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OPTIMIZING EFFICIENTNETV2 MODEL WITH RANDAUGMENT DATA AUGMENTATION FOR DETECTING WHEAT DISEASES IN SMART FARMING

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Abstract. Wheat diseases threaten global food security, necessitating improved detection methods. In this paper, we integrate EfficientNetv2 model and RandAugment data augmentation to accurately and efficiently identify wheat diseases. EfficientNetv2, known for its optimal mix of accuracy and computing efficiency, is reinforced by RandAugment, a versatile data augmentation approach that randomly modifies training data. This augmentation method greatly enhances the model's generalisation and performance on new data. Our extensive experimentation reveals that this integrated technique improves model accuracy and robustness relative to baseline models. Proposed model gained the 96.73% accuracy on prescribed dataset. The results show that EfficientNetv2 and RandAugment can detect wheat illnesses on a large scale. This could change precision agriculture by enabling early and accurate disease management.

Key words: Deep Learning, Wheat Diseases, Detection, EfficientNetV2, Image Recognition, RandAugment

1. Introduction. Wheat is vital to global food security, yet various diseases endanger it. These diseases lower crop yields and quality, causing farmers and the food sector enormous problems. Understanding and treating these diseases is essential for wheat crop sustainability. Puccinia fungus causes wheat rust. The three most common rust species are Puccinia graminis, triticina, and striiformis. When conditions are right, many diseases spread quickly. Ug99 and other novel strains have panicked the world, and stem rust has destroyed crops. Powdery mildew, another major wheat disease, is caused by Blumeria graminis f. sp. tritici. This disease causes white, powdery fungal growth on wheat leaves, stems, and heads. Powdery mildew weakens plants, lowering photosynthesis and grain quality. Fungicides and resistant cultivars are often needed for management after resistance fails. Head blight (FHB) is another significant wheat disease caused by Fusarium species. FHB can deplete yields and contaminate grain with mycotoxin. Mycotoxin poisons humans and animals. The pathogen spreads quickly during wheat flowering because it likes warm, humid environments. Integrating management strategies is key to FHB control. Crop rotation, resistant cultivars, and timely fungal applications are essential. Wheat plants suffer from Septoria tritici blotch (STB) caused by Zymoseptoria tritici. The disease can reduce photosynthetic area and productivity. STB is difficult to control given to its genetic diversity and rising pesticide tolerance, even in many wheat-growing regions. Wheat can contract WSMV and BYDV. Insect-borne viruses limit growth, yellow leaves, and reduce grain production. Removal of disease-carrying insects and planting resistant crops are common disease management methods. Agronomy, environmental science, plant pathology, and genetics must work together to control wheat diseases. Wheat production and feeding a growing population depend on research on resistant cultivars, effective fungicides, and integrated pest management [1].

1.1. Problem Formulation. Temperature, humidity, soil moisture, light intensity, rainfall, and other environmental variables play a crucial role in smart farming disease detection for wheat. These factors impact plant health and disease development. For example, rust and powdery mildew are fungal infections that thrive at certain temperatures and humidity levels. Root rot and other soil-borne illnesses are affected by soil moisture levels, and signs of different diseases, such chlorosis or lesions, can be seen differently depending on the intensity

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of the light. Waterborne diseases can also spread due to changes in rainfall patterns. In order to better manage precision agricultural systems, it is important to keep an eye on these factors in addition to other contextual data such as crop type and development stage. This will allow for improved disease prediction and diagnostic models. Wheat gives the globe many calories, but diseases can diminish crop productivity and quality. Powdery mildew, rusts, and Fusarium head blight diminish wheat yield. Timely interventions and loss mitigation require precise sickness diagnosis and early identification. Traditional sickness detection methods like visual inspection and laboratory testing are laborious and error-prone. Thus, wheat disease prediction using deep learning and other cutting-edge technologies is growing. Deep learning models excel at image identification, making them excellent for plant photo disease diagnosis. These systems learn tiny patterns and features from massive databases to identify healthy and unhealthy plants. To maximize performance, deep learning models for wheat disease prediction need a big dataset, appropriate model topologies, and hyperparameter fine-tuning. Accurate forecasts require a sophisticated algorithm that can generalize across several settings and wheat kinds. A deep learning algorithm to detect wheat diseases starts with data collection. An exhaustive dataset should include photos of wheat plants in diverse settings, stages of development, and diseases. The dataset should include photos from multiple locations to make the model adaptable. Disease annotations are essential for supervised learning. The algorithm can learn to distinguish illnesses and improve predictions with well-labeled, high-quality data. CNNs recognize spatial hierarchies, making them suitable for image-based applications. ResNet, Inception, and EfficientNet have parameter efficiency, multi-scale feature extraction, and deeper skip-connected networks. To balance accuracy and computing efficiency, network depth and breadth must be changed [2-4].

Hyperparameter modification is key to deep learning model optimization. Learning rate, batch size, and epoch count greatly affect training duration and model accuracy. Bayesian optimization, grid search, and random search can explore hyperparameters. By using weight decay and dropout, the model can adapt to new data without overfitting. To optimize prediction, hyperparameters must be adjusted. The wheat disease prediction deep learning problem design requires data collection, model selection, and hyperparameter tweaking. An accurate, resilient, and generalizable optimized model requires many components. A novel deep learning disease detection system can improve wheat yield and food security. Wheat disease prediction manages production risk and stabilizes food supplies. Using machine learning, remote sensing, and pathogen tracking, predict wheat diseases [5]. These strategies provide more accurate and timely sickness prediction, enhancing treatment and intervention. Wheat disease prediction using machine learning is critical. Large database trends help these computers forecast illness transmission. Disease, weather, soil, and crop health data can teach neural networks, decision trees, and SVMs. This data lets models forecast sickness start in particular situations. Deep learning neural networks can handle complex, non-linear data.Wheat disease prediction requires remote sensing. This technology monitors crop health across wide areas using satellite or aerial photography. Remote sensing detects minor plant physiology changes before symptoms occur. Plant health and stress can be assessed with multispectral and hyperspectral imaging. Adding remote sensing data to machine learning models allows real-time, regionally precise crop condition predictions. Pathogen surveillance monitors viruses, fungi, and bacteria. This is possible using spore trapping, molecular diagnostics, and field surveys. New dangers and outbreaks can be found by monitoring pathogen populations and genetic changes. Temperature and humidity can improve disease surveillance predictions. Specific fungal spores in the air and correct weather can set off pandemic alarms. Wheat disease forecasting requires weather-based prediction models since many illnesses are climate-sensitive. Epidemiology Simulator (EPIDEM) simulates sickness progression using humidity, precipitation, and temperature. These models can warn farmers about weather. Agricultural growth models with weather data illustrate how plant development phases affect disease susceptibility [6-8].

