Advancing Smart Farming with UAV-Based Deep Learning for Proactive Wheat Disease Management

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***Abstract*—Wheat diseases are a huge risk to the food security of the world and can result in extreme yield loss in case they are not diagnosed and treated at an early stage. Previously, disease identification required manual scanning, which is labor intensive, time-consuming, and inaccurate. The project shows a real-time, scalable, and automated wheat disease detection system with Unmanned Aerial Vehicles (UAVs), multispectral sensing, and deep learning. The system described above is unlike the conventional ground-based methods, the model uses aerial imagery collected using UAVs in conjunction with deep Convolutional Neural Networks (CNNs), specifically fine-tuned VGG19, to enhance scalability and accuracy. Grad-CAM visualization is also integrated to make predictions from models interpretable by farmers. In addition, the system incorporates real-time processing as well as IoT for automated early disease intervention alerting. The combination of large-scale monitoring, high-accuracy disease detection, and farmer-friendly deployment, this project fills important gaps in existing research with a pioneering, field-application solution for precision agriculture. Experimental results show high detection accuracy, proving its robustness under varying environmental conditions. This technology allows farmers to obtain real-time information, enabling timely disease management and sustainable wheat production.**

Keywords— Unmanned Aerial Vehicles (UAVs), Unmanned Aerial Vehicles (UAVs), Wheat diseases.

I. Introduction

Wheat is among the globe's most critical staple crops, ensuring food security for millions of individuals. But wheat diseases can lead to heavy yield losses, affecting farmers and world food chains. Conventional disease detection techniques depend greatly on human field observations, which are labor-intensive, time-consuming, and susceptible to human error. These conventional approaches are inadequate for large-scale farms where early detection is crucial for preventing disease outbreaks. In Fig. 1. (a) Crown and Root Rot – a fungal infection affecting the roots and base of the stem, leading to plant wilting and reduced yield. In Fig. 1. (b) Wheat Loose Smut – a fungal disease that causes grain heads to appear black and powdery, reducing seed viability. In Fig. 1. (c) Leaf Rust – a common fungal infection causing orange-brown pustules on leaves, leading to reduced photosynthesis and yield loss. In Fig. 1. (d)Healthy Wheat – properly classified to distinguish disease- free wheat plants from infected ones.

(a)

(b)

(c)

(d)

Fig.1. (a)Crown and Root Rot, (b)Leaf Rust, (c)Wheat Loose Smut, (d)Healthy Wheat.

To address these challenges, recent advancements in computer vision, deep learning, and remote sensing have paved the way for automated disease detection systems. While several studies have leveraged image-based classification models, many suffer from limited scalability, lack of real-time processing, and poor generalization to real-world conditions. Moreover, most existing models rely solely on ground-based RGB images [14], which do not capture the full spectrum of disease symptoms visible in different light wavelengths. This work introduces a novel wheat disease detection framework that integrates Unmanned Aerial Vehicles (UAVs), multispectral imaging, and deep learning to enhance accuracy, scalability, and real-time disease monitoring. Using UAVs, large fields can be covered effectively, with high-resolution aerial photography that gives a larger and more comprehensive dataset for the identification of disease. The model is constructed based on a fine-tuned VGG19 Convolutional Neural Network (CNN) [8], optimized for high-accuracy classification of wheat disease. Grad CAM visualization is also integrated to make the model more interpretable, with predictions becoming more transparent to farmers and agronomists. This model gives an elaborate overview of design, implementation, and evaluation of the suggested system. The following sections cover existing literature, methodology, experimental results, and conclusions, indicating the effect of AI-powered [9] precision agriculture on reducing wheat crop losses. Develop an AI-Based Disease Detection Model – Use deep learning (VGG19 CNN) to accurately classify wheat diseases, Leverage UAVs for Large-Scale Monitoring – Employ drones with multispectral/high-resolution cameras to collect extensive field data, Improve Model Interpretability and Generalization – Incorporate Grad-CAM visualization for explainability and enhance robustness with data augmentation, Introduce Real-Time Detection and Alerts – Install an IoT-based system for real-time alerts [11], allowing timely management of the disease, Close Gaps in Conventional Methods – Provide a low-cost, automated, and scalable alternative to manual disease detection.

