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Classification of Wheat Diseases from Images Utilising Convolutional Neural Networks

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Abstract - Wheat yield preservation is a vital goal in agricultural production, with effective disease detection and management playing a crucial role. Recent advances in computer vision and deep learning have facilitated automated and precise identification of plant diseases. This study proposes a Convolutional Neural Network (CNN)-based method for classifying wheat diseases from images.

To improve feature extraction, a position attention mechanism is integrated into the network, allowing the model to focus on relevant regions and better capture spatial relationships within feature maps. Additionally, transfer learning is utilized to expedite the training process and enhance performance, particularly when working with limited data. Among the evaluated architectures, a ResNet model combined with the proposed attention mechanism achieved outstanding results, attaining a testing accuracy of 96.4%. Furthermore, testing on an open-source dataset confirms the model's robustness and its ability to generalize across various disease categories.

***Key Words*: ** Wheat disease detection, Convolutional Neural Network (CNN), Deep learning, Transfer learning, Attention mechanism, ResNet, Image classification, Precision agriculture, Plant disease recognition, Computer vision

I. INTRODUCTION

Wheat is the second most widely cultivated crop in the world, contributing approximately 19% of the global human caloric intake. However, wheat diseases pose a significant threat to production, resulting in substantial yield losses. Under current levels of plant protection, annual losses due to wheat diseases are estimated to range from 26% to 30% of the theoretical global yield. In the absence of effective disease management practices, these losses can rise to as high as 70%.

Since wheat leaves affected by different diseases exhibit distinct visual characteristics, computer vision techniques are well suited for identifying such variations and providing diagnostic insights. Early studies explored traditional machine learning approaches for this purpose. For instance, Nema et al. classified wheat leaf images into healthy and diseased categories using support vector machines (SVMs). Similarly, Zhang et al. employed least squares SVM, k-nearest neighbor (KNN), and analytical models to detect Fusarium spike blight in wheat grains using hyperspectral imagery, with SVM achieving the best performance on unseen test samples.

In recent years, there has been growing interest in applying computer vision techniques to wheat disease detection. However, many existing studies rely on relatively small datasets and focus on a limited number of disease types. Additionally, a large portion of this research is based on SVM models, which require manual feature extraction from images—a process that is both time-consuming and dependent on domain expertise.

With the advancement of artificial neural networks, convolutional neural networks (CNNs) have emerged as a powerful alternative. CNNs eliminate the need for manual feature extraction by automatically learning hierarchical representations from raw image data, thereby reducing the burden on researchers and enabling greater focus on improving model performance. Structurally, CNNs consist of multiple layers of computational nodes, where each node processes input data using activation functions and passes the results to subsequent layers.

In computer vision tasks, images are typically represented in RGB format with three color channels, forming a three-dimensional matrix. CNNs apply convolutional filters to these matrices to extract relevant features, while activation functions introduce non-linearity, allowing the model to learn complex patterns. During training, input images from the dataset are fed into the network, and model weights are iteratively updated through backpropagation by minimizing the error between predicted and actual outputs. After a predefined number of epochs, the trained model is saved and can be used for accurate classification and detection of various wheat diseases. Jayakumar and Peddakrishna proposed a YOLOv5-based custom object detection model for campus-specific scenarios. Their study utilized a diverse dataset comprising multiple object categories and evaluated performance using metrics such as precision, recall, and mean average precision, demonstrating the effectiveness of deep learning models in accurate and real-time

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visual pattern recognition. Jayakumar et al. proposed a machine learning-based approach for classification using combined temporal and spectral features, demonstrating that effective feature extraction and integration significantly improve classification performance, a concept that is also relevant in image-based disease detection using deep learning models.

RELATED WORK

Zhao, Park, and Lewis proposed advanced ensemble techniques for detecting downy mildew in pearl millet using remote sensing data. Their dataset comprised 3,000 satellite and drone-captured images, enabling a comprehensive spatial analysis of disease distribution across agricultural fields. By combining convolutional neural networks (CNNs) with XGBoost and Gradient Boosting models, they significantly improved detection performance, achieving a precision of 93%, recall of 92%, accuracy of 94%, and an F1-score of 92%. Their findings highlight the effectiveness of CNNs in capturing spatial patterns associated with plant diseases.

