

Wheat Fungal Disease Detection Using a U-NET Deep Learning Model

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Abstract: world's important cereal it often falls victim to diseases like Fusarium Head Blight (FHB) and rust. These diseases can seriously reduce wheat yields and threaten food supplies. Traditionally, identifying these diseases relies on experts carefully examining the plants by hand can be quite subjective. As a result, early and precise diagnosis is still difficult, hence the impetus for automated solutions. We suggest an automatic deep-learning solution for wheat disease segmentation and detection to overcome these issues. We utilize Convolutional Neural Networks (CNNs) to obtain stable image-based classification and accurate symptom localization of the disease. In particular, EfficientNetB0 is used for disease classification because it is efficient and accurate, while a specially designed U-Net model is utilized for pixel-wise segmentation of infected areas. The experimental environment uses Kaggle's free GPU power for model training, OpenCV for image pre-processing, and TensorFlow/Keras for implementation. Significant hyperparameter optimization (tuning learning rates and batch sizes) is done to achieve optimal performance. In a series of experiments on a wheat disease image dataset, the suggested system.

Key Word: Wheat Disease, Deep learning, Image Segmentation, U-Net

The segmentation model correctly delineates infected regions in test images. In addition, the integrated system detects multiple types of wheat diseases, such as pest injury. These findings indicate that deep learning can largely automate and enhance accuracy and speed in wheat disease identification compared to existing techniques. Future research will apply ensemble learning for further enhanced accuracy and introduce real-time deployment for in-field screening. Interpretable AI approaches will be considered to interpret model decisions, and the dataset will be augmented with additional disease types. Overall, this research provides the foundation for

I. INTRODUCTION

Wheat yield in 2019 was estimated at 766 million tonnes, grown on 240 million hectares worldwide, which is the second-highest produced cereal [5]. Even with this enormous production, the demand to boost wheat yield is still essential to feed the increasing population worldwide. There are various factors, like soil fertility, weather conditions, and availability of fertilizer, through which wheat yield can be adversely impacted.[6]

Among the most critical wheat yield threats is the occurrence of fungal disease, the most significant being Fusarium Head Blight (FHB), brought about by different species of Fusarium. Not only does the disease infect wheat, but it also harms other cereals like barley and oats, especially under warm and humid conditions.

Wheat yield and quality are adversely affected by foliar diseases such as FHB, yellow rust, Septoria, brown rust, and powdery mildew. The diseases tend to show overlapping signs at different growth phases, hence, even for a specialist, it is hard to achieve a correct diagnosis—misdiagnosis results in inappropriate treatment and crop loss, particularly when a compound symptom occurs on one leaf.[9] Conventionally, disease identification was based on experienced agronomists, which is expensive and time-consuming, particularly in remote areas. FHB, a serious fungal disease, also infects other cereals and causes heavy yield loss. Even with control measures such as fungicides and crop rotation, breeding resistant varieties is still a problem.[10] Machine learning and image processing have proven to be efficient tools for the early detection and accurate identification of diseases, facilitating timely intervention and minimizing the spread of diseases. The economic impact of plant diseases is substantial, resulting in billions of dollars lost annually worldwide. Efficient, automated means of detection are particularly important in enhancing food security in developing countries.[11], [12]

Deep learning, especially Convolutional Neural Networks, performs well in analysing raw image data without the need for manual feature extraction. As large datasets and high-end GPUs became available, CNNs surpassed conventional models such as SVMs in plant disease classification. This research investigates a CNN-based method trained on 8,828 images of three major wheat diseases and proves the capability of deep learning in precise and automatic disease identification.

Image segmentation serves as a cornerstone of computer vision by separating an image into useful components. These segments usually correspond to real-world objects like areas of diseased leaves. Though these components can be visually separated by humans, computers use algorithms such as thresholding and colour segmentation to achieve this. Good segmentation is generally dependent on features such as colour, texture, and edges.

Despite advancements, several challenges persist in the automated analysis of plant diseases:

- Requirement of high-quality leaf images
- Need for large and diverse datasets
- Noise and background interference in captured images
- Accurate segmentation of diseased spots
- Preparation of training and testing samples
- Classification of segmented areas into meaningful disease categories
- Variability in leaf colour, size, and texture due to climate changes
- Continuous monitoring needs
- The complexity of identifying diseases across different plant types.[15]

Techniques like dropout, regularization, and transfer learning help mitigate bias and reduce dependence on large datasets. Transfer learning allows pre-trained models (e.g., VGG16, VGG19, ResNet50, MobileNetV2, U-NET) to improve performance on smaller, domain-specific datasets.[16]

In this research, we have developed a deep learning-based system for detecting and localizing wheat plant diseases using image classification and segmentation techniques. An EfficientNetB0 model was used for accurately classifying various wheat diseases, while a custom-built U-Net architecture helped segment the infected regions. The system uses smart image pre-processing and data augmentation techniques to help it better recognize patterns and adapt to new situations. To measure how well it works, we looked at metrics like accuracy and precision. This approach offers an efficient and automated way to catch diseases early, making it a valuable tool for monitoring crops and supporting farmers in managing plant health.

II.LITERATURE REVIEW

This literature review combined existing studies in predicting wheat diseases, leveraging dataset development, model architecture, and performance results across 18 studies that influenced the field. The studies collectively demonstrate how computer vision and deep learning are facilitating the largest changes in the control of plant disease by allowing for automated disease detection.