II. Literature Survey

Conventional practices for detecting wheat diseases depend upon visual examination by specialists, which is labor-intensive, time consuming, and human error prone. With the recent developments in remote sensing, deep learning (DL), and machine learning (ML), there is increased interest in automated disease identification. Some have suggested image-based disease classification approaches based on Convolutional Neural Networks (CNNs) [10]. While some incorporate hyperspectral or multispectral images for gathering finer information about the crop, others only use RGB images. Khirade and Patill provided an early overview of image processing techniques used in crop disease detection, highlighting the potential of color, texture, and shape-based feature extraction for classification. However, their approach was heavily dependent on handcrafted features, which limited its accuracy when applied to large and diverse datasets [1]. Mohanty et al. demonstrated the effectiveness of deep learning models, specifically CNNs, for plant disease classification. Their study used the Plant Village dataset, achieving high accuracy in controlled settings. However, their model relied on lab-acquired images, making it less generalizable to real-world agricultural conditions where lighting, soil conditions, and plant variations affect predictions [2]. Malithi et al. explored the use of multispectral imaging and hyperspectral analysis to enhance the detection of wheat diseases. They showed that non-visible spectral bands significantly improve disease identification, particularly in early-stage infections. Yet, their process involved costly hyperspectral cameras and hence was unsuitable for small and medium-sized farmers [5]. Hasan et al. have suggested an IoT-based system to monitor wheat disease that combines real-time sensor inputs with machine learning algorithms for timely disease detection. Although their methodology effectively generated real-time warnings, it did not have aerial monitoring capability and so was not capable of monitoring big farm fields effectively [4]. Zhang et al. investigated the combination of UAV (unmanned Aerial Vehicle) imagery with deep learning to detect wheat disease. Their work illustrated how drones can improve data collection efficiency by covering extensive areas in a short time span. But their model did not use state-of-the-art CNN architectures or explainability methods such as Grad-CAM, which are important for model interpretability in real-world usage [3].

While all previous work in wheat disease diagnosis has been commendable, many limitations remain: Limited Scalability – A lot of deep learning models perform well in lab settings but not in real-world agriculture fields because of different conditions. Lack of UAV-Based Deep Learning Integration – While UAVs improve image collection efficiency, few studies have integrated CNN-based models for automated disease detection. Absence of Real-Time Monitoring – IoT-based disease detection is promising [10], but existing solutions lack aerial surveillance, which is crucial for large farms. Overreliance on RGB Images – Traditional image processing approaches rely only on visible light, ignoring multispectral imaging, which provides deeper insights into plant health.