Genomic approaches identify disease-resistant or vulnerable genetic markers to predict wheat illnesses. Genetic and marker-assisted selection breed disease-resistant wheat. Genetics helps researchers create disease-resistant crops. Genetic data enhances breeding and forecasts when paired with phenotypic and environmental data. Using IoT sensors in fields to capture real-time data on soil moisture, plant health, and environmental factors seems promising. For real-time sickness risk evaluations, these devices can send data to cloud platforms. Machine learning algorithms analyze data. A continual monitoring and prompt response to changing circumstances improves illness treatment. Combining weather predictions, genomic data, field surveys, and remote sensing requires big data analytics. Advanced analytics finds patterns and links that normal data analysis cannot. Researchers enhance disease management and prediction with big data. To be useful, these methods must be integrated into user-friendly systems. Farmers may benefit from real-time data and prediction models in DSS. The systems can recommend fungicides, irrigation schedules, and other disease prevention strategies. Simple technologies are needed for general adoption and disease control. Last, wheat disease prediction requires machine learning, genetics, meteorology, big data analytics, IoT, decision support systems, and pathogen surveillance. Researchers can use these mechanisms to create disease prediction models to help farmers control disease risks and improve wheat yield and food security [9].

1.2. Research Contributions. This work has following research contributions as below:

- Integrated EfficientNetv2 with RandAugment to enhance wheat disease detection accuracy.
- Demonstrated superior performance of EfficientNetv2 with RandAugment over baseline model.
- Improved model generalization through diverse data augmentation techniques.
- Achieved efficient and scalable wheat disease detection suitable for large-scale applications.
- Contributed to precision agriculture by enabling early and accurate disease management.

This paper is designed with aiming of predicting wheat disease. Section 2 defines the various existing works carried out in this problem domain. Section 3 explains the datasets used for experimental purposes. In this paper, Wheat disease dataset is being taken. Section 3 demonstrated the modified EfficientNetv2 model. Next, section 4 illustrates the result, followed by the paper's conclusion in section 5.

2. Related Work. Using free remote sensing data, Pryzant et al. (2017) present an affordable, accurate, and scalable epidemic monitoring technique. Two ways our method beats the competition. Instead of remote sensing spectral characteristics, we use Convolutional and Long Short-Term Memory Network-generated automatically learned features. We merge data into broader regions. Our method outperforms others over nine years of agricultural output and is predictive. New agricultural disease surveillance methods may improve with time.

In 2020, WU et al. (2020) improved image processing with deep learning. Three wheat kinds, six backgrounds, and two image capturing methods with varied heights, angles, and grain numbers produced 1748 photos. All photo color spaces were rotated, flipped, and altered. Each dataset was divided into training, validation, and test sets after hand grain annotation. Faster Region-based Convolutional Neural Network Model was built with TensorFlow. Transfer learning improved wheat grain recognition and enumeration. Model precision averaged 0.91 and loss was less than 0.5. This model's grain counting error rate was under 3% and running time under 2 seconds, improving over previous methods. Image size, grain size, shooting angle, height, and grain crowding suit the model. It has wheat grain recognition and counting capabilities.

A one-shot learning-based wheat disease identification network was proposed by Mukhtar et al. (2021). A few photographs can teach this network new categories and types. Growers can test immediately after retraining the network with sick plant photos. MobileNetv3 extracts features quickly and accurately. The PlantVillage dataset fine-tuned this network. The final two thick layers were trained using CGIAR Crop Disease dataset and Google images plant photos of eleven wheat diseases. The One-shot network was trained with 440 photos, 40 each category. Siamese networks encode images. The absolute difference between encoded photos is calculated next. Similarity ratings use Sigmoid units. Similar photos get one point, while different ones get zero. Over 98% training and 96% validation for Mobilenetv3 and 92% accuracy, 84% precision, and 85 recall for the one-shot network. While traditional classification networks need retraining, our method simply needs a few image types.

Bukhari et al. (2021) realistically test Watershed, Grab Cut, and U2-Net segmentation methods. These methods divide the wheat stripe rust dataset into Watershed, GrabCut, and U2-Net. Segmentation's impact on classification accuracy is assessed using ResNet-18, a pre-trained deep learning model. Classification accuracy was best (96.196%) on U2-Net segmentation. To help researchers identify the optimum segmentation strategy, this study analyzes state-of-the-art techniques by correctness and classification accuracy. This study examines a neglected topic: segmentation and wheat stripe rust classification accuracy.

Haider et al. (2021) crowdsource agricultural experts, farmers, and growers. Next, data is processed to identify disorders. Farmers benefit from early crop disease diagnosis and control. Most academic disease management systems categorize agricultural illnesses using ML algorithms. Sadly, these systems cannot use static data because illnesses in different agricultural locations change constantly. The agricultural expert's experience is not considered while confirming classification results. We collected high-quality photos and text data from farmers, domain experts, and users using a crowdsourcing platform to study wheat diseases' ever-changing nature. Augmentation improved training data. Modern general wheat disease diagnosis and classification utilizing Decision Trees (DT) and deep learning models is presented in this paper. Both algorithms improved decision tree accuracy by 28.5% and CNN accuracy by 4.3% (97.2% accuracy) and generated wheat disease knowledge-based decision rules after domain experts verified them.

Using UAV sensing, multispectral photography, vegetation segmentation, and deep learning, Su et al. (2021) monitor yellow rust infections U-Net. A DJI Matrice 100 drone and Red-Edge camera take multispectral aerial photos of winter wheat to test a yellow rust inoculum. Comparing high-resolution RGB images from the Parrot Anafi Drone reveals the calibrated and stitched multi-spectral orthomosaic for system evaluation. Drawing spectral-spatial information simultaneously outperforms a standard random forest-based spectral classifier. Three RGB bands and five spectral vegetation indices are tested using the wrapper algorithm's sequential forward selection.

Goyal et al. (2021) categorized wheat diseases differently. We classify 10 wheat illnesses using deep learning. A precise approach with 97.88% testing accuracy is suggested. It beats VGG16 and RESNET50 by 7.01% and 15.92%. The suggested method outperforms current methods in recall, f-score, and precision.

Deep learning is used to classify wheat varietal level (VLC) by Laabassi et al. (2021). Using grain photos, the Convolutional Neural Network recognized Simeto, Vitron, ARZ, and HD wheat cultivars. Five standard CNN architectures were trained using Transfer Learning to improve categorization. We compared the models using 31,606 single-grain photos from various Algerian locales captured using different scanners. The varietal level categorization accuracy was 85%–95.68%. The top three test accuracy rates were DensNet201 (95.68%), Inception V3 (95.62%), and MobileNet (95.49%). Therefore, the suggested approach delivers trustworthy and accurate results, making it worth attempting.