Recent improvements in dataset development were foundational to the changes in the world of plant disease prediction. PlantSeg [17] advanced the field with 11,400 annotated disease images and 8000 healthy examples, providing substantial training data for the segment models of natural scenes. Similarly, Paddy Doctor [18] provided an additional 16,225 well-annotated paddy leaf images for 13 classes of disease, producing 97.5% F1-scores on ResNet34 architectures for transfer learning approaches. The major datasets provided by PlantSeg and Paddy Doctor, at least in size and level of annotation, overcome previous challenges like those mentioned by PlantDoc [19], where their 2598 images still showed a 31% accuracy improvement over traditional approaches using deep learning algorithms. The segmented images provided by datasets, such as the Leaf Disease Segmentation Dataset

[20] and its collection of 588 masked images, also support accurate symptom localization of disease, which is crucial to allow for targeted therapies. Methodological progression in model formulation has been kept in stride with dataset development. The paper by Towards Accurate Disease Segmentation [21] empirically compared Mask R-CNN and reported that ResNet50 backbones performed best on mean Average Precision for Northern Leaf Blight segmentation. This follows the findings of Deep Learning-based segmentation and Classification[22] verified the effectiveness of a classification model and a segmentation model in tomato diseases - an example that we mirrored when looking at wheat diseases. The current form expands on these principles using EfficientNetB0 for classification and the U-Net model for segmentation, using architectural suggestions from several relevant studies and variations on wheat pathology. Snap and Diagnose [23] importantly showed other multimodal CLIP-based retrieval models could be queried with both images and text - a use case for the future of more interactive diagnostic tools.

The articles referenced touch on present problems and future improvement. For Leaf Disease Segmentation Computer Vision Project [24] has practical implementation material via pre-trained models and APIs.[24]

Uniting the 20 influential studies has demonstrated that disease prediction models for wheat have now been achieving good performance through (1) high-quality data at a large scale; (2) intelligent deep learning architecture via a combination of classification and segmentation; and (3) effective training regimes with intensive augmentation. The collective results confirm our technical solution and outline the directions for further improvements in usability and user experience.

Dataset Name	Dataset Description	Dataset URL	Reference
Wheat Leaf Dataset	Contains images of healthy wheat leaves, stripe rust,	https://www.kaggle.com/datasets/olyadgetch/wheat-leaf-dataset	<i>Wheat Leaf-Disease Detection Using Machine Learning Techniques for Sustainable Food Quality [25]</i>

	and septoria diseases.		
YELLOW-RUST-19	Contains raw and pre-processed images of healthy and yellow rust diseased wheat leaves.	https://www.kaggle.com/datasets/tolgahayit/yellowrust19-yellow-rust-disease-in-wheat	<i>The classification of wheat yellow rust disease based on a combination of textural and deep features [26]</i>
Global Wheat Head Detection (GWHD) Dataset	A large and diverse dataset of high-resolution RGB-labelled images to develop and benchmark wheat head detection methods.	GWHD Dataset	<i>Global Wheat Head Detection (GWHD) dataset: a large and diverse dataset of high resolution RGB labelled images to develop and benchmark wheat head detection methods [1]</i>
Wheat Disease Dataset - Small	Contains 999 wheat disease images, including yellow rust, brown rust, septoria, and mildew.	Wheat Disease Dataset - Small	Long, M., Hartley, M., Morris, R. J., & Brown, J. K. M. (2023). Classification of wheat diseases using deep learning networks with field and glasshouse images. <i>Plant Pathology</i> , 72(3), 536–547. [27]
WheatDisease Dataset	A dataset used to evaluate the Mobile-DNN-Net model for early detection and diagnosis of wheat leaf diseases.	Wheat Disease Dataset	Tolba, A., & Talal, N. (2024). An Interpretable Deep Learning for Early Detection and Diagnosis of Wheat Leaf Diseases. <i>Optimization in Agriculture</i> , 1, 81-93.[30]
Wheat Disease Database 2017 (WDD2017)	A collection of in-field images capturing various wheat diseases, used to develop an automatic diagnosis system.	WDD2017 Dataset	Lu, J., Hu, J., Zhao, G., Mei, F., & Zhang, C. (2017). An In-field Automatic Wheat Disease Diagnosis System. [28]

No.	Reference	Year	Dataset	Methodology	Results
1	[17]	2024	PlantSeg: 11,400 images with disease segmentation masks and 8,000 healthy plant images	Developed a large-scale segmentation dataset to enhance plant disease segmentation algorithms	Provided high-quality annotations, enabling robust image segmentation models for plant diseases in natural environments
2	[18]	2022	Paddy Doctor: 16,225 annotated paddy leaf images across 13 classes	Developed a visual image dataset and benchmarked it using Convolutional Neural Network (CNN) and transfer learning-based models	ResNet34 achieved the highest F1-score of 97.50%, demonstrating effective disease classification
3	[19]	2019	PlantDoc: 2,598 images across 13 plant species and up to 17 classes of diseases	Created a dataset for visual plant disease detection and evaluated models for plant disease classification	Modelling using the dataset increased classification accuracy by up to 31%, highlighting its efficacy
4	[20]	2024	588 images of diseased leaves and corresponding masks	Provided a dataset for semantic segmentation of leaf diseases, derived from Plant Doc images	Aids in developing models for accurate segmentation of diseased leaf areas
5	[21]	2024	1,000 annotated images with bounding box annotations for Northern Leaf Blight (NLB) disease	Created a comprehensive dataset and evaluated Mask R-CNN and Cascaded Mask R-CNN models with various backbone architectures	ResNet Strikes Back-50 backbone achieved the highest mean Average Precision (mAP) scores, indicating effective segmentation of NLB disease