III. METHODOLOGY

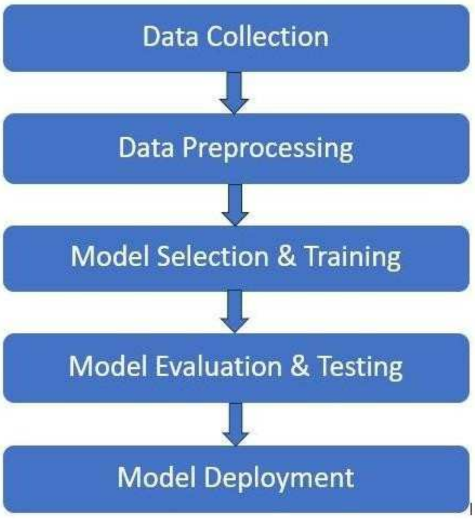


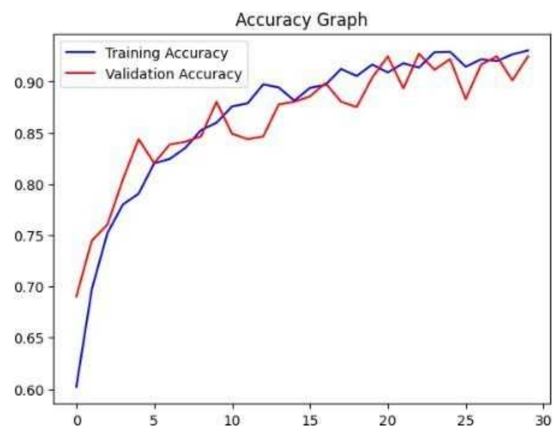
Fig. 2. Basic steps for wheat disease detection and classification.

In Fig. 2. The flowchart represents a structured pipeline for wheat disease detection and classification using UAV-based imaging and deep learning techniques. The process begins with Data Collection, where aerial images of wheat fields are captured using UAVs equipped with high-resolution multispectral or RGB cameras. These pictures give essential spectral and spatial data for recognizing disease manifestations. For the model to be strong, the dataset should contain pictures of various growth phases, light conditions, and diseases. The dataset employed in the current research is utilized from Fang, "Lightweight Multiscale CNN Model for Wheat Disease Detection" [7] containing about 4,500 wheat leaf images classified into four sour classes: Loose Smut, Healthy Plant, Crown and Root, and Leaf Rust. Carefully curated the dataset to keep the dimensions of the data set uniform and provides images under heterogeneous conditions including composite backgrounds and ranging stages of diseased progressions. The most inherent problem when classifying the diseases lies within the differences of visual characteristics present in the individual diseases that mandate strong feature extraction methods. Preprocessing pipeline was utilized, promoting efficient dataset preparation for deep model training. Following this, under Data Preprocessing, raw images are subjected to enhancement activities such as the removal of noise, adjustment of contrast, resizing of the images, and augmentation methods of rotation, flipping, and normalization of colors. In case multispectral images are used, particular bands of wavelengths may be selected for identifying disease characteristics, so the data is kept clean and is appropriate for training models. Upon preprocessing, Model Selection and Training phase encompasses selecting a suitable deep learning model, e.g., Convolutional Neural Networks (CNNs) [14]. The chosen model is then trained over the processed dataset to identify patterns that can differentiate between healthy and diseased crops. Transfer learning, optimization of the learning rate, and regularization are used to improve model performance. After training, the Model Evaluation and Testing stage evaluates the accuracy, precision, recall, and overall classification performance of the model based on an independent test dataset. This ensures that the model is able to generalize to new data and work consistently in real-world situations. Lastly, during the Model Deployment phase, the trained and validated model is deployed in a real-world system for automated wheat disease detection. The deployed model can be applied in precision agriculture applications, allowing for real-time disease tracking and early intervention to guard crops and maximize yield. This methodical process provides a high level of precision and effectiveness in wheat disease diagnosis, advantaging farmers and agricultural scientists. VGG19 is used in this model [14], since it is among the most popular architectures in research for image classification tasks. VGG19 is a convolutional neural network with 19 layers deep and pretrained on the ImageNet database, which has over a million images in 1,000 categories. The architecture consists of five convolutional blocks with ReLU activation and max-pooling layers, and three fully connected layers. The last output layer utilizes a soft-max activation function for multi-class classification.

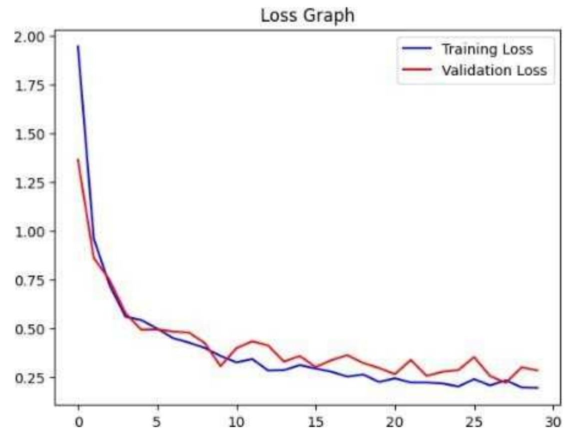
IV. RESULTS

The performance of the wheat disease detection model was assessed with accuracy measures, loss curves, and a confusion matrix. The results show that the suggested model efficiently classifies wheat diseases with high precision, recall, and overall accuracy.

