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RESEARCH ARTICLE

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Attention-Guided Wheat Disease Recognition Network through Multi-Scale Feature Optimization

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Abstract

Accurate and timely detection of wheat diseases remains crucial for sustainable agriculture, particularly in major wheat-producing regions. Wheat diseases pose a significant threat to global food security, need precise and timely detection to promote sustainable agriculture. Existing approaches consistently employ single-scale features with shallow-layered convolutional neural networks (CNNs). To bridge the research gaps, we introduce a novel Multi-Scale Wheat Disease Network (MSWDNet) with feature collaboration for wheat disease recognition supported by a comprehensive dataset collected from wheat fields. This study fills research gaps by introducing a novel technique to improve detection accuracy and promote wheat agriculture. Our network uses multistage architecture with progressive feature fusion, incorporating dilated convolution blocks and efficient channel attention mechanisms to capture both fine-grained details and broader contextual patterns. The custom dataset comprises 3,351 high-quality images across five classes collected under diverse environmental conditions. Through extensive experimentation with various CNN backbones, EfficientNet-B7 emerged as the optimal feature extractor, achieving 92.55% accuracy. Our complete architecture, enhanced with multi-scale feature integration and channel attention mechanisms, achieved 98.50% accuracy. Comprehensive ablation studies validate the effectiveness of each architectural component.

Keywords: visual intelligence, wheat diseases, deep learning, machine vision, attention network.

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1 Introduction

Wheat is the most widely eaten food crop worldwide. It meets a substantial amount of the human body's daily energy needs. Wheat is well-known for its significant nutritional value, containing a rich supply of key elements such as carbohydrates, lipids, proteins, and vital nutrients necessary for human existence [1–4]. However, various diseases significantly impact wheat yield and quality, threatening food security

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and agricultural economies. Wheat rusts, smuts, and leaf blight are among the most detrimental diseases, reducing production by over one-third [5, 6]. As global population and nutritional demands increase, improving wheat quality and productivity has become imperative for sustaining human well-being [7].

Traditional methods of wheat disease identification rely on inadequate conventional features due to issues with accuracy, efficiency, and subjectivity [8, 9]. Recent technological advancements have led to the application of deep learning (DL) and spectrum analysis in disease diagnosis [10–13]. However, these approaches often face limitations due to the consideration of straightforward features, the utilization of attention in unfeasible stages of the networks, and mostly relying on shallower layered networks. Artificial neural networks (ANNs) and deep neural networks (DNNs) often require extensive training data, while convolutional neural networks (CNNs) incur significant processing costs and longer training times [27]. Furthermore, these systems suffer from poor robustness under a variety of environmental situations and frequently rely on shallow-layered designs that fail to capture both fine-grained information and contextual patterns. Poor attention mechanisms further impede feature representation, overall accuracy. These constraints emphasize the need for a more efficient, scalable, and robust approach. To fill these gaps, We propose a feasible Multi-Scale Wheat Disease Network (MSWDNet). This approach efficiently captures multi-scale features and contextual information, potentially improving accuracy while reducing reliance on large datasets. Unlike typical CNN designs, our network leverages a multi-stage architecture with feasible intermediate features to learn discriminative patterns. We incorporate dilated convolution blocks to capture contextual cues, complemented by progressive feature fusion to retain fine-grained details. The network also employs efficient channel attention (ECA) to learn important feature channels while maintaining computational efficiency. To enhance the robustness of our approach, we have expanded the dataset by integrating additional challenging images, resulting in a highly diverse collection for wheat disease recognition. This enhanced dataset, collected from wheat fields in Pakistan under the supervision of field experts, provides a comprehensive representation of various wheat diseases. Our empirical validation, based on extensive analysis, demonstrates the effectiveness of the proposed method in accurately identifying wheat diseases. The main contributions of our work are outlined below:

1.1 Our contribution

- We have made a significant contribution by using our exclusive wheat dataset that was carefully collected in various environmental situations, guaranteeing a thorough depiction of wheat disease symptoms in actual agricultural environments. The proposed dataset is highly diverse and can challenge the attentional capabilities of the models.