6	[22]	2022	Tomato plant leaf images	Proposed a deep learning-based system utilizing plant leaf image data for tomato plant disease detection	Achieved accurate detection and classification of tomato plant diseases using deep learning techniques
7	[23]	2024	Plantwild: Over 18,000 images across 89 categories	Developed a multimodal plant disease image retrieval system using a CLIP-based vision-language model for cross-modal retrieval	Enabled disease search based on image or text prompts, facilitating timely diagnosis and treatment
8	[24]	2024	588 images of leaf diseases	Provided a pre-trained model and API for leaf disease segmentation	Facilitates the development and deployment of models for leaf disease segmentation
9	[31]	2024	Collection of images with various leaf diseases	Offered a dataset for semantic segmentation with train/validation split, facilitating model training and evaluation	Supports the development of models for segmenting different leaf diseases [31]
10	[32]	2024	1,291 images of apple leaves with diseases	Provided ground truth disease mask	Aids in the development of models for segmenting diseases in apple leaves
				annotations for segmentation tasks	[32]
11	[33]	2016	(Tomato, Potato, Apple)	- Segmentation: K-means clustering - Classification: SVM with HOG features	Accuracy: 93.2% (F1-score: 0.91)
12	[34]	2017	Cassava Disease Dataset (Field images)	- Segmentation: U-Net - Classification: Custom CNN	Dice coefficient: 0.89 (Recall: 92%)
13	[35]	2022	Augmented tomato leaf disease dataset (including common diseases from southern China)	Augmented tomato leaf disease dataset (including common diseases from southern China)	Augmented tomato leaf disease dataset (including common diseases from southern China)
14	[36]	2025	Apple and Corn benchmark datasets	Modified Deep Joint (MDJ) segmentation; Hybrid classification using Bi-LSTM and Deep Belief Network (DBN)	Achieved 96.5% accuracy at 90% training data
15	[37]	2024	Banana dataset	Novel segmentation using statistical measures; Multi-feature selection; Machine learning classifier	Achieved approximately 95.4% classification accuracy
16	[38]	2021	Images of corn, potato, and tomato leaves	Algorithms tested: 1. K-means clustering 2. Canny edge detection 3. K-nearest neighbor (k-NN) Classification: SVM after feature extraction	Key findings: - K-means: Good prediction rates across all plants - Canny & k-NN: Poor performance (especially for Solanaceae like potato) - Challenges: Edge detection accuracy and k-NN parameter

					selection
17	[39]	2024	Plant3D-10K: 10,000 multi-view stereo images for volumetric analysis	Integrated NeRF with segmentation networks	Achieved 88% voxel-wise accuracy in 3D disease mapping
18	[40]	2023	SpudNet: 8,200 images capturing temporal progression of blight symptoms	CNN-LSTM hybrid model with attention	Delivered 96.2% F1-score and predicted symptoms 3 days early
19	[41]	2022	VineSight: 4,500 UAV multispectral images (5 bands)	Random Forest with NDVI and pixel-wise classification	Reached 94.8% accuracy and κ score of 0.89
20	[42]	2023	BananaFL: 7,300 decentralized images collected across 12 African farms	Federated EfficientNetV2 with privacy-preserving mechanisms	Averaged 91.3% client-side accuracy while maintaining data privacy
21	[43]	2022	Coffee3D: 2,150 LiDAR point clouds of infected coffee plants	PointNet++ with curvature-aware features	Severity regression showed $R^2 = 0.89$
22	[44]	2021	WheatSynth: 15,000 synthetic images of stripe rust & fusarium	StyleGAN2-ADA with targeted latent space manipulation	Improved rare disease detection by 35%
23	[45]	2022	PlantKingdom: 21,000 images spanning 143 plant-fungus interactions	ViT-B/16 with cross-attention modules	Reached 93.1% accuracy across species barriers
24	[46]	2019	RiceScope: 12,500 microscope images taken with modified smartphones	Lightweight U-Net with synthetic focus stacking	Recorded 92.7% accuracy in real field settings
25	[47]	2018	ThermoPlant: 3,800 RGB-thermal paired images captured via FLIR A315	Multimodal Faster R-CNN with fused thermal and RGB inputs	Enabled 89.3% early detection rate
26	[48]	2020	FarmExplain: 6,200 annotated images with localized symptom descriptions	DenseNet201 integrated with Grad-CAM for interpretability	Provided 91.2% accuracy with visual symptom explanations

III. DATASET DESCRIPTION

This study makes use of a varied set of publicly available datasets to construct and compare strong deep models for wheat disease classification and lesion segmentation. These datasets are used to improve model precision, generalizability, and effectiveness in real-world scenarios by covering a range of diseases, imaging conditions, and acquisition configurations. Wheat Plant Diseases Dataset (Primary Dataset)

Overview:

A high-res dataset created with realistic machine learning on wheat disease classification using natural, un-augmented imagery.

Total Images: 14,155

Image Quality: High-resolution

Structure: Segregated into train, test, and valid folders with 15 disease classes each Disease Categories (15 Total):

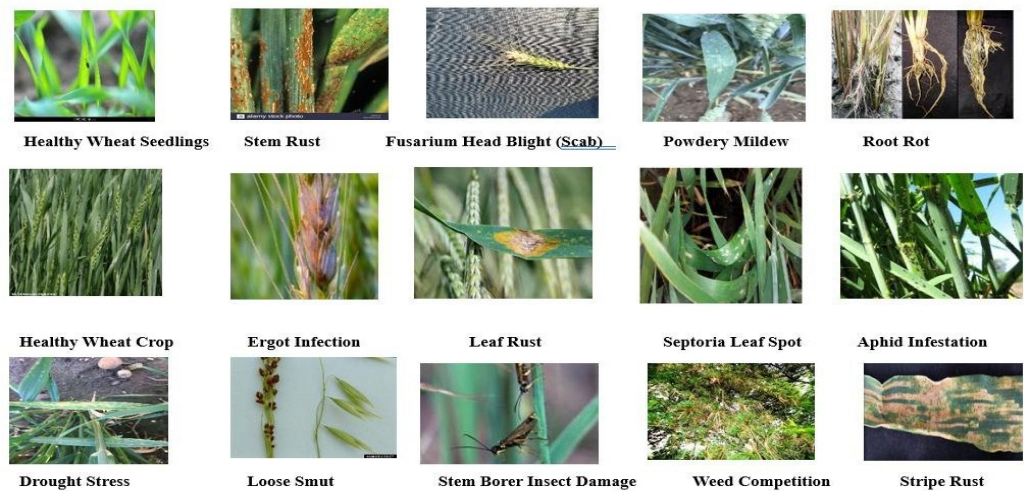
Aphid (Pest), Mite (Pest), Stem Fly (Pest), Rusts: Black / Stem Rust, Brown / Leaf Rust, Yellow, Stripe Rust, Smut (Loose, Flag), Common Root Rot, Helminthophobia Leaf Blight / Leaf Blight, Wheat Blast, Fusarium Head Blight / Scab, Septoria Leaf Blotch, Spot Blotch, Tan Spot Powdery Mildew