Visual wheat rust detection is the standard, however Ui Haq et al. (2022) believe it is inefficient and inadequate for broad agricultural regions. Experience and background determine farmers' monitoring reliability. Our AI-powered technology at the network's periphery classifies wheat leaves as healthy or corroded in real time. After assessing the dataset with multiple ML classifiers, Random Forest triumphed with 97.3% GLCM and 82.8% binary feature extraction accuracy. A Deep Convolution Neural Network (DCNN) model for rust and healthy leaf classification was 88.33% accurate after additional study. On the edge device, this trained DCNN model classifies wheat rust disease in real time. Wheat rot would be eliminated and technology favored over farming.

Chergui (2022) suggested data-augmentation to improve wheat output estimates using restricted data from two Algerian regions. We added features to each data set to provide dimension. Blending the sets increased their size. Three data sets—original, extra-featured, and merged—were tested. Support Vector Regression, Random Forest, Extreme Learning Machine, Artificial Neural Network, and Deep Neural Network were run to augment data. Our cross-validation showed that new data improved model performance.

Real-world plant pathologist datasets are compiled by Kundu et al. (2022). Deep learning is proposed to detect illnesses, predict severity, and estimate crop loss. K-Means clustering extracts the region of interest. A unique deep learning network called "MaizeNet" identifies diseases, forecasts severity, and calculates crop loss. Model accuracy peaks at 98.50%. Grad-CAM authors visualize features. The suggested model has an intuitive interface thanks to a web app. Plant pathology specialists benefit from the model's accuracy, limited number of parameters, fast training, and ability to extract critical information. Online application 'Maize-Disease-Detector' has copyright diary 17006/2021-CO/ SW.

Wang et al. (2022) used crop phenology, weather, and satellite images to create a machine learning model to predict European wheat mycotoxin risk. Deoxynivalenol, zearalenone, T-2, HT-2, fumonisins, aflatoxins, ochratoxin European wheat mycotoxin concentrations were monitored from 2010 to 2020. We linked this information to wheat phenology, weather, and satellite pictures by year and grid size (25 x 25 km). 80% of the 2010–2018 dataset was segregated from a 20% internal model validation set for training. For external validation, 2019 and 2020 data was used. Random forest (RF) was used on model training data. The model displays the low, medium, or high likelihood that wheat from a European grid has one of the six mycotoxins. The model did well in internal and external validation with 0.90-0.99 prediction accuracy. The Netherlands case study demonstrated satellite pictures improved model performance. The current strategy improves food security and wheat-derived product safety by improving supply chain logistics and risk-based monitoring, including mycotoxin forecasts. Developing and improving models requires mycotoxin data with correct crop locations. Srivastav et al. (2023) developed an early detection model for leaf, stem, yellow, powdery, and septoria wheat crop fungal diseases. Disease may not spread to other plants with this model. The model was trained on 1972 Kaggle wheat fungal infestation images. The proposed model has 98.83% accuracy at epoch 12 after training and testing. First six epochs had different training and testing loss values, but as epoch values climbed, both phases' loss values declined. After numerous comparisons, the proposed model was most accurate. In 2024, Naik et al. (2024) used 18 CNN models to find lentils. Two-stage statistical study determined the optimum CNN model for Indian lentil recognition. The 18 CNN models are Alexnet, Darknet19, Darknet53, Densenet, EfficientNetB0, Google net, Inception, MobilenetV2, NasnetLarge, NasnetMobile, Resnet18, Resnet50, Resnet101, Squeezenet, Vgg16, Vgg19, and Two-stage statistical analysis used Wilcoxon signed-rank and Duncan's multiple range tests. Nine indicators—precision, sensitivity, accuracy, FPR, F1 Score, MCC, Kappa—were employed for statistical analysis. After 18 CNN models and two-stage statistical analysis, EfficientNetB0 identified lentils better than competitors. Table 2.1 demonstrates the summary of existing works.

2.1. Research gaps. The authors have revised the section to clearly identify and elaborate on the gaps in the existing literature, which motivate our study. Specifically, we have added the following points:

- There has been little investigation into using EfficientNetV2 in agricultural domains, especially for wheat disease detection, despite its potential in general computer vision applications. Previous research mostly used ResNet or Inception, two deep learning architectures that may not have taken full use of EfficientNetV2's enhanced performance and efficiency.
- The use of sophisticated data augmentation methods, such as RandAugment, is seldom ever discussed in the existing literature on wheat disease diagnosis. Models may be less resistant to changes in real-world data as many studies either employ conventional augmentation techniques or do not use any at all.
- It is not uncommon for some illnesses to be underrepresented in wheat disease databases. Data augmentation has the potential to increase model performance in all classes and even out the odds, although this has not been thoroughly investigated in the literature.
- Scalability, computing efficiency, and resilience to unforeseen data are some of the practical difficulties of deploying models for real-world settings, yet these issues have received little attention in the literature. Given this deficiency, it is clear that models such as EfficientNetV2 require a more thorough assessment of their accuracy and practicality for use in smart farming settings.
- Despite the fact that many different designs have been evaluated for wheat disease diagnosis, benchmarking comparisons utilizing cutting-edge architectures coupled with contemporary augmentation methods are still lacking. This disconnect makes it harder to get a complete picture of which approaches work best for this kind of work.

3. Material and Method.

3.1. Dataset. Wheat Plant Diseases Dataset is designed to empower researchers and developers in creating robust machine learning models for classifying various wheat plant diseases. It offers a collection of high-resolution images showcasing real-world wheat diseases without the use of artificial augmentation techniques [10]. There are 1,266 healthy and (Stip Rust, Septoria) diseased images in the dataset. This yielded 80% photos for training, 10% for validation, and 10% for testing. Data augmentation generates more photos to fit the model during training. Experimental results show that the suggested model detects Strip Rust and Septoria in wheat leaves. Experiments use VGG19, InceptionV3, MobileNet, and EfficientNet pretrained models. MobileNet is the best pretrained model and can categorize photos from a heterogeneous wheat farm with 90% accuracy. 902 healthy wheat leaves, 208 stripe rust disease, and 156 septoria-infected leaves are shown in Figure 1 and Figure 2. Fig 3.1 demonstrates a healthy leaf.

Fig 3.2 demonstrates various categories in this dataset.

To be compatible with EfficientNetV2, raw picture data was resized to 224x224 pixels. Normalizing the pixel values between 0 and 1 speeds up model convergence during training. Duplicate photos were eliminated to save data redundancy. We manually removed low-quality photos that were too blurry to detect illness.