- We enhance the network's feature extraction capabilities by leveraging multi-scale features from the EfficientNet backbone. Specifically, we extract four distinct feature scales, encompassing low-level, medium-scale, and high-level representations. This multi-scale approach provides a comprehensive set of features, enabling the network to capture a rich spectrum of visual information. By incorporating features from various scales, our model can effectively analyze fine-grained details and broader contextual patterns, leading to a more robust and accurate recognition of wheat disease.

- We introduce an efficient feature integration mechanism incorporating channel attention, focusing on the mature Layer 3 features processed through an ECA module. This approach enhances the network's ability to focus on the most informative channels. We implement a progressive fusion strategy combining the initial layer's refined features with medium-scale (Layer 2) and high-level (Layer 4) representations. This multi-stage fusion process strengthens the feature set, creating a more comprehensive and discriminative representation before passing it to the prediction layers.

- We conducted extensive experiments on our custom-collected Pakistani wheat disease dataset consisting of 3,351 images across five classes. Our systematic evaluation encompassed multiple experimental dimensions: (1) a comprehensive comparison of twelve CNN backbone architectures, where EfficientNet-B7 emerged superior with 92.55% accuracy, (2) an in-depth ablation study demonstrating the incremental benefits of each proposed component, culminating in 98.50% accuracy for our complete architecture, and (3) detailed performance

Table 1. Overview of the ML-based employed networks for crop diseases recognition.

Authors	Approach	Dataset	Accuracy
Treboux et al. [14]	Decision Tree Ensemble (DTE), Color Analysis	Aerial images from five wineries in Switzerland	94.27%
Rump et al. [15]	SVM with Spectral Vegetation Indicators	Sugar beet leaves	97%
Ramesh et al. [16]	Random Forest Classifier (RFC) with HOG	Papaya leaves (160 images)	70%
Phadikar et al. [17]	SVM and Bayes' Theorem	Rice leaves (India)	68.1%, 79.5%
Prajapati et al. [18]	SVM with K-means Clustering	Rice field images (India)	93.33%
Ahmed et al. [19]	Decision Tree, Logistic Regression, KNN, Naïve Bayes	Rice leaves (480 images)	97.91%
Panigrahi et al. [20]	SVM, RFC, Decision Trees, KNN	Maize crops (3823 images)	79.23%
Waghmare et al. [21]	Multi-class SVM	Grape leaves (450 samples)	96.6%
Zhao et al. [22]	SVM, PNN, RFC	Hyperspectral images of wheat leaves	93.33%
GuanLin et al. [23]	SVM with Radial Basis Function	Wheat rust (stripe and leaf rust)	96.67%
Xu et al. [24]	Flood Filling Algorithm	Wheat Dataset	92.3%
Proposed model	MSWDNet	Own collected Wheat Dataset	**98.50%**

Table 2. Performance analysis of the CNN-Based approaches for crop disease classification.

References	Approach	Dataset	Accuracy
Ennadifi et al. [25]	CNNs with visualization methods	CRAW dataset (1163 images)	93%
Zhou et al. [26]	CNN-F5 on 60-channel features	Image-based data	90.20%
Ashraf et al. [27]	CNN (8 layers)	Not specified	93%
Baranwal et al. [28, 29]	CNN-based detection techniques	Apple tree diseases dataset	96.7%
Zhang et al. [30]	Customized CNN for disease detection	Cucumber plants dataset	94.65%
Dang et al. [31, 32]	CNN model for fusarium wilt classification	Radish plant diseases dataset	97.4%
Kurmi et al. [33]	CNN on a diverse dataset	Pepper plants dataset	95%
Karlekar et al. [34]	CNN architecture for grapevine and soybean disease classification	Grapevines and soybean dataset	98.14%
Islam et al. [35]	EffcientNetB0 with Spatial Attention	Proposed WD5CC	92.12%
Proposed model	MSWDNet	Own collected Wheat Dataset	**98.50%**

analysis through accuracy-loss curves and confusion matrices to validate the model's robustness and generalization capabilities.