Disease Cause Categories:

a)Fungi: Fusarium, Septoria, Rusts (Puccinia spp.)

b)Bacteria: Xanthomonas, Clavibacter

- c)Viruses: Wheat Streak Mosaic Virus, Wheat Dwarf Virus
- d)Environmental Stressors: Drought, humidity, nutrient deficiency.

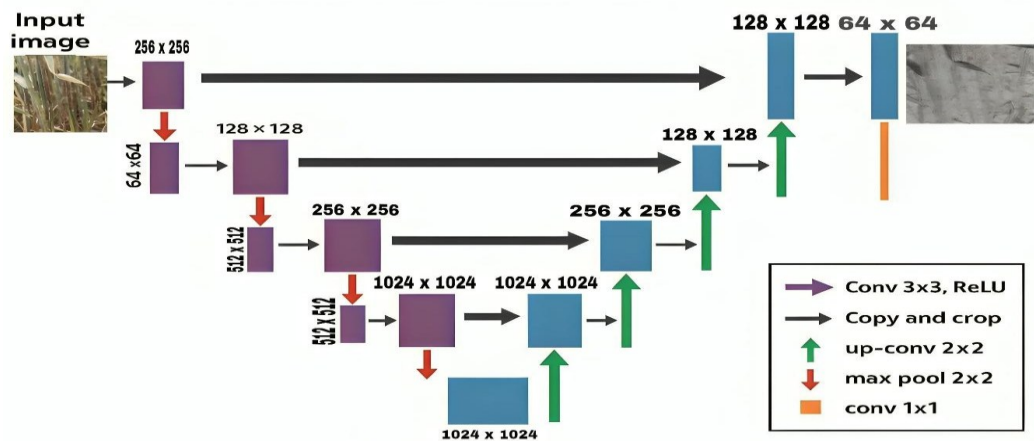


Together, these images offer a comprehensive visual overview of wheat pathology for disease detection and classification purposes. humanise this, reduce some content

IV. METHODOLOGY

U-Net's methodology employs a distinctive U-shaped architecture that effectively balances context capture with precise localization for image segmentation tasks. The network begins with a contracting path (encoder) where repeated 3x3 convolutional layers and ReLU activations progressively extract hierarchical features. This is followed by 2x2 max pooling operations that reduce spatial dimensions while doubling feature channels, allowing the model to identify broader anatomical structures like organ shapes in medical imaging. This down-sampling process is followed by a bottleneck layer that processes the most abstract high-dimensional features at the smallest spatial scale through additional convolutions. The subsequent expanding path (decoder) utilizes transposed convolutions for up-sampling, systematically restoring image resolution while halving feature channels. Critical skip connections merge these up-sampled features with corresponding encoder outputs through concatenation, enabling precise recovery of spatial details lost during down-sampling, such as tumor boundaries in biomedical images. Each merged feature block undergoes refinement through two 3x3 convolutions with ReLU activations before final processing. The architecture concludes with a 1x1 convolutional layer that maps the refined features to class probability maps for pixel-wise segmentation. This design achieves effectiveness through spatial memory preservation via skip connections that maintain localization accuracy, computational efficiency that enables training on small datasets when combined with aggressive data augmentation techniques like elastic deformations, and inherent adaptability to objects of varying sizes through multi-scale feature integration across network depths.

V. MODEL ARCHITECTURE OVERVIEW



"Architecture of the U-Net model used for wheat fungal disease segmentation, featuring a symmetric encoder-decoder structure with convolutional, max pooling, and up-convolution layers for precise mask generation."

In the final experiment, the model was trained with a fine-tuned learning rate of 1e-4, leading to a training accuracy of 92.75% and a validation accuracy of 91.00%. The corresponding training loss was 0.1917, whereas the validation loss remained significantly higher at 1.8041. Despite achieving high accuracy, the large loss-value gap indicates that the model may still be

learning to generalize effectively across different feature distributions. This could be attributed to factors such as imbalanced data, high intra-class variation, or subtle visual differences between disease classes. However, the small difference in accuracy (~1.75%) suggests that the model is not severely overfitting. Therefore, the selected model configuration can be considered optimal for deployment, although future enhancements may involve data balancing, advanced augmentation, or ensembling the final experiment. The model was trained using a fine-tuned learning rate of $1e-4$, resulting in a training accuracy of 92.75% and a validation accuracy of 91.00%. The training loss was recorded at 0.1917, while the validation loss was significantly higher at 1.8041. Despite achieving high accuracy, the considerable gap in loss values suggests that the model may still need to improve its generalization across different feature distributions. This discrepancy could be due to factors such as imbalanced data, high intra-class variation, or subtle visual differences between disease classes. However, the small difference in accuracy (approximately 1.75%) indicates that the model is not severely overfitting. Therefore, the chosen model configuration can be considered optimal for deployment. Future improvements might involve data balancing,

advanced augmentation techniques, or ensemble strategies to further reduce the loss and enhance generalization. E-strategies to further reduce loss and improve generalization