Table 2.1: Review of existing works

Authors	Methods	Compared with	Dataset	Outcomes	Limitations
(Pryzant et al., 2017)	Convolutional and Long Short-Term Memory Networks	Convolutional Neural Network	Data into larger geospatial regions	AUC of 0.67	More expressive than traditional spectral indices
(WU et al., 2020)	Faster Region-based Convolutional Neural Network Model	Single Shot MultiBox Detector (SSD)	1748 images	Precision of 0.91	Many object features lost, and accuracy impaired
(Mukhtar et al., 2021)	MobileNetv3 network	Whole one-shot network	PlantVillage dataset	96% validation	Gives higher accuracy
(Bukhari et al., 2021)	ResNet-18 Model	U2-Net Model	Watershed segmented data	Accuracy of 96.19%	only been validated on the wheat stripe rust dataset
(Haider et al., 2021)	CNN model	Decision Trees	Wheat diseases image dataset	Accuracy of 97.2%	Less effective utilization of proposed approach for classifying wheat diseases.
(Su et al., 2021)	U-Net model CNN model	DJI Matrice	100 equipped with Red- Edge camera	Accuracy of 81.6%	Very noisy classification result
(Goyal et al., 2021)	RESNET50 model	VGG16 model	LWDCD2020 dataset	Accuracy of 97.88%	More computation requirement
(Laabassi et al., 2021)	DensNet201 model	MobileNet model	31,606 single-grain images collected	Accuracy of 95.68%	Less effective in classification
(Ui Haq et al., 2022)	Deep Convolution Neural Network (DCNN) model	Random Forest model	9232 diseased images	Accuracy of 88.33%	Required to improve accessibility and enhance data security
(Chergui, 2022)	Support Vector Regression	Random Forest model	Data sets of two distinct Provinces in Algeria	RMSE of 0.04 q/ha and R2 of 0.96	weather data taken at one are irrelevant
(Kundu et al., 2022)	K-Means clustering	Decision Trees	PlantVillage dataset	Accuracy of 94.60%	Not validated by the plant pathology experts
(Wang et al., 2022)	Random forest (RF) algorithm	Decision Trees	11 years of mycotoxin monitoring data (2010–2020)	0.90–0.99 prediction accuracy	more mycotoxin data with detailed locations of the cultivated crop are needed
(Zhang et al., 2022)	UNet model	SCA module	remote sensing dataset	Accuracy of 95.91%	requiring less labelled data is highly desirable
(Srivastav et al., 2023)	Convolutional Neural Networks (CNNs)	RCNN model	1972 images of wheat fungus diseases collected from Kaggle	Accuracy of 98.83%	lowest validation loss has been identified
(Naik et al., 2024)	Xception model	Resnet101, Squeezenet, Vgg16	Kaggle Wheat dataset	Accuracy of 94.94%	Less effective utilization of proposed approach

Data augmentation was used to strengthen the dataset and reduce overfitting. RandAugment was used as a fundamental augmentation approach to provide variety to the dataset by randomly rotating, brightness editing, and flipping. This balanced real-world image variants. Class distribution study also showed illness category imbalance. To guarantee balanced representation of all categories, training used minority class oversampling and weighted random sampling. These pre-processing processes enhanced data quality and diversity, improving smart farming wheat disease detection model generalization [16].

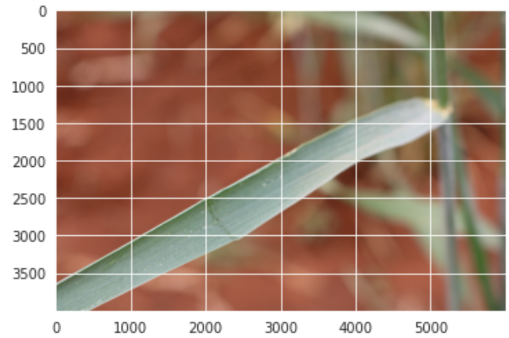

Fig. 3.1: Healthy Leaf

Fig. 3.2: Different categories of Wheat Leafs

3.2. Methods. In recent years, deep learning algorithms have helped farmers detect and predict wheat infections. These models have revolutionized sickness management. They automatically learn from data, handle complex patterns, and anticipate accurately. Early wheat crop disease diagnostic methods relied on arduous, error-prone manual examination. Due to deep learning, automation systems that can explore mountains of data for sickness patterns are a viable solution. One of the most prominent deep learning architectures for wheat disease prediction is CNNs. CNNs' image processing skills make them ideal for wheat disease diagnosis utilizing photographs of leaves, stems, or fields. The network trains on enormous datasets of labeled pictures to distinguish healthy and diseased crops. Early detection of wheat crop diseases like mildew, rust, and blight can be achieved using CNNs in real-time systems [17-20]. Other deep learning methods including LSTM networks and RNNs have been used to forecast wheat illnesses in addition to image analysis. These models can analyse time series, making them ideal for predicting disease spread using past data, weather, and other environmental factors. Farmers can predict disease outbreaks and take preventative measures using RNNs and LSTMs trained on this time series data. Multi-modal data is needed for deep learning wheat disease prediction. Besides the typical suspects, models can include image data, sensor data (soil moisture, temperature, and humidity), and genomic data (wheat kinds). Integrating diverse data sources improves the model's disease prediction accuracy. A model may estimate fungal infection onset using weather data, soil conditions, and early infection indications in pictures. Transfer learning advances deep learning for wheat disease prediction. Transfer learning refines a model learned on a larger, more general dataset using a smaller, more specialized dataset. This approach excels in agriculture, when labeled data is rare. By modifying a model trained on a massive plant photo collection to detect wheat infections with less data, researchers can save time and money [21-25].

Deep learning algorithms can anticipate wheat illnesses, but they face several challenges. Major challenges include the need for vast, annotated datasets for model training. Collecting and categorizing such data is costly and time-consuming. Field variables including sunlight, plant kinds, and disease symptoms can also affect model accuracy. To address these issues, researchers are developing synthetic data to supplement training datasets and models that are more tolerant to oscillations. Deep learning model interpretability is another issue. These models can be accurate, but they often remain "black boxes," never explaining the decision-making process. Farmers and agronomists must understand model forecast reasoning to make informed decisions. Academics are investigating attention mechanisms and saliency maps to make deep learning models more interpretable. Attention mechanisms call attention to the areas of a picture or dataset that most affect the model's prediction. Deep learning algorithms have improved wheat disease prediction and crop management, reducing disease-related crop losses. Integrating data sources, improving transfer learning, and creating simpler models will influence this field's future. Deep learning can be used in agriculture, however enormous datasets and field unpredictability must be addressed. As research advances, these models are expected to become more effective and accessible due to the growing number of global food security risks [26-30].