2 Related Work

Wheat diseases pose significant risks to global food security; thus, their precise classification is critical for optimal crop management. As agricultural output is under growing strain from climate change, pests, and disease outbreaks, early and precise disease detection is critical to ensuring sustainable farming methods and increasing crop yields. The classification of wheat diseases is a crucial field of study in agricultural science and technology since prompt and precise detection of diseases can greatly improve crop management and production. A wide range of strategies has been utilised over the years, progressing from conventional machine learning methods to more sophisticated DL approaches [36]. This growth exemplifies the overarching patterns in artificial intelligence and computer vision, wherein progressively advanced models are created to tackle complex problems [37, 38]. This section provides an overview of the existing research in wheat disease classification.

2.1 Machine Learning-based Approaches

The concept of smart agriculture has prompted the utilization of several machine-learning algorithms to identify wheat diseases. Zhang et al. [39] successfully employed hyperspectral wheat images and classification regression trees to accurately evaluate the intensity of powdery mildew. Their approach obtained an identification accuracy of over 87.8% for disease infection levels. Nevertheless, they faced challenges in accurately discerning slightly contaminated wheat, leading to a significant probability of misidentifying it as either healthy or substantially affected leaves. Zhang et al. [40] utilized hyperspectral remote sensing to differentiate and classify yellow rust from nutritional stress. Their methodology successfully identified occurrences of yellow rust and precisely delineated its geographical distribution by employing the physiological response index PhRI. Khan et al. [41] developed a specialised least squares regression model to accurately identify the severity of early wheat infections. This model enables the prevention, early identification, and effective control of crop diseases, attaining an impressive overall accuracy of over 82.35%. Nevertheless, the exorbitant expenses linked to hyperspectral technology provide a significant financial obstacle for the average farmer. Wang et al. [42] utilised spectral data to develop a comprehensive model that can identify and classify wheat leaf rust and wheat stripe rust. The model achieved an overall accuracy of 82% on a test set. However, the model's recognition accuracy may decrease until the impact of several elements, such as soil composition, weather, and complex backdrops on spectral data, is minimized. Bao et al. [43] developed an algorithm to address this challenge, which focuses on identifying leaf diseases and assessing their severity. Their methodology consisted of initially segmenting the images of wheat illnesses to extract the characteristics of the disease spots. This was followed by identifying the segmented diseases and determining their severity. The strategy achieved a maximum accuracy of 94.16% in recognizing the diseases. This invention greatly enhances the ability to accurately identify illnesses affecting wheat leaves. The remaining work is summarized in the Table 1, which highlights machine learning-based approaches, including author information, methodologies, datasets, and accuracies; the last rows of the Table represent our proposed model.