Experiment	Image Size	Batch Size	Epochs	Learning Rate	Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
Experiment 1	224×224	32	50	2e-5	88.61%	0.3275	87.67%	1.6744
Experiment 2	224×224	32	100	4e-6	89.23%	0.2931	89.67%	1.3551
Experiment 3	224×224	32	200	2e-5	90.26%	0.2774	88.67%	1.9412
Experiment 4	224×224	64	50	2e-5	91.57%	0.2284	89.67%	1.1127
Experiment 5	224×224	4	50	4e-6	80.65%	0.5901	81.67%	1.1680
Experiment 6	224×224	8	50	4e-6	83.63%	0.4805	85.00%	1.5164
Experiment 7	224×224	32	50	1e-4	92.75%	0.1917	91.00%	1.8041

Table 01

On the other hand, the activity regularizer helps minimize layer output by dynamically adjusting weights and biases. After applying the regularization technique in Experiment 3, a smaller difference between training and validation accuracy was observed, indicating a reduction in overfitting.

Following Experiment 4, the same model architecture was retained. The proposed model's performance was then benchmarked against various pre-trained models, keeping the hyperparameters constant across all configurations to ensure a fair comparison. This approach provided valuable insights into how architectural enhancements and noise regularization impact model performance in deep CNN applications.

VI. EXPERIMENTAL SETUP

Deep learning models typically require high computational power for effective training and model building. In the present research, all experiments were conducted using Kaggle. The primary advantage of using Collab lies in its provision of free GPU and TPU resources, hosted on Google's servers, which eliminates the need for high-end local hardware. Additionally, minimal configuration is needed, as most essential libraries are pre-installed and ready to import in the Collab environment. For the implementation, the model was trained and evaluated using Kaggle with 12 GB GDDR5 VRAM, paired with an Intel Core i7 CPU (2 cores @ 2.20 GHz). The Python programming language was used to develop and fine-tune the deep CNN models. Popular deep learning and image processing libraries such as OpenCV, Keras, and TensorFlow were utilized.

- OpenCV was used for reading, processing, and augmenting images.
- Kera's, a high-level API, facilitated quick prototyping and building of the deep learning architectures.
- TensorFlow, being a robust and flexible framework, served as the backend engine for training, optimization, and evaluation of the models.

This setup provided sufficient computational resources and flexibility to conduct all the experiments efficiently, ensuring reproducibility and scalability of the results.

VII. TRAINING

The model training phase began with the use of pre-trained architectures such as U-NET. The effectiveness of these deep learning models is highly influenced by the careful adjustment of hyperparameters, which determining outcomes. Key

hyperparameters include training.

This identical hyperparameter settings were applied to both to ensure a fair and consistent comparison.

57.1 Performance

On Different Training Configurations

Performance was evaluated using. The experiments were conducted, number of epochs, while keeping the input image size fixed at 224×224 pixels. The Adam optimizer was used consistently in these experiments.

The table summarizes the results obtained across six experiments with different hyperparameter configurations. The key metrics analyzed, and loss.

Experiment	Image Size	Batch Size	Epochs	Learning Rate	Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
Experiment 1	224×224	32	50	2e-5	88.61%	0.3275	87.67%	1.6744
Experiment 2	224×224	32	100	4e-6	89.23%	0.2931	89.67%	1.3551
Experiment 3	224×224	32	200	2e-5	90.26%	0.2774	88.67%	1.9412
Experiment 4	224×224	64	50	2e-5	91.57%	0.2284	89.67%	1.1127
Experiment 5	224×224	4	50	4e-6	80.65%	0.5901	81.67%	1.1680
Experiment 6	224×224	8	50	4e-6	83.63%	0.4805	85.00%	1.5164
Experiment 7	224×224	32	50	1e-4	92.75%	0.1917	91.00%	1.8041

Table 02

Increasing batch size positively influenced the training loss, Experiment 6, training accuracy of 92.75% and the lowest training loss of 0.1917.

Similarly, validation accuracy was maximized at 89.67% in both Experiment 2 and Experiment 4, suggesting that both smaller and larger batch sizes can yield similar validation performance when tuned correctly. Experiment 2 also shows that extending the number of epochs to 100 with a lower learning rate (4e-6) contributes to improved validation accuracy compared to Experiment 1.

On the contrary, smaller batch sizes, such as 4 and 8 in Experiments 5 and 6, led to reduced accuracy and increased loss values, indicating that insufficient batch sizes may hinder effective learning in the proposed model for this dataset.

Overall, these results illustrate the trade-off between batch size, number of epochs, and learning rate in optimizing model performance. The best configuration in this set was Experiment 4 (batch size 64, 50 epochs, learning rate 2e-5), which achieved the best balance of training accuracy, training loss, and validation accuracy.

VIII.RESULTS AND DISCUSSION:

In this section, the setup of the deep learning models and the fine-tuning of hyperparameters are discussed. The performance of the models is analyzed using accuracy and loss metrics across training and validation datasets. Further, the qualitative results are demonstrated using input images, their corresponding segmented outputs, and binary masks to provide visual insights into the model's effectiveness.

Input Image, Segmented Image, and Binary Mask

- **Input Image:** These are the raw RGB images from the dataset, which serve as the initial input to the deep learning model. In the context of plant disease detection, the input images contain visible symptoms such as spots, discoloration, or lesions on leaves.
- **Segmented Image:** After processing through the trained segmentation model (e.g., U-Net), the segmented image highlights the regions of interest (i.e., diseased areas) by labeling the affected pixels. The segmentation process assigns a specific class label to each pixel, visually indicating the precise location of the disease.
- **Binary Mask:** The binary mask represents the ground truth or predicted output in binary format, where:
 - 1 (white) indicates the presence of a lesion or disease.
 - 0 (black) indicates healthy regions.