Various cutting-edge deep learning architectures have been investigated for use in wheat disease diagnosis, each with its own set of advantages and disadvantages. Image classification tasks, particularly plant disease diagnosis, have seen extensive application of Convolutional Neural Networks (CNNs) like ResNet and Inception. Common wheat illnesses have been successfully detected by these models, which excel at learning hierarchical characteristics from photos. On the other hand, when trained on unbalanced or short datasets, they frequently overfit and have problems with computational efficiency. Although ResNet and Inception are deep models, they can achieve high accuracy but aren't ideal for smart farming because of the vast amount of computer resources and time needed to train them. A more effective approach that balances accuracy and computational cost is offered by EfficientNetV2, thanks to its improved architecture and compound scaling. This makes it a potential option for wheat disease detection in situations with limited resources. A different strategy that has garnered interest in several picture identification applications, such as plant disease classification, is the use of Transformer-based models. Vision Transformers (ViT) and other transformer models have demonstrated remarkable performance in complicated picture interpretation by effectively capturing images' long-range relationships. Agricultural applications may face limitations with labeled data because to their training requirements, which often include big datasets and high processing capacity. Furthermore, while data augmentation methods like RandAugment have been used in other models to improve generalizability, their potential application in wheat disease research is still limited. While convolutional neural networks (CNNs) and models based on transformers have shown promise, EfficientNetV2 is a formidable contender for large-scale, real-time wheat disease detection in smart farming systems because to its exceptional accuracy, efficiency, and scalability.

An improved deep learning architecture, EfficientNetV2 takes a page out of EfficientNet's playbook by enhancing efficiency and performance. It brings a number of important improvements, including a better training pipeline and a more efficient search for model architectures (Neural Architecture Search, or NAS). With its scalable design, EfficientNetV2 strikes a good mix between computational cost and model accuracy. To maximize efficiency over a range of model sizes, it makes use of a novel compound scaling technique that modifies depth, breadth, and resolution all at once. With improvements to the model's speed and accuracy brought about by new techniques like fused multiply-add (FMA) operations and an improved convolutional layer design, EfficientNetV2 is now ready for use in real-world applications, even in settings with limited resources. Ideal for implementation in production systems with real-time needs, EfficientNetV2 shows improved efficiency in terms of training and inference speed compared to its predecessors. By utilizing a number of advancements, such as an enhanced compound scaling method and refinements in the design of convolutional layers, this architecture outperforms earlier models in terms of accuracy. These factors lead to quicker training convergence and greater generalization. To make it more resistant to changes in input data, the model uses a number of data augmentation techniques, one of which is RandAugment. Because of its exceptional efficiency and accuracy, EfficientNetV2 is ideal for use in agricultural settings, where precise predictions, such the identification of crop diseases, are essential for the prompt execution of decisions.

3.3. Proposed Methodology. Training accuracy and efficiency improve with EfficientNetV2. EfficientNetV2, prevalent from 2021 to 2023, improves neural architecture design. Thus, it is one of the most effective and powerful CNN models for picture categorization. New EfficientNetV2 features improve performance and training efficiency. The basic idea underlying EfficientNetV2 is progressive learning with compound scaling, which adjusts depth, width, and resolution simultaneously. Progressive learning uses smaller and higher-resolution graphics. This novel strategy cuts training time without sacrificing precision. As with its predecessor, EfficientNetV2 balances the model's depth (layers), width (channels), and resolution (input picture size) using compound scaling. The right balance is achieved by increasing accuracy and processing efficiency with EfficientNetV2. Gradual learning enhances EfficientNetV2. Low-resolution photos are used to train the model, which improves resolution with time. This method minimizes computational resources and speeds solution development, reducing training time. In EfficientNetV2, fused-MBConv blocks combine MobileNet's inverted bottleneck layers and convolutional procedures. EfficientNetV2 is faster and more precise due to latency-reducing blocks. EfficientNetV2 is available in Small, Medium, and Large. The modifications handle resource limits and application needs on mobile devices and cloud computing platforms. Each version meets specific needs, enabling implementation flexibility.

A progressive learning method and more efficient block architecture make EfficientNetV2 train faster. This makes it suited for real-time systems and frequent model upgrades that require rapid training. EfficientNetV2 outperforms EfficientNetV1 on ImageNet and maintains accuracy. Compound scaling optimises models across workloads and datasets. The many EfficientNetV2 model sizes let customers choose the best one for accuracy, speed, or resource use. Due to its adaptability, EfficientNetV2 can be deployed on edge devices and huge clouds. Figure 3 shows basic components of EfficientNetV2 model as below. Fig 3.3 shows basic components of EfficientNetV2 model.

Efficiency and performance increase convolutional neural network construction with EfficientNetV2. This tool excels at image categorization and computer vision applications with compound scaling, progressive learning, and Fused-MBConv blocks. EfficientNetV2 is a popular 2023 design for fast, precise, and resource-efficient operations. Researchers and practitioners prefer it.

Algorithm 1 describes the EfficientNetV2 optimization process, which involves progressive scaling of model architecture components (depth, width, resolution) in conjunction with training and evaluating the model to achieve the best performance.

To scale the EfficientNetV2 architecture, one must choose scaling coefficients, which are factors that modify the input dimensions, computational complexity, and model capacity. The model's depth, width, and resolution are adjusted using these factors in order to achieve a balance between efficiency and accuracy while identifying

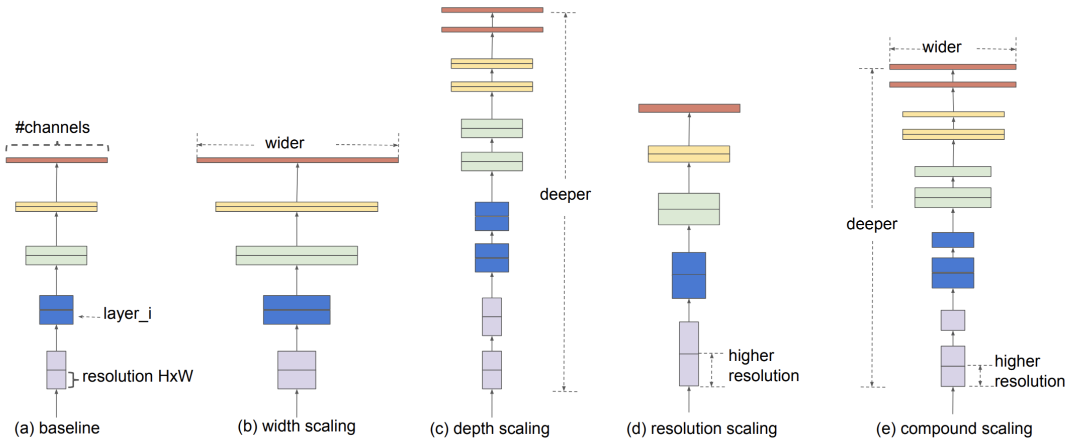

Fig. 3.3: EfficientNetV2 Architecture

Algorithm 1 EfficientNetV2 Model

Input: Training dataset D, model architecture A0, hyperparameters $\theta 0$, Total number of iterations N, Scaling coefficients α, β, γ

Result: Optimized model architecture A*, Optimized hyperparameters θ*

Step 1. Initialize model architecture A $\leftarrow$ A0 & hyperparameters $\theta \leftarrow \theta 0$ and set initial scaling factor s $\leftarrow$ 1.