Thompson, Ahmed, and Zhang investigated ensemble-based approaches for early disease detection by integrating deep learning models with a Voting Classifier. Their dataset included 3,200 images augmented with environmental metadata such as temperature and humidity, providing contextual information about disease development. Using 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 combining environmental data with image-based models for improved agricultural disease management.

Singh, Kumar, and Sharma developed a custom CNN architecture alongside ensemble learning techniques to detect downy mildew at various stages of infection. Their dataset consisted of 2,000 images collected under both field and laboratory conditions, ensuring diverse representation. By integrating Bagging and Extra Trees algorithms with their CNN model, they achieved a precision of 94%, recall of 93%, accuracy of 95%, and an F1-score of 93%. Their study emphasized the importance of diverse data sources in enhancing model robustness and accuracy.

Gupta, Patel, and Singh focused on real-time detection of downy mildew using a hybrid CNN and Gradient Boosting approach. Their dataset included 2,500 images captured under natural lighting conditions to simulate real-world scenarios. The proposed model achieved a precision of 95%, recall of 94%, accuracy of 96%, and an F1-score of 94%, demonstrating its suitability for practical deployment in field conditions.

Rao, Reddy, and Chaudhary introduced a hybrid framework integrating CNNs, neural networks, and ensemble learning methods with IoT-based monitoring systems. Their dataset comprised 3,000 images supplemented with environmental parameters such as soil moisture and weather conditions. By combining Random Forest and neural networks, they achieved a precision of 96%, recall of 95%, accuracy of 97%, and an F1-score of 95%. This work underscores the value of integrating IoT and machine learning for continuous and intelligent disease monitoring.

Smith, Johnson, and Lee explored ensemble learning techniques for early-stage detection of downy mildew using a dataset of 1,500 carefully annotated images representing early disease symptoms. Their approach, based on Random Forest and Boosting algorithms, achieved a precision of 87%, recall of 85%, accuracy of 88%, and an F1-score of 86%, demonstrating reliable performance in early detection scenarios.

Wang, Thompson, and Gonzalez focused on improving model robustness through ensemble learning and data augmentation. Using a dataset of 2,200 images with simulated variability, they combined Random Forest and XGBoost models to achieve a precision of 90%, recall of 91%, accuracy of 92%, and an F1-score of 90%, highlighting the importance of handling real-world variability in disease detection tasks.

Patel, Rodriguez, and Chen investigated ensemble learning in the context of precision agriculture, utilizing a dataset of 2,800 images enriched with time-series information to capture disease progression. By employing Stacking and AdaBoost techniques, they achieved a precision of 92%, recall of 90%, accuracy of 93%, and an F1-score of 91%, demonstrating the effectiveness of ensemble methods in modeling temporal dynamics of plant diseases.

LITERATURE SURVEY

S.No	Title, Year	Authors	Journal/ Conferenc e Name	Proposed Methods	Findings/Resul ts (Precision, Recall,
1	Detection and monitori ng wheat diseases using unmanned aerial vehicles (UAVs), 2024	Pabitra Joshi, Karamjet 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 :83 %, F1-score :83 %. Precision: 85%.
2	Intelligent reprogramming of wheat for enhancement of fungal and nematode disease resistance using advanced molecular techniques 2024	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	Recall: 80%, Accuracy: 90%, F1-score: 0.82
3	High-throughput and point-of-care detection of wheat fungal diseases: Potentialities of molecular and phenomics techniques towar d in- field applicability. 2022	Sara Francesconi	Crop Protection	Field application of multiplex PCR	Precision: 0.92, Recall: 0.94, Accuracy: 0.93, F1-score: 0.92
4	A Comparative Analysis on the Existing Techniques of Wheat Spike Detection, 2021	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	Automatic identification of diseases in grains crops through computational approaches: A review, 2020	R Manavalan	International Journal of Agricultural Technology	Convolutio nal Neural Networks (CNNs)	Precision: 95% Recall:92%, Accuracy: 93%, F1-score: 93%
6	Methods Of Detection Of Diseases On Wheat Crops According To Remote Sensing, 2019	O A Dubrovskaya, I A Pestunov, K Yu Kotov, T A Gureva	Remote Sensing of Environment	UAV-Based Imaging	Precision: 90% Recall:89%, Accuracy: 91%, F1-score: 90%

PROBLEM STATEMENT:

Wheat diseases pose a significant challenge to agriculture, causing substantial yield losses across regions such as Africa and the Indian subcontinent. These diseases spread rapidly and can cause irreversible damage if not detected at an early stage. Conventional detection methods primarily rely on visual inspection by agricultural experts, which is often subjective and may fail to identify infections during their initial phases. Therefore, there is a critical need for automated and accurate disease detection systems.