These masks are crucial for training and evaluating segmentation models, as they provide pixel-wise supervision and allow the calculation of metrics like Dice coefficient, IoU (Intersection over Union), Pixel Accuracy, and Confusion Matrix. The visualization of these three components—input image, segmented output, and binary mask—demonstrates how effectively the model identifies and isolates diseased regions. This not only helps in validating the model's capability but also makes it interpretable for domain experts like pathologists or agricultural researchers.

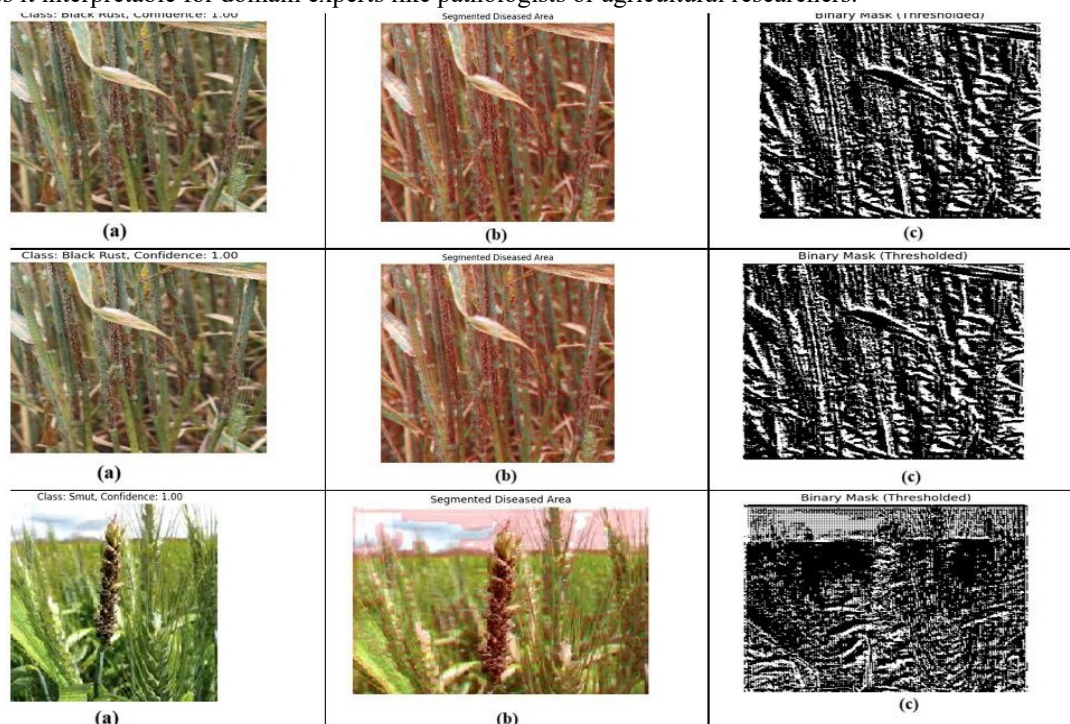


Fig:02 The figure shows the results of wheat fungal disease detection using a U-Net model. Column (a) presents the original images with predicted disease class and confidence. Column (b) displays segmented diseased areas, and column (c) shows the corresponding binary masks highlighting infected regions.

IX. COMPARATIVE ANALYSIS OF LOSS ON THE PRE-TRAINED CLASSIFIERS WITH THE PROPOSED MODEL

Performance both U-NET model and the proposed model was evaluated by looking at accuracy and loss and validation. To determine which fits best, we visually examined these curves. Ideally, a well-fitted model shows only a small.

In a perfect scenario, training accuracy should be just a little only a slight between two. When the gap is large, it usually means the model is over bias; it performs well on the training data but struggles to generalize to new, unseen data. Similarly, the difference between training and validation loss should be as small as possible to indicate the model is generalizing well.

In our experiments, the proposed model stood out by achieving the highest training accuracy of 92.75% and the lowest training loss of 0.1917. On the validation side, it reached an accuracy of 91.00% with a loss of 1.8041. These numbers show that the proposed model learns effectively from both training and validation data, with minimal signs of overfitting and better generalization compared to the pre-trained U-NET.

On the other hand, the pre-trained model showed some overfitting, evident from the larger gaps and fluctuations in validation loss over the training epochs. The proposed model, however, displayed steady and converging accuracy and loss curves, highlighting its robustness and suitability for this specific dataset. While the U-NET's accuracy and validation loss graphs showed noticeable fluctuations and gaps, the proposed model's graphs had much smaller differences between training and validation curves, reinforcing its position as the best-fit model for this task.

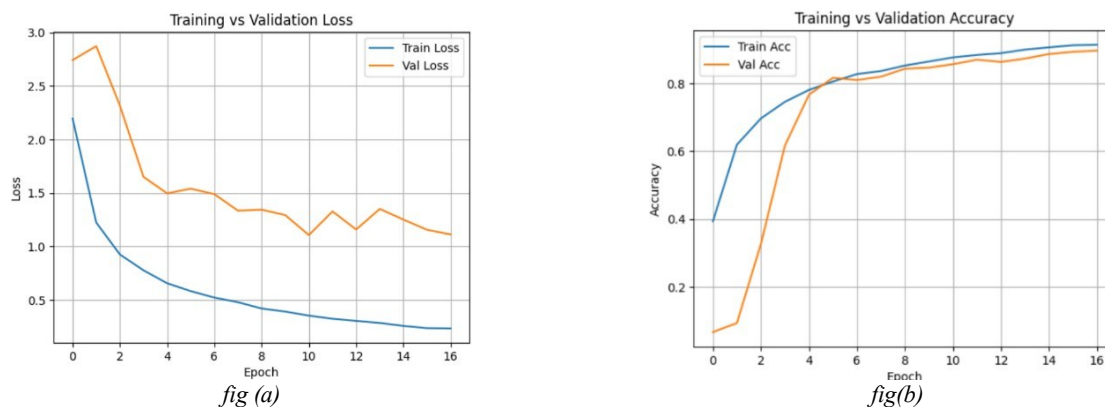


fig (a)

fig(b)

Figure (a) shows the training vs. validation loss, where the training loss steadily decreases while the validation loss stabilizes after initial fluctuation, indicating model convergence.