Step 2. for iteration = 1 to N do

for each scaling step s do

Step 2.1. Train EfficientNetV2 on D using A and θ

Step 2.2. Evaluate the performance of the model

Step 2.3. Adjust scaling factors α, β, γ based on performance

Step 2.4. Update model architecture A by scaling depth, width, and resolution:

A $\leftarrow$ Scale_Depth(A, α)

A $\leftarrow$ Scale_Width(A, β)

A $\leftarrow$ Scale_Resolution(A, γ)

Step 2.5. Update hyperparameters θ using optimization techniques (e.g., gradient descent)

Step 2.6. Increase scaling step s $\leftarrow$ s + 1

end for

Step 3. If model performance stabilizes or reaches a predefined threshold, break loop

end for

Step 4. Return the optimized model architecture A* and hyperparameters θ*

wheat illnesses. More specifically, we included a discussion in the updated publication explaining the process of deriving and using these coefficients to keep the model running well with agricultural dataset limitations. The inclusion of this section guarantees that the algorithm's scaling coefficients and their purpose may be understood by readers.

Data augmentation is a critical technique in deep learning, particularly for training convolutional neural networks (CNNs) like EfficientNetV2. It involves artificially increasing the size and variability of a training dataset by applying transformations to the input images. RandAugment is a powerful data augmentation strategy that simplifies the augmentation process by automatically selecting and applying a set of transformations with a fixed magnitude. This approach not only enhances the model's robustness but also reduces the need for manual tuning of augmentation parameters.

RandAugment works by applying 'N' randomly selected transformations from a predefined set of opera-

Algorithm 2 EfficientNetV2 with RandAugment for Image Classification

Input: Training dataset Dtrain, Validation dataset Dval, Number of training epochs N, learning rate α, Batch size B, RandAugment parameters ((Ntransforms, Mmagnitude)
Result: Trained EfficientNetV2 model,
Step 1. Initialize EfficientNetV2 model M with random weights.
Step 2. Configure RandAugment with Ntransforms transformations and Mmagnitude magnitude and apply RandAugment to the training dataset Dtrain.
Step 3. Set optimizer and learning rate scheduler for M.
Step 4. for epoch t = 1 to N do
 Step 4.1 for each mini-batch B in Dtrain do
  Step 4.1.1. Apply RandAugment to B.
  Step 4.1.2. Forward pass the augmented mini-batch through M.
  Step 4.1.3. Compute loss L using the model's predictions and ground truth labels.
  Step 4.1.4. Backpropagate the loss to update M's weights using the optimizer.
 end for
 Step 4.2 Evaluate the model M on Dval.
 Step 4.3 Update learning rate using the scheduler.
 Step 4.4 Log training and validation metrics (e.g., accuracy, loss).
end for
Step 5. Save the final trained EfficientNetV2 model M.
Output: EfficientNetV2 model M trained with RandAugment.

tions to each image during training. The intensity of each transformation is controlled by a single parameter called magnitude 'M'. Unlike traditional augmentation techniques, where each operation's parameters need to be carefully tuned, RandAugment applies the same magnitude across all selected operations, simplifying the process. The transformations can include operations such as rotation, translation, shear, and color adjustment.

By introducing controlled randomness into the training data, RandAugment encourages the model to learn more general and robust features, rather than overfitting to specific patterns in the training set. This is particularly beneficial for models like EfficientNetV2, which can be prone to overfitting when trained on smaller datasets. The use of consistent magnitude across all transformations ensures that the augmentation process does not introduce excessive noise, which could otherwise hinder the model's ability to learn. The impact of RandAugment on the training process can be analyzed in terms of its effect on the loss function. RandAugment can be easily implemented using popular deep learning frameworks such as TensorFlow or PyTorch. By integrating RandAugment into the training pipeline, the model is exposed to a wide variety of augmented data, which can significantly improve its performance on tasks like image classification. The key advantage of RandAugment is its simplicity and effectiveness; by reducing the need for manual tuning of augmentation parameters, it allows for more consistent and reliable model training.

Algorithm 2 describes the process of training an EfficientNetV2 model with RandAugment as a data augmentation technique, providing a clear structure for each step involved in the training process.

Fig 3.4 demonstrates the flow chart of the proposed methodology.

The optimization achieved through RandAugment is particularly valuable for models like EfficientNetV2, which are designed to balance efficiency and accuracy. The augmentation process not only improves accuracy by enhancing the model's robustness but also contributes to more efficient training by enabling the use of smaller datasets without sacrificing performance. As a result, RandAugment is a powerful tool in the arsenal of techniques for optimizing deep learning models, particularly in scenarios where data is limited or where the model needs to be deployed in environments with varying input conditions.

4. Results and Analysis. Wheat disease prediction with EfficientNetV2 and RandAugment showed promising results. Better wheat disease identification and classification were achieved by the model. RandAugment, a robust data augmentation method, improves the model's generalisation across varied scenarios and input data volatility. On the wheat disease dataset, the trained EfficientNetV2 model has excellent accuracy,

