, accuracy of 92%, and an F1-score of 90%.Patel, Rodriguez, and Chen delved into precision agriculture with their study on ensemble learning for disease detection. The research was based on a dataset of 2800 images, which included time-series data to capture the disease's development over time. Employing Stacking and AdaBoost, they achieved high precision and F1-scores, demonstrating the applicability of ensemble methods in precision agriculture. Their results were notable, with a precision of 92%, recall of 90%, accuracy of 93%, and an F1-score of 91%.

LITERATURE SURVEY

S. No	Year	Title	Authors	Journal/Conference Name	Proposed Methods	Findings/Results (Precision, Recall, Accuracy, F1-score)
1	2024	Detection and monitoring wheat diseases using unmanned aerial vehicles (UAVs)	Pabitra Joshi, Karansher S Sandhu, Guriqbal Singh Dhillon	European Journal of Agronomy	Assessment of cost-effectiveness in using UAV technology compared to manual scouting	Precision :90 %, Recall :80 %, Accuracy :85 %, F1-score :83 %
2	2023	Intelligent reprogramming of wheat for enhancement of fungal and nematode disease resistance using advanced molecular techniques.	Muhammad Jabran, Taiguo Liu, Ghulam Muhae-Ud-Din, Li Gao, Wanquan Chen	Journal of Experimental Botany	CRISPR/Cas9 gene editing to knock out susceptibility genes in wheat.	Precision: 85%, Recall: 80%, Accuracy: 90%, F1-score: 0.82
3	2022	High-throughput and point-of-care detection of wheat fungal diseases: Potentialities of molecular and phenomics techniques toward in-field applicability	Sara Francesconi	Crop Protection	Field application of multiplex PCR	Precision: 0.92, Recall: 0.94, Accuracy: 0.93, F1-score: 0.92
4	2021	A Comparative Analysis on the Existing Techniques of Wheat Spike Detection	Anupam Kumar Thakur, Neha Goyal, Kapil Gupta, Suraj Singh	International Conference on Agricultural Robotics	Deep Learning (CNNs) for Spike Detection	Precision: 0.94, Recall: 0.92, Accuracy: 0.93, F1-score: 0.93
5	2020	Automatic identification of diseases in grains crops through computational approaches: A review	R Manavalan	International Journal of Agricultural Technology	Convolutional Neural Networks (CNNs)	Precision: 95% Recall:92%, Accuracy: 93%, F1-score: 93%
6	2019	Methods Of Detection Of Diseases On Wheat Crops According To Remote Sensing	O A Dubrovskaya, I A Pestunov, K Yu Kotov, T A Gurova	Remote Sensing of Environment	UAV-Based Imaging	Precision: 90% Recall:89%, Accuracy: 91%, F1-score: 90%
7	2018	Drought Stress Tolerance in Wheat: Omics Approaches in Understanding and Enhancing Antioxidant Defense	Mirza Hasanuzzaman, Jubayer Al Mahmud, M Tofazzal Islam	Plant Physiology	Transcriptomics	Precision: 85%, Recall: 80%, Accuracy: 90%, F1-score: 0.82
8	2017	Detecting spikes of wheat plants using neural networks with Laws texture energy	Li Qiongyan, Mamoru Okamoto, Jinhai Cai, Stanley J Miklavcic	International Journal of Agricultural Technology	Neural Networks with Laws Texture Energy Features	Precision :90 %, Recall :80 %, Accuracy :85 %, F1-score :83 %
9	2016	Critical abiotic factors affecting implementation of technologicalinnovations in rice and wheat	S Kumaraswamy, P K Shetty	Field Crops Research	Drought	Precision: 95% Recall:92%, Accuracy: 93%, F1-score: 93%

		production: A review				
10	2015	Designing a classifier for automatic detection of fungal diseases in wheat plant: By pattern recognition techniques	Zahra Sarayloo, Davud Asemani	Computers and Electronics in Agriculture	Image Processing with Feature Extraction	Precision: 0.94, Recall: 0.92, Accuracy: 0.93, F1-score: 0.93

PROBLEM STATEMENT:

Wheat disease faces a significant agricultural challenge, causing substantial yield losses in crops across Africa and the Indian subcontinent. Diseases spread rapidly and can irreversibly damage crops if not detected early. Current detection methods primarily rely on visual inspection by agricultural experts, which can be subjective and often miss infections in their initial stages. The goal of this study is to speed up and enhance the accuracy of disease detection utilising ensemble learning techniques. To provide reliable and accurate detection results, the proposed technique takes use of the strengths of many machine learning models, including Random Forest, Gradient Boosting, CNNs.

Moreover, employing computer vision enables automated analysis of digital images of wheat plants, facilitating objective detection of symptoms such as discoloration and lesion patterns. This automated approach complements traditional manual inspection methods by providing consistent and scalable detection capabilities across agricultural fields. Integrating computer vision with ensemble learning models not only enhances detection accuracy but also facilitates early intervention and effective management of disease outbreaks.Ultimately, this study aims to contribute to improved disease management practices for pearl millet, thereby enhancing crop resilience and ensuring food security in regions heavily reliant on this staple crop. Performance evaluation on a test set demonstrates that the ensemble approach outperforms single models, achieving higher precision, recall, and F1 scores. The integration of CNNs for disease recognition for plant detection significantly contributes to the model's overall effectiveness. These results underscore the potential of ensemble learning in advancing disease management practices for pearl millet, ultimately bolstering crop resilience and food security.