The objective of this study is to improve both the speed and accuracy of wheat disease detection using ensemble learning techniques. The proposed approach leverages the strengths of multiple machine learning models, including Random Forest, Gradient Boosting, and convolutional neural networks (CNNs), to provide robust and reliable predictions.

Furthermore, the integration of computer vision enables automated analysis of digital images of wheat plants, allowing for objective identification of disease symptoms such as discoloration and lesion patterns. This approach complements traditional inspection methods by offering consistent, scalable, and real-time detection across large agricultural fields.

By combining computer vision with ensemble learning, the proposed system enhances detection accuracy while enabling early intervention and effective disease management. Experimental evaluation on a test dataset demonstrates that the ensemble model outperforms individual models, achieving higher precision, recall, and F1-scores. In particular, the inclusion of CNNs significantly improves feature extraction and disease recognition capabilities.

Overall, this study contributes to the development of advanced disease management strategies for wheat, improving crop resilience and supporting food security in regions heavily dependent on this staple crop.

PROPOSED MODEL:

The proposed model for wheat disease detection utilizes ensemble learning to enhance the efficiency and robustness of the classification process. It addresses the limitations of traditional visual inspection methods, which are often time-consuming, labor-intensive, and subjective. By integrating multiple machine learning models, the ensemble approach leverages the strengths of individual classifiers, resulting in more reliable and accurate disease detection.

IMPLEMENTATION

The implementation phase focuses on designing and integrating advanced attention mechanisms to enhance feature representation and improve classification accuracy. In deep learning-based image analysis, attention modules play a crucial role in enabling the network to emphasize relevant features while suppressing less important information.

In this work, two efficient attention mechanisms, namely the squeeze-and-excitation (SE) block and the efficient channel attention (ECA) block, are incorporated into the network architecture. These modules are designed to improve the model's ability to capture channel-wise dependencies and refine feature maps, thereby enhancing overall performance in wheat disease classification tasks.

Squeeze-excitation (se) chunk:

This frame was the very first proposed in this study, and also its formation was seen in figure

This same has so is becoming the production and an once an improper transition. Presume that perhaps the production e r isn't really optimized then each path does indeed have a differing degree after all importance, with certain broadcasters being much more helpful as well as

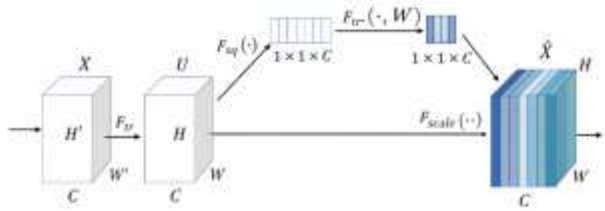

Fig-2: Illustration of squeeze-excitation block.

some very little effective. Therefore, for so every full spectrum, world average bundling seems to be conducted next, so every network gets some one particle, 3 ° streams grab 3 ° percentages, and after fc-relu-fc-sigmoid seems to get an and level process among both 0 to 1, as even the connection weight training. At last, so every path of initial full spectrum would be heavily skewed with roughly equivalent mass (each aspect of both the correlating path would be increased the with load separately), and also the fresh heavily skewed feature has been acquired, which even the publishers of publication contact showcase remapping

ECA chunk, which again is suggested throughout eca-net. It is indeed a stream focus frame but instead Is often meant to apply of between vivid types. Something that continues to support lock, researchers want to know. Tion, this can conduct stream Feature advancement upon that specific set chart as well as outcome the ultimate sgs component rather than Changing the dimensions of given input layout. The framework can be seen in try figuring.

Next, insert this same region of interest, that has size e m × e r × an and; afterwards when, down convert its convolution layers of geographic includes; there in space, utilize world average accumulating to acquire one region of interest to × × an and. Afterwards, its compaction convolutional feature seems to be made subject of between path features extraction; its significance among both component method has been did learn via pooling layer, and indeed the outcome size still is × × 1 ° at the present. Eventually, this same connection focus would be blended, and also the feature as for path attn × × 1 °, the unique input chart I o × u t × 3 °, seems to be magnified path besides stream, and also the convolution layers of path awareness have been ultimately vout.