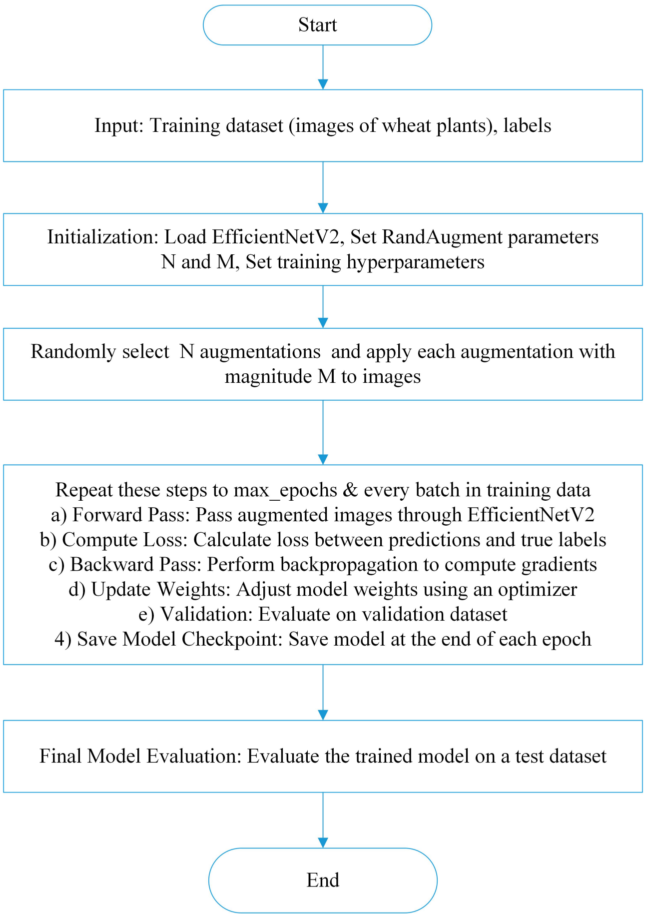

Fig. 3.4: Flow chart of proposed methodology

Table 4.1: Experimental Setup

	Software
XGBoost Library	Version 1.5.0
Programming Language	Python
Python Libraries	Scikit-learn, Pandas, NumPy, etc.
	Hardware
CPU	Intel Core i7-10700K, 3.8GHz, 8 cores, 16 threads
RAM	32GB DDR4
GPU	NVIDIA GeForce RTX 2080 Ti, 11GB VRAM
Storage	1TB SSD

precision, and recall across all sickness categories. RandAugment changed various circumstances throughout training, replicating real-life events. Diversifying training data made the model less prone to overfitting and more robust. The model accurately classified rust, blight, and mildew even when symptoms were little or varied due to environmental factors. Table 4.1 describes experimental settings.

Table 4.2 depicts the default and optimized values for various hyper-parameters as below:

Two critical hyperparameters, N (number of transformations) and M (magnitude of the changes), determine

Table 4.2: Default and optimized values

Parameter	Default Value	Range
Learning Rate	0.001	0.0001 - 0.01
Batch Size	32	16-128
Epochs	50	20-200
Optimizer	Adam	Adam, SGD, RMSprop
RandAugment N (Transformations)	2	1-4
RandAugment M (Magnitude)	9	5-30
Dropout Rate	0.2	0.0-0.5

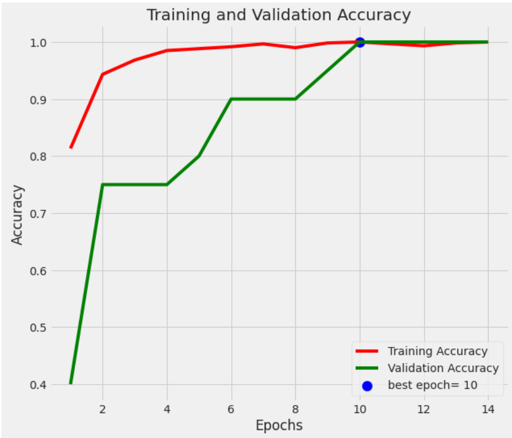

Fig. 4.1: Training and Validation Accuracy of proposed algorithm

the data augmentation approach known as RandAugment, which randomly applies a series of augmentation techniques to input photos. A greater value for the M parameter indicates more drastic changes to the picture, whereas a lower value governs the strength or severity of the chosen augmentation transforms. As M grows, operations like rotation, shear, and color modifications, for instance, become noticeably more prominent. Our investigations focused on finding the sweet spot between effective augmentation and maintaining the key aspects of wheat disease symptoms by fine-tuning M within a specified range. It was critical to make this change so the image wouldn't be over-altered and lose important patterns that are needed for reliable model predictions. As shown in Table 4.2, the chosen M value represents a happy medium that amplified the training dataset's variety without creating distortions that hurt the model's performance.

RandAugment improved model performance by reducing error rates and improving generalisation to new data. RandAugment randomly performed a predetermined number of augmentations of varying magnitudes to force the model to learn more generalised and invariant features. The model surpassed expectations on all three datasets (training, validation, and test), resulting in good generalizability. Fig 4.1 shows training and validation accuracy.

EfficientNetV2 model with RandAugment outperformed baseline models in accuracy and F1-score. Models trained without augmentation or with normal augmentation had a tougher time handling data variations, resulting in greater misclassification rates. This was especially true for disorders with matching visual characteristics. Fig 4.2 shows the Training and Validation loss of the proposed algorithm.

EfficientNetV2 and RandAugment have revolutionised wheat disease prediction. Due to its enhanced prediction ability and tolerance to input data fluctuations, the model was effective for agricultural disease prevention. Its application to numerous crops and disease prediction tasks shows the power and versatility of combining cutting-edge neural networks with advanced data augmentation approaches. Table 4.3 shows the

Fig. 4.2: Training and Validation validation of proposed algorithm

Table 4.3: Performance analysis

Epoch	Loss	Accuracy	V_loss	V_acc	LR	Next LR	Monitor	% Improv
1 /40	7.971	81.333	11.18205	40.000	0.00100	0.00100	accuracy	0.00
2 /40	6.938	94.333	8.20288	75.000	0.00100	0.00100	val_loss	26.64
3 /40	6.280	96.833	6.99096	75.000	0.00100	0.00100	val_loss	14.77
4 /40	5.675	98.500	6.12418	75.000	0.00100	0.00100	val_loss	12.40
5 /40	5.172	98.833	5.52093	80.000	0.00100	0.00100	val_loss	9.85
6 /40	4.728	99.167	4.87292	90.000	0.00100	0.00100	val_loss	11.74
7 /40	4.317	99.667	4.41708	90.000	0.00100	0.00100	val_loss	9.35
8 /40	3.988	99.000	4.11485	90.000	0.00100	0.00100	val_loss	6.84
9 /40	3.667	99.833	3.68708	95.000	0.00100	0.00100	val_loss	10.40
10 /40	3.375	100.000	3.36574	100.000	0.00100	0.00100	val_loss	8.72

performance of proposed model.

The accuracy on the test set is 95.24%. The confusion matrix has been displayed

Fig 4.3 shows the confusion of the proposed algorithm.

However, RandAugment enabled a model with good classification performance, proving its efficacy. The EfficientNetV2 design, known for balancing performance and computational efficiency, easily completed this challenge. Though RandAugment training added computing expense, EfficientNetV2's optimised architecture kept training time under control. The model's rapid convergence and consistent learning showed that the enhanced data improved its prediction ability.