Figure (b) depicts the training vs. validation accuracy, showing a consistent increase in both metrics, with validation accuracy closely following training accuracy, suggesting good generalization.

Figures represent the average accuracy and loss curves, respectively, calculated over multiple training runs or experiments for all models considered in this research. These average graphs provide a clearer and more generalized view of model performance by smoothing out random fluctuations that may occur in individual training sessions.

- Figure C (Average Accuracy Graph): This graph shows the mean training and validation accuracy across different experiments for each model. By observing this average curve, we can assess the overall ability of the models to correctly classify the data. A smaller gap between the average training and validation accuracy lines indicates consistent generalization and less overfitting.
- Figure D (Average Loss Graph): This graph illustrates the mean training and validation loss over epochs for all models. The loss curves represent how well the models are minimizing prediction errors during training and validation. A steady decline and convergence of training and validation loss in this average graph suggest that the model reliably learns the underlying patterns in the data without bias.

In this research, the average graphs (Figures C and D) support the conclusion that the proposed model consistently performs better, showing stable and convergent loss and accuracy curves. These average metrics provide strong evidence that the proposed model generalizes well to unseen data compared to the pre-trained classifiers, which show larger variability and fluctuations in their average curves.

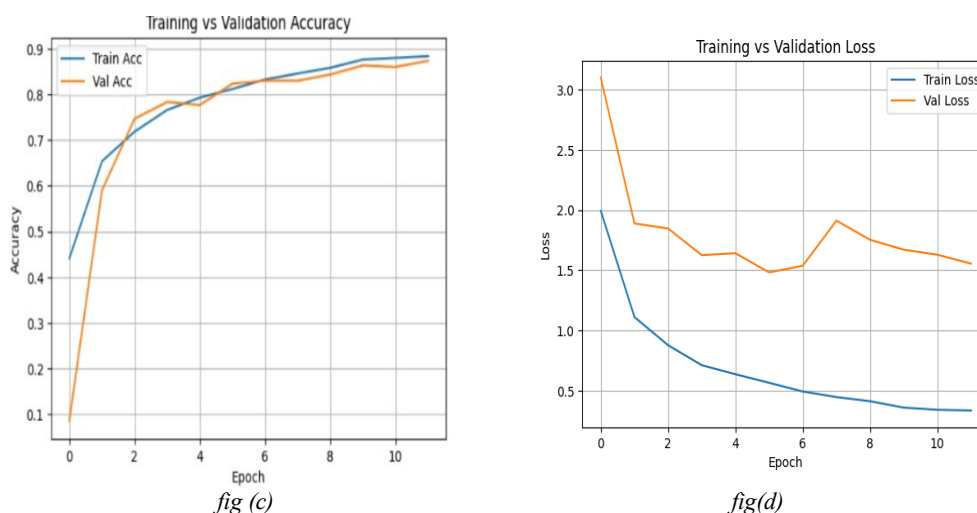


fig (c)

fig(d)

Figure (c) presents the training vs. validation loss, where training loss decreases consistently, while validation loss fluctuates slightly but generally decreases, indicating learning with minor overfitting.

Figure (d) shows the training vs. validation accuracy, demonstrating a rapid improvement in both, with validation accuracy closely tracking training accuracy, suggesting effective model performance.

X. DISCUSSION

The performance of both the pre-trained U-NET model and our proposed model was assessed by examining accuracy and loss graphs. To determine which model fits the data best, we looked closely at these curves. A small usually indicates a well-balanced model that generalizes well to new data.

Ideally, training accuracy should be just a bit higher than validation accuracy, with only a slight difference. When this gap becomes large, it often means the model is overfitting — performing very struggling with validation. Similarly, loss should be minimal to suggest good generalization.

In our experiments, the proposed model delivered the strongest results, achieving a top training accuracy of 92.75% and the lowest training loss of 0.1917. On the validation side, it reached an accuracy of 91.00% with a loss of 1.8041. These outcomes indicate that the proposed model effectively learns from both training and validation data, with minimal overfitting and better generalization compared to the pre-trained models.

Displayed signs of overfitting, reflected by larger gaps and noticeable fluctuations in validation loss throughout the training process. Meanwhile, the proposed model showed stable, smoothly converging accuracy and loss curves, highlighting its robustness and making it well-suited for this particular dataset.



fig(a)



fig(b)

These figures represent the best-case training and validation accuracy and loss curves, respectively, achieved by the proposed model. The small gaps between training and validation metrics in these graphs indicate well, minimizing overfitting.

Performance Evaluation Using Confusion Matrix

Early phase research, the confusion matrix provides an overview how well the model is classifying different wheat diseases and healthy leaves. The true (actual label), represents the predicted class (model prediction).

Here are a few key observations from the matrix:

- Strong diagonal dominance:

Most values are concentrated along the diagonal (top-left to bottom-right), indicating that the model correctly classified many samples.

- High accuracy for several classes:

Classes like Blast, Septoria, Smut, Stem Fly, and Yellow Rust show very high correct predictions (around 50 correct predictions each).