2.2 Deep Learning-based Approaches

In recent times, the fields of agricultural disease identification have seen a rise in the importance of DL and computer vision techniques. Aboneh et al. [44] methodically collected and labeled datasets consisting of images of wheat diseases. They employed five separate deep-learning models to differentiate various forms of wheat illnesses. After conducting meticulous experimental comparisons, it was found that the VGG19 model had superior effectiveness, achieving the greatest classification accuracy. Liu et al. [45] proposed a novel method that combines a two-layer inception structure and cosine similarity convolution with a traditional convolution block. This innovative model showed a remarkable accuracy of 97.54%, specifically in the identification of buckwheat illnesses. Nevertheless, it is important to mention that the inclusion of the inception structure led to a rise in computing time. Jin et al. [46] emphasized the transformation of wheat head spectral data into a two-dimensional format and then inputting it into a hybrid neural network, with the aim of highlighting the model's capacity to generalize. The use of this strategic approach resulted in an accuracy rate of 84.6% when applied to the validation dataset. This spurred progress in the field of large-scale agricultural disease detection. In order to address the fundamental issue of low accuracy in traditional methods, Deng et al. [47] employed the Segformer algorithm to effectively segment pictures of stripe rust disease. The model's performance significantly improved after implementing data augmentation techniques. It is important to emphasize that this approach is especially suitable for illnesses affecting fall wheat. Su et al. [48] suggested an integrated strategy using Mask-RCNN to accurately assess the severity of Fusarium Head Blight (FHB) in wheat spikes, even in challenging field settings. This technique enables efficient detection of wheat spikes and precise segmentation of FHB infestation, hence assisting in selecting wheat types that are resistant to the disease. In order to effectively reduce damage caused by yellow rust, Shafi et al. [49] did a thorough categorization research on several forms of wheat yellow rust infection. The ResNet-50 model was implemented on smart edge devices for the purpose of detecting the severity of yellow rust. Utilizing drones to capture high-resolution, cost-effective, and comprehensive remote sensing data shows potential for enhancing the accuracy and effectiveness of disease detection. Huang et al. [50] employed UAV remote sensing technology to enhance the effectiveness of identifying and detecting wheat leaf spots. Pan et al. [51] developed a poorly supervised approach to identify yellow showers disease in wheat footage taken by UAV. This system achieved a remarkable accuracy of 98%, considering the substantial effort needed for data annotation. The identification of many diseases is challenging due to their subtle qualities. In order to improve the identification of disease characteristics, Mi et al. [52] implemented the CBAM module using DenseNet. This resulted in an impressive test accuracy of 97.99% on the wheat stripe rust dataset. Nevertheless, these approaches need complex models and significant processing resources,

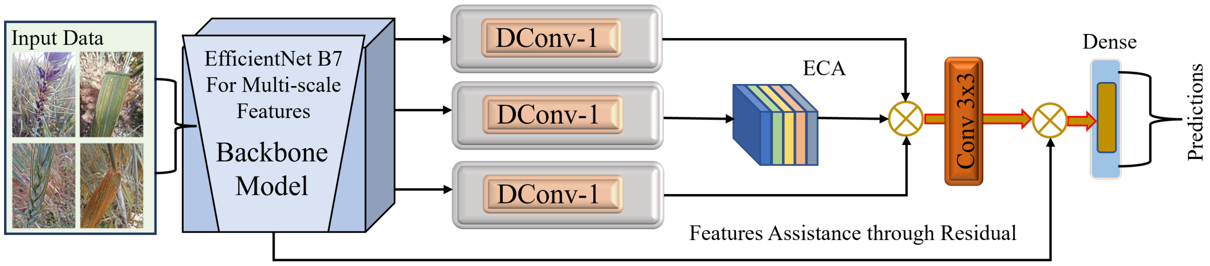

Figure 1. Overview of the proposed network for wheat disease classification.

making them difficult to execute on mobile devices. Bao et al. [53] introduced a lightweight model called SimpleNet to reduce the load on model parameters and computing resources. This model achieved an accuracy of 94.1%. The wheat disease information was effectively emphasized by including the CBAM attention mechanism in the inverted residual blocks of this model. However, it is important to recognize that this procedure cannot be used for other crop images. Similarly Kong et al. [54] introduced Fe-Net, a neural network for fine-grained pest and disease detection in precision agriculture. It obtained 85.29% accuracy on the CropDP-181 dataset while maintaining efficient feature extraction and minimal computational cost, making it acceptable for practical usage. Building on advances in precision agriculture, Kong et al. [55] created MCF-Net, a fine-grained recognition model for crop species classification. The model, which used CSPNet and a cross-level fusion technique, obtained 90.6% accuracy and an F1-score of 0.962, indicating excellent performance and efficiency for agricultural IoT applications. Garima Shrestha et al. [56] present a CNN-based system for plant disease diagnosis that employs image-processing techniques to study agricultural diseases. The study assesses 15 cases and achieves an 88.80% accuracy in recognizing damaged and healthy plant leaves.