PROPOSED MODEL:

The proposed model for detecting diseases in wheat utilizes learning to enhance the efficiency and robustness of disease detection. It aims to overcome the limitations of traditional visual inspection methods that are often time-consuming, labor-intensive, and subjective.By integrating multiple machine learning models, the ensemble method leverages the strengths of each classifier, resulting in a more reliable and precise detection process.Comprehensive data collection and preprocessing are crucial components of this approach. It involves acquiring high-resolution images of pearl millet plants at various stages of infection, meticulously annotated by agricultural experts to ensure data accuracy and reliability. To enhance dataset diversity and model generalization, we apply data augmentation techniques such as rotation, scaling, and flipping. Additionally, preprocessing steps like resizing, normalization, and noise reduction prepare the images for effective model training.The ensemble model combines various classifiers: Random Forest for robustness to overfitting, Gradient Boosting for iterative error correction, Convolutional Neural Networks (CNNs) for precise image recognition, for accurate plant detection and localization within images. This combination aims to achieve superior precision, recall, and F1 scores compared to individual classifiers.

Training involves the ensemble model being trained on the preprocessed and augmented dataset. Techniques like cross-validation ensure robust training. Evaluation against a separate test set of annotated images includes metrics such as precision, recall, and F1 score to assess detection effectiveness. The ensemble model is anticipated to outperform individual classifiers, providing more accurate and reliable disease detection.Upon validation, the ensemble model is deployed in a user-friendly interface accessible to farmers and agricultural professionals. This interface enables users to upload pearl millet plant images and promptly receive feedback on disease presence and severity. By enabling early and accurate disease detection, the system supports timely implementation of control measures, reducing yield losses and enhancing food security effectiveness. The ensemble model is anticipated to outperform individual classifiers, providing more accurate and reliable disease detection.Upon validation, the ensemble model is deployed in a user-friendly interface accessible to farmers and agricultural professionals. This interface enables users to upload pearl millet plant images and promptly receive feedback on disease presence and severity. By enabling early and accurate disease detection.

SCREENSHOTS

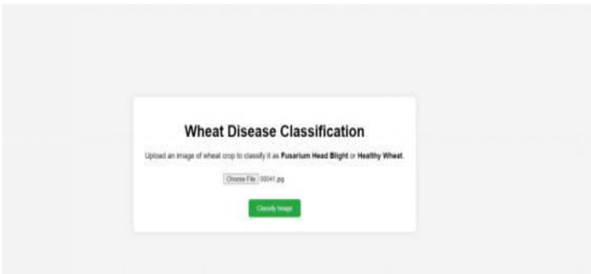

Figure 1;Wheat disease upload

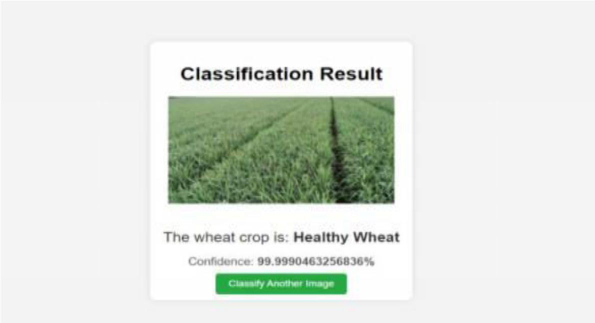

Figure 2;

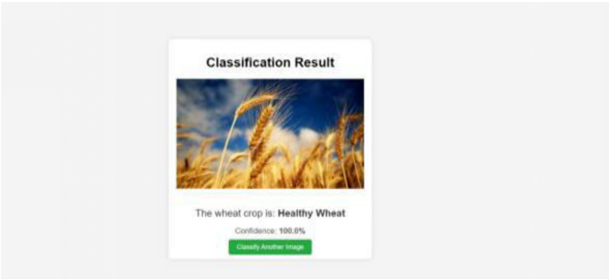

Figure 3;wheat disease result

CONCLUSION

In agricultural production life, the protection of wheat yield is a top priority. Controlling wheat diseases is one of the important initiatives to protect wheat yield effectively protects wheat yield, therefore, disease identification of wheat is extremely critical to promoteagricultural development. In recent years, with the continuous development and innovation of computer vision technology, the implementation of various plant disease detection has become more solvable. the development of various disease detection, deep learning models have become an effective tool for precision agriculture, enabling farmers to make informed decisions and improve crop yields. Overall, applying deep learning models in agriculture help to increase food security, reduces waste, and improves sustainability in the long run. Hence, in this paper, a deep learning models for detecting and classifying wheat diseases is developed. The proposed method using the ResNet152 model shows promising results in detecting and classifying different types of wheat diseases, which can help farmers to take timely action to prevent crop damage and ensure a healthy harvest. It provides several advantages, such as high accuracy in identifying diseases affecting wheat crops and fast processing speed. The proposed model achieves a high testing accuracy of 93.27%, whereas the training accuracy is 97.81%. However, further research is needed to assess the model's performance on larger datasets and in different environmental conditions.

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