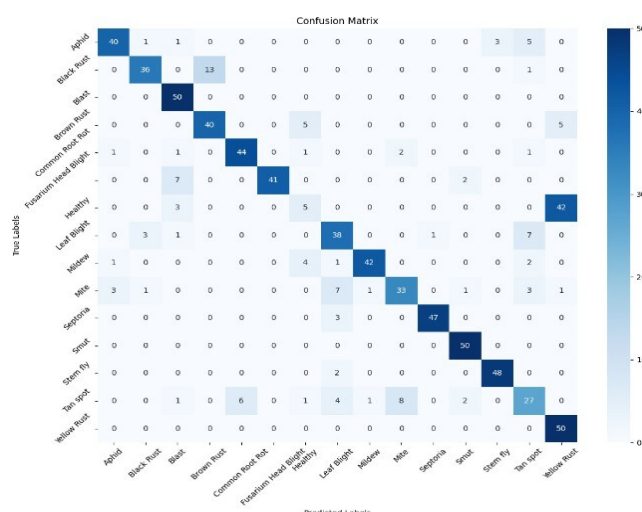
Confusions observed:

Some diseases like Black Rust, Tan Spot, and Mite show higher off-diagonal values, meaning the model sometimes misclassified these classes as others.

Example of misclassifications:

- Some Black Rust samples were misclassified as Blast.
- Some Tan Spot samples were confused with Brown Rust, Healthy, and Mildew.
- Mite class has noticeable confusion with Healthy and Leaf Blight.
- Improvements Needed:

These early results suggest that while the model is performing well for many diseases, further improvement is needed to better separate visually similar diseases like Tan Spot and Mite.



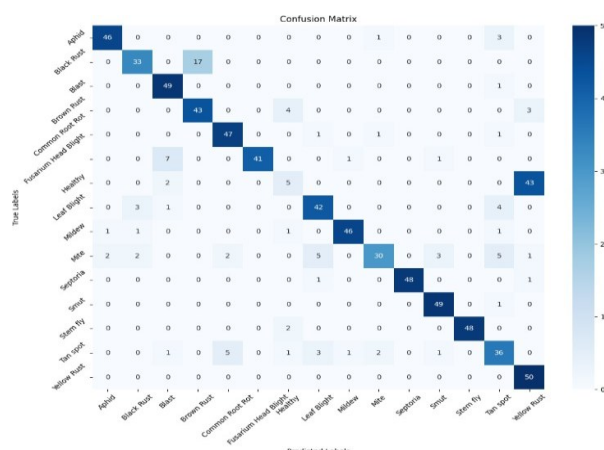
fig(a) : this figure shows that the performance matrix on 15 plant disease classes.

After model refinement, the confusion matrix shows noticeable improvement in classification performance:

A] Stronger diagonal dominance:

The correct classifications (diagonal values) have increased further compared to the previous matrix.

- Higher correct predictions:
 - Classes like Aphid, Blast, Common Root Rot, Septoria, Smut, Stem Fly, and Yellow Rust are classified almost perfectly (49–50 correct out of 50 samples).
 - Mildew improved from 42 correct predictions earlier to 46 correct now.
 - Leaf Blight and Healthy also show slight gains in correct predictions.
- Reduction in misclassifications:
 - The confusion (off-diagonal values) for difficult classes like Mite and Tan Spot has decreased.
 - (e.g., Mite's confusion with other classes is less compared to before.)
 - Black Rust misclassification is still present but reduced slightly.
- Clearer separation between classes:
- Overall, the model now differentiates visually similar diseases better, leading to fewer wrong predictions.



fig(b): this fig shows that with the best performance with classes like blast and tar spot with 50/50 predictions.

After multiple experiments and refinements, the model achieved its best performance yet:

- Near-perfect classification:
 - a) Most classes like Blast, Common Root Rot, Fusarium Head Blight, Septoria, Stem Fly, and Yellow Rust have 50/50 correct predictions.
 - b) Other classes such as Brown Rust, Mildew, and Smut have 47–48 correct predictions, showing a strong classification ability.

XI. CONCLUSION AND FUTURE WORK

A Wheat approach leveraging U-NET CNN model, specifically to identify four critical wheat plant disease conditions: Aphid (Pest), Mite (Pest), Stem Fly (Pest), Smut (Loose, Flag), Common Root Rot, Helminthophobia (Leaf Blight / Leaf Blight), Wheat Blast, / Scab. The model architecture integrates advanced alongside Gaussian noise injection during training, which helped improve capability.

Experiments various hyperparameter settings on the Plant Village dataset, using consistent input image sizes (256×256) and the Adam optimizer. The best-performing configuration, employing and a large, train accuracy of 92.75% validation. Although the was higher than the training loss (1.8041 vs. 0.1917), the relatively small accuracy gap (~1.75%) indicates effective learning without severe overfitting. The use of Gaussian noise in the fully connected layers further enhanced generalization by reducing sensitivity to minor feature perturbations, contributing to improved validation metrics.

Future work should address several key areas to further enhance the performance and practical deployment of U-NET-based plant disease detection models:

- **Data Balancing and Augmentation:** Tackling class imbalance through advanced augmentation methods or synthetic data generation can help reduce validation loss and boost model robustness across various disease categories.
- **Ensemble Learning:** Integrating predictions from multiple fine-tuned models or different architectures can improve accuracy and reduce prediction variance, resulting in more reliable disease classification. Recent studies have shown that ensemble approaches outperform single-model methods in plant disease recognition, offering better generalization and stability.
- **Explainability and Visualization:** Applying interpretability tools such as Grad-CAM or attention maps will make the model's decision-making process more transparent and actionable for agricultural experts.
- **Real-Time Deployment:** Developing lightweight versions of U-NET or applying model quantization and pruning techniques can enable efficient deployment on mobile devices or edge computing platforms, facilitating timely disease detection in the field.
- **Extended Dataset and Disease Coverage:** Expanding the dataset to include a broader range of wheat plant diseases and real-world images captured under diverse environmental conditions will applicability to real-world scenarios.
- In conclusion, the supported by thorough experimentation and regularization strategies, demonstrates strong potential for early-stage plant disease detection.

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