The remaining work is summarised in the Table 2, which highlights deep learning-based approaches, including author information, methodologies, datasets, and accuracies; the last rows of the table represent our proposed model.

2.3 Challenges and Proposed Solution

Despite great progress in wheat disease classification, certain challenges remain. Existing methods have limitations such as environmental sensitivity, high processing demands, and reliance on big annotated datasets, which are sometimes rare. Furthermore, many datasets may not accurately reflect the different real-world conditions found in agriculture. These constraints limit the scalability and resilience of existing models. MSWDNet, our technique, uses multi-scale feature extraction and attention processes to improve model robustness across a wide range of situations. By using our own dataset, we overcome the dataset limitation and improve the model's generalizability and accuracy.

3 Proposed Methodology

This section outlines our innovative approach to enhancing wheat disease classification. As shown in Figure 1, our method seamlessly integrates cutting-edge DL techniques to improve feature extraction and classification accuracy significantly. The proposed methodology comprises four key components, each addressing a crucial aspect of the classification challenge: (1) Deep Feature Extraction, which forms the backbone of our model; (2) Dilated Convolution Blocks for Contextual Enhancement, enabling multi-scale analysis; (3) ECA for Feature Refinement, focusing on the most informative aspects of the data; and (4) Progressive Feature Fusion, which combines information from multiple levels for comprehensive disease characterization. Together, these components form a robust framework designed to tackle the complexities of wheat disease identification with unprecedented precision.

3.1 Deep Feature Extraction

We utilized EfficientNetB7 as the backbone architecture for deep feature extraction, leveraging its =SOTA compound scaling method and proven effectiveness in complex visual tasks. The network, pre-trained on ImageNet, serves as a powerful feature extractor that captures hierarchical representations of wheat disease symptoms at various levels of abstraction. Our approach implements a multiscale feature extraction strategy by utilizing four distinct layers of the network, enabling the capture of both fine-grained disease patterns and broader contextual information. The feature extraction process begins at the lower layers of the network, where fundamental visual elements such as edges, textures, and color variations are captured. These low-level features are particularly crucial for detecting fine-grained lesion patterns and early disease symptoms. As we progress to the intermediate layers, the network learns to represent more complex disease-specific patterns, detecting localized texture patterns and spot configurations characteristic of various wheat diseases.

Higher-level features are extracted from deeper layers of the network, encoding more abstract disease-specific patterns and capturing the spatial relationships between different symptom characteristics. The final block provides global semantic information, representing high-level disease concepts and contextual features. This hierarchical approach ensures comprehensive feature representation across multiple scales and abstraction levels. The fourth block features are extracted for the progressive feature fusion in the later stage of the proposed network. The extracted features undergo a systematic processing pipeline where each input image is processed through the network to obtain feature maps at the selected layers. These feature maps are then processed using adaptive average pooling to normalize spatial dimensions, ensuring consistent feature representation regardless of input image size. The multi-scale features are subsequently concatenated along the channel dimension, creating a rich feature representation that captures disease characteristics at multiple scales.

3.2 Dilated Convolution Blocks for Contextual Enhancement

We employ three parallel dilated convolution blocks operating on the extracted backbone features to enhance the contextual field of view and capture multi-scale disease patterns effectively. Each block implements different dilation rates (2, 4, and 6), enabling the network to capture increasingly broader contextual information while maintaining the original feature resolution. This architectural design allows for comprehensive disease pattern analysis at varying receptive fields without the loss of spatial resolution that typically occurs with traditional pooling operations. The first dilated convolution block, with a dilation rate of 2, expands the receptive field moderately to capture local disease patterns and their immediate surrounding context. This block detects the subtle transitions between healthy and diseased tissue regions and early-stage disease manifestations. The second block employs a dilation rate of 4, further expanding the receptive field to capture medium-range contextual information. This is crucial for understanding the spatial distribution of disease symptoms across larger tissue areas. With the largest dilation rate of 6, the third block enables the network to capture long-range dependencies and global contextual information, essential for understanding the overall disease spread patterns and their spatial relationships. Each dilated convolution block follows a systematic structure: a 3×3 dilated convolution layer, followed by batch normalization and ReLU activation. This configuration ensures effective feature transformation while maintaining training stability.