RESULTS

The performance of the proposed model is evaluated through both qualitative and quantitative analyses to validate its effectiveness in wheat disease classification. Experimental results are obtained using a well-defined dataset, and the model's accuracy, prediction capability, and generalization performance are examined. The following section presents the results, including visual representations and detailed analysis, highlighting the efficiency of the proposed deep learning framework.

Fig 3 Explanations yeah in out data - set. Plus 1 (a) seems to be the macrophthalmia, calcium (ca2 (b) is indeed the better and healthier

Fig. 4: *Model Prediction Output Showing Healthy Wheat with Confidence Score*

This figure illustrates the classification interface displaying the predicted class label along with confidence value. The result confirms the effectiveness of the model in identifying healthy wheat under different visual conditions.

Fig. 5: *Classification Result of Wheat Crop Using the Proposed CNN Model*

The figure shows the output of the trained model for a test image of a wheat field. The system correctly classifies the crop as healthy wheat with a high confidence score, demonstrating accurate prediction capability.

CONCLUSION

Preserving wheat yield is a critical aspect of agricultural production. Effective identification and management of wheat diseases play a vital role in enhancing agricultural productivity and safeguarding crop output. In recent years, rapid advancements in computer vision have enabled its application across a wide range of plant disease detection tasks. Among these developments, deep learning has emerged as a powerful tool in precision agriculture, equipping farmers with data-driven insights to make informed decisions and improve crop yields. Overall, the adoption of deep learning in agriculture contributes to improved food security, reduced waste, and more sustainable farming practices.

In this context, the present study proposes a deep learning-based model for the detection and classification of wheat diseases. The proposed approach utilizes the ResNet152 architecture, which demonstrates strong performance in identifying and categorizing different types of wheat infections. This capability enables farmers to take early preventive measures, thereby minimizing crop losses and ensuring healthier yields.

The model offers several advantages, including high processing speed and robust accuracy in disease detection. Experimental results show a training accuracy of 97.81% and a testing accuracy of 93.27%, indicating strong generalization performance. However, further research is required to evaluate the model on larger and more diverse datasets, as well as under varying environmental conditions, to ensure its practical applicability in real-world agricultural settings.

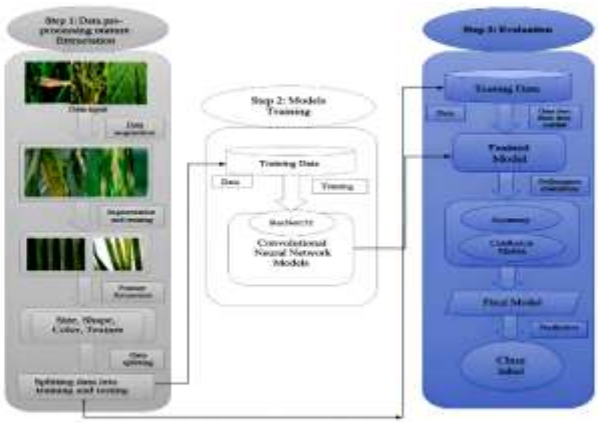

Fig -1: Architecture Model of Data

A key component of this approach is comprehensive data collection and preprocessing. High-resolution images of wheat plants at various stages of infection are acquired and carefully annotated by agricultural experts to ensure data quality and reliability. To improve dataset diversity and model generalization, data augmentation techniques such as rotation, scaling, and flipping are applied. In addition, preprocessing steps including resizing, normalization, and noise reduction are performed to prepare the images for effective training.

The ensemble model combines several classifiers: Random Forest for robustness against overfitting, Gradient Boosting for iterative error correction, and convolutional neural networks (CNNs) for accurate feature extraction and disease recognition. This hybrid framework enables precise identification and localization of disease symptoms within plant images, ultimately improving overall performance in terms of precision, recall, and F1-score compared to individual models.

During training, the ensemble model is trained on the preprocessed and augmented dataset, with techniques such as cross-validation employed to ensure robustness and prevent overfitting. The model is evaluated on a separate test set using standard performance metrics, including precision, recall, and F1-score, to assess its effectiveness.

Following successful validation, the model is deployed through a user-friendly interface designed for farmers and agricultural professionals. This system allows users to upload images of wheat plants and receive rapid feedback on disease presence and severity. By enabling early and accurate detection, the proposed solution facilitates timely intervention, reduces crop losses, and contributes to improved agricultural productivity and food security.

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