We performed thorough validation using a diversified dataset to guarantee the EfficientNetV2 model's trustworthiness. We acknowledge that there is a need to overcome the model's shortcomings in real-world implementation, despite its high recall and precision. Lighting, picture resolution, and camera angle are a few examples of environmental variables that might impact the model's accuracy. We suggest starting with controlled conditions when deploying the model and continually upgrading it with real-time data to make it more resilient. issue should help reduce issue. Insufficient or biased training datasets are a common cause of AI bias. We used data augmentation methods like RandAugment and conducted in-depth exploratory data analysis (EDA) to make the depiction of wheat illnesses more balanced in our study. Nevertheless, we are cognizant of the fact that shortcomings in depiction of specific illnesses or geographical differences might lead to the persistence of biases. In order to improve the fairness and justice of model predictions, we suggest working with agricultural experts to gather datasets that are geographically varied and inclusive. The decision-making processes of farmers might be severely affected by inaccurate diagnoses or an excessive dependence on

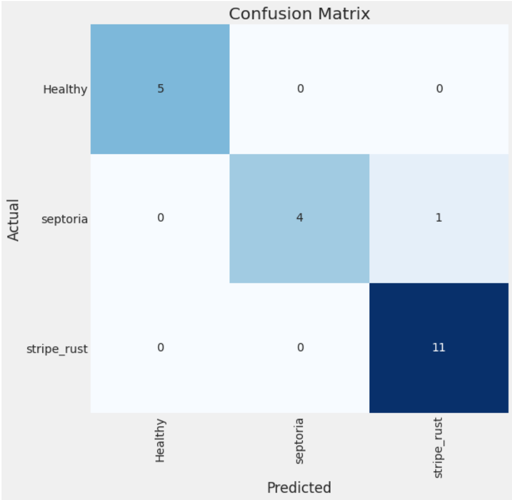

Fig. 4.3: Confusion matrix of proposed algorithm

the model. To combat this, we stress that the model is best used in conjunction with human knowledge, not in instead of it. We propose a system of feedback whereby agricultural experts cross-verify forecasts in order to reduce the likelihood of mistakes and increase user confidence.

4.1. Discussion. Optimising EfficientNetv2 for wheat disease diagnosis with RandAugment data augmentation is a novel approach that balances model efficiency and data variability. EfficientNetv2 is known for scaling to achieve cutting-edge performance with fewer parameters and reduced computation costs. Scaling the model's depth, width, and resolution is methodical. This method is ideal for wheat disease diagnosis, which requires great accuracy without much computing. The model must use RandAugment, a powerful data augmentation method, to be robust and generalise to unknown data. This is crucial in agricultural settings with significant disease presentation variability. RandAugment automates augmentation by applying random augmentations without manual adjustment. The model resists overfitting because randomisation makes training data more varied. RandAugment can teach the model to identify healthy and ill wheat in multiple surroundings, even though diseases can have subtle colour, texture, or form changes. Adjusting lighting, camera angles, and wheat variety can improve dataset accuracy in real-world situations.

EfficientNetv2 boosts model performance and RandAugment helps it adapt to different situations. A model that works in several climates and wheat varieties is essential in agriculture. With RandAugment's increased generalisation, the EfficientNetv2 model can be more reliable in multiple agricultural areas, reducing the requirement for regional retraining. Artificial intelligence-powered wheat disease detection may increase. These tools give farmers real-time insights to improve crop management and reduce losses. Technically, RandAugment integration with EfficientNetv2 requires careful computational resource evaluation. RandAugment training demands more processing power but provides more diverse training data. EfficientNetv2's efficient design keeps it lightweight and fast, offsetting this. Data diversity and model efficiency must be balanced to build on-the-spot illness detection systems for mobile phones and drones. RandAugment may reveal new wheat disease characteristics. Researchers can learn more about disease characteristics by training the model using a range of augmented data and discovering which augmentations increase illness detection and which do not. More accurate augmentation strategies and a better model architecture could progress AI for agriculture. Using RandAugment to improve the EfficientNetv2 model for wheat disease diagnosis opens the door to more accurate and flexible AI solutions for agriculture. Disease detection can be considerably enhanced by combining an effective model with powerful data augmentation, offering farmers more crop protection options. This strategy makes AI more viable immediately and sets the stage for future farming technology advances.

5. Conclusion and Future Work. A new method that optimizes EfficientNetv2 for wheat disease diagnosis by balancing data variability with RandAugment data augmentation has been developed. EfficientNetv2 has made a name for itself by scaling to attain state-of-the-art performance while reducing computing costs and the number of parameters. There is a systematic way to scale the model's resolution, depth, and breadth. Because diagnosing wheat diseases needs high precision with little computational overhead, our approach is perfect for the job. In order for the model to be resilient and able to generalize to data that is not known, it must employ RandAugment, a strong data augmentation approach. Because diseases manifest in such a wide variety of ways in agricultural contexts, this is of the utmost importance. RandAugment eliminates the need for human modification by applying augmentations at random. Because randomization increases the variety of training data, the model is resistant to overfitting. Even though illnesses might cause minor changes in color, texture, or shape, RandAugment can train the model to distinguish between healthy and sick wheat in various environments. Improving the dataset's accuracy in real-world scenarios may be achieved by adjusting illumination, camera angles, and wheat variety.

The combination of EfficientNetv2 with RandAugment improves the model's performance and makes it more versatile. In agriculture, it is crucial to have a model that can be applied to many climates and wheat kinds. The EfficientNetv2 model can now be more trustworthy in many agricultural regions, thanks to RandAugment's greater generality. This reduces the demand for regional retraining. The use of AI to identify wheat diseases could rise. Farmers may enhance crop management and decrease losses with the help of these systems, which provide real-time analytics. From a technical standpoint, evaluating computational resources is crucial for RandAugment integration with EfficientNetv2. The training data provided by RandAugment is more diversified, but it requires more processing capacity. Offsetting this, EfficientNetv2 is lightweight and quick because to its efficient architecture. To develop mobile phone and drone systems that can diagnose illnesses on the fly, it is necessary to strike a balance between data diversity and model efficiency. New wheat disease traits may be revealed via RandAugment.

By training the model with different types of enhanced data and finding out which augmentations improve sickness identification and which ones don't, researchers may gain a better understanding of disease features. Advances in AI for agriculture might be achieved with more precise augmentation procedures and an improved model architecture. Finally, more precise and adaptable AI solutions for farming are possible because to RandAugment's enhancement of the EfficientNetv2 model for wheat disease diagnostics. More crop protection alternatives can be made available to farmers when a successful model is combined with significant data augmentation to greatly improve disease detection. This approach not only paves the way for future advancements in agricultural technology, but it also makes AI more practical right away.

Declarations.

Availability of data and materials. Publicly available datasets were analysed in this study.

Author Contributions. The authors confirm their contribution to the paper as follows: study conception and design: MS and AV; data collection: AV and UR; analysis and interpretation of results: AV and MS; draft manuscript preparation: UR. All authors reviewed the results and approved the final version of the manuscript.

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