3.3 Efficient Channel Attention

Attention mechanisms have emerged as powerful tools in DL architectures, enabling networks to selectively focus on the most informative features [57–59]. Following the multi-scale feature extraction through dilated convolution blocks, we incorporate an ECA mechanism to recalibrate channel-wise feature responses adaptively. The ECA module processes input features of dimension $C \times H \times W$, where C represents the concatenated channels from our three dilated convolution paths, and H, W represents the spatial dimensions of the feature maps. This lightweight attention mechanism is designed to capture channel-wise dependencies efficiently while maintaining computational efficiency. Our ECA implementation follows a systematic processing pipeline, as illustrated in Figure 2. Initially, the input features undergo Global Average Pooling (GAP) to aggregate spatial information into channel-wise descriptors. A key distinguishing feature of our implementation is using an adaptive kernel size K = 7 for local cross-channel interaction modeling. This specific kernel size was chosen empirically to provide optimal coverage of channel relationships while maintaining computational efficiency. The adaptive convolution operation can be formally expressed as:

$$w = \sigma(\text{Conv1D}(\text{GAP}(X), K = 7)) \quad (1)$$

where σ represents the sigmoid activation function, and Conv1D denotes a one-dimensional convolution operation with a kernel size 7. This operation enables the module to capture local channel interactions effectively while avoiding the computational overhead of fully connected layers used in traditional channel attention mechanisms. The generated attention weights undergo sigmoid activation to normalize them to the range [0,1], creating channel-specific importance

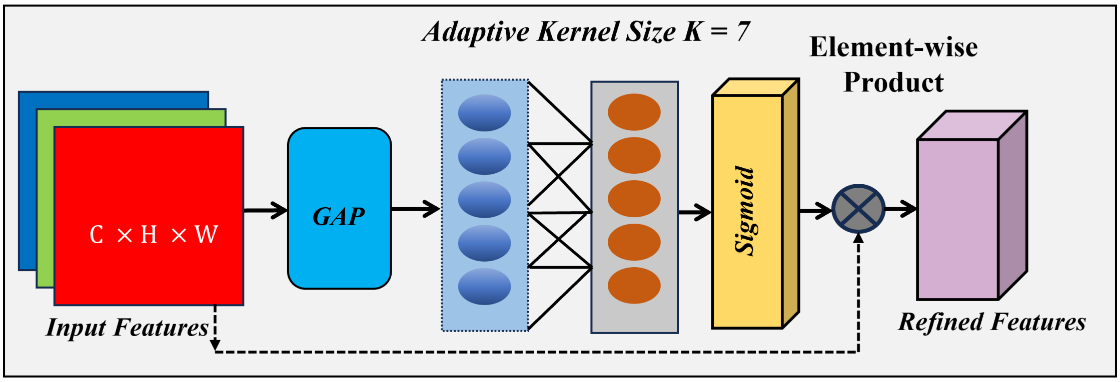

Figure 2. Features flow visualization in the efficient channel attention module of the proposed network.

scores. These scores are then applied to the original input features through element-wise multiplication:

$$Y = X \otimes w \tag{2}$$

where $\otimes$ represents channel-wise multiplication, the attention weights broadcast across the spatial dimensions.

A distinctive feature of our implementation is the inclusion of a residual connection, which allows the network to maintain access to the original features while benefiting from the attention-refined representations. The refined features demonstrate enhanced channel-wise discrimination capability, which is particularly important for distinguishing subtle disease patterns in wheat images. The attention mechanism effectively learns to emphasize channels that carry disease-relevant information while suppressing less informative ones. This adaptive feature refinement proves especially valuable when processing the multi-scale features from our dilated convolution blocks, as it helps prioritize the most relevant spatial scales for different disease manifestations.