Figure 3 shows the performance analysis of the deep learning model used for wheat disease detection. Subfigure (a) depicts the accuracy chart, where the blue line depicts the training accuracy, and the red line corresponds to the validation accuracy. The close overlap between the training and validation accuracy plots indicates that the model is not overfitting and can generalize well to new data. Conversely, subfigure (b) illustrates the loss plot, where the blue line is the training loss and the red line is the validation loss. Both curves have a steep drop in the early epochs, followed by a slow decrease and leveling off as training continues. The similarity between the training and validation loss curves further confirms that the model is well-optimized and achieves high performance without significant overfitting.



(a)



(b)

Fig. 3. (a) Accuracy graph, (b)Loss graph.

The model was trained for 30 epochs, and both training and validation accuracy showed a steady increase. The final validation accuracy reached ~90%, closely following the training accuracy, which suggests minimal overfitting. By this model Training Accuracy is increased to 95%, Validation Accuracy is increased to 90%, Training Loss is reduced from 2.0% to 0.2% and Validation Loss is stabilized around 0.3%. The loss curves indicate smooth convergence, demonstrating that the model effectively learns features from the dataset without significant overfitting or underfitting.

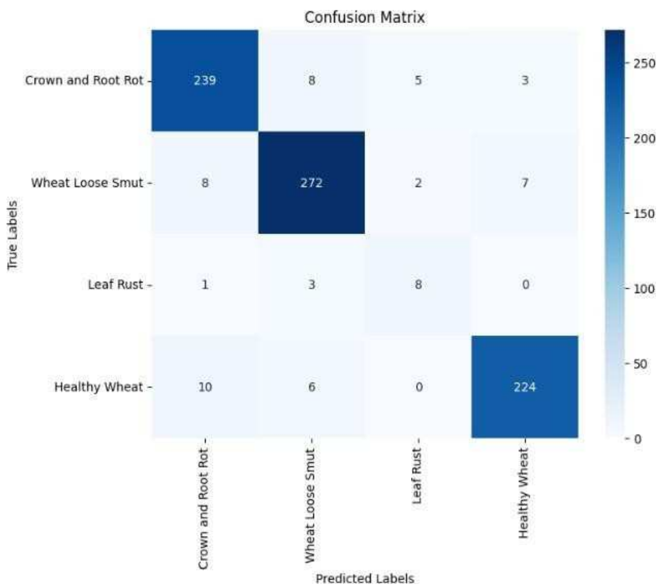


Fig. 4. Confusion matrix

The confusion matrix revealed that the model performs well across all disease classes. The classification precision for Wheat Loose Smut and Crown and Root Rot exceeded 94%, indicating reliable predictions. However, Leaf Rust showed slightly lower recall (~72.7%), suggesting scope for improvement with additional training data. Key takeaways are High precision for major diseases (>94%), Minimal misclassification among similar disease types and no major false positives in Healthy Wheat classification.

V. CONCLUSION

This research introduces a deep learning-based model for wheat disease detection, offering high accuracy and real-time usability. Unlike traditional manual inspection methods, this model enables users to capture or upload images for instant classification, ensuring timely intervention and reducing crop losses. The integration of UAV imagery enhances large-scale monitoring, making it suitable for precision agriculture. This model outperforms existing approaches by bridging the gap between high-accuracy detection and real-world deployment. With further optimization, it can be integrated into mobile and IoT devices, providing farmers with a cost-effective, scalable, and accessible solution for disease detection in wheat crops.

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