3.4 Progressive Feature Fusion

Our network implements a progressive feature fusion strategy that systematically integrates multi-scale features through multiple stages of refinement. The fusion process begins with the rich hierarchical features extracted from the EfficientNetB7 backbone, which are then enhanced through parallel dilated convolution pathways and further refined using channel attention mechanisms. This progressive approach ensures the effective combination of spatial and channel-wise information for robust disease detection. The feature fusion process operates in three primary stages. In the first stage, the backbone features undergo parallel processing through three dilated convolution blocks (DConv-1, DConv-2, and DConv-3) with different dilation rates, enabling the network to capture multi-scale contextual information. The features from these parallel pathways are initially fused through concatenation, preserving the distinct spatial receptive fields captured at each dilation rate. This can be expressed mathematically as:

$$F_{\text{multi-scale}} = \text{Concat}[F_{\text{DConv-1}}, F_{\text{DConv-2}}, F_{\text{DConv-3}}] \tag{3}$$

where $F_{\text{DConv-i}}$ represents features from each dilated convolution block. The second stage involves feature refinement through the ECA module, which adaptively weights the concatenated features based on channel-wise importance. This attention-based fusion can be represented as:

$$F_{\text{refined}} = \text{ECA}(F_{\text{multi-scale}}) \otimes F_{\text{multi-scale}} \tag{4}$$

These connections enable direct feature propagation from earlier stages to later ones, facilitating better gradient flow and preserving fine-grained information. The final fusion stage combines the attention-refined features with the residual features through element-wise addition:

$$F_{\text{final}} = F_{\text{refined}} + F_{\text{residual}} \tag{5}$$

where F_{final} represents the final fused features passed to subsequent layers for disease classification. The progressively fused features undergo a final convolution operation (Conv 3×3) before passing to the dense prediction layers. This design creates a hierarchical feature representation that effectively combines local disease patterns with global contextual information while maintaining the ability to capture fine-grained disease-specific details. The progressive nature of our fusion strategy ensures that the network can adaptively emphasize the most relevant features at each scale, leading to more accurate disease classification. Our experiments demonstrate that this progressive fusion approach significantly enhances the network's ability to detect and classify wheat diseases by effectively combining information across multiple scales and receptive fields.

4 Experiments

In this section, we present a comprehensive evaluation of our proposed network for wheat disease recognition. Our experiments begin with a detailed description of our custom dataset collected in Pakistan, comprising 3,351 images across five classes: Slightly Rust, Severe Rust, Smuts, Healthy Leaf, and Healthy Wheat. The training methodology incorporates various data augmentation techniques and optimization strategies, implemented using PyTorch on Google Colab with an NVIDIA T4 GPU. We extensively analyzed different CNN backbone architectures, with EfficientNet-B7 emerging as the optimal feature extractor. Through systematic ablation studies, we demonstrated the effectiveness of each component in our network, with the final architecture achieving 98.50% accuracy.

4.1 Dataset

We collected our comprehensive dataset of wheat diseases in Pakistan, encompassing various growth stages and capturing diverse environmental conditions. The dataset consists of high-quality images representing five distinct classes: Slightly Rust, Severe Rust, Smuts, Healthy Leaf, and Healthy Wheat. As shown in Figure 3, the images were captured from different angles and under varying lighting conditions to ensure robust model training. The dataset comprises 3,351 total images distributed across the five classes, with detailed allocation shown in Table 3. The largest class is Healthy Wheat with 767 images, followed by Smuts (722 images), Healthy Leaf (633 images), Slightly Rust (618 images), and Severe Rust (611 images), maintaining a relatively balanced distribution among classes. We partitioned the dataset into training, validation, and testing sets to ensure proper model evaluation using a 70-10-20 split ratio. This resulted in approximately 430-537 images per class for training, 61-77 images for validation, and 122-153 for testing, maintaining consistent proportions across all classes. The custom-collected wheat disease dataset will be made available on Google Drive and provided upon request. Researchers can contact the corresponding author to ask for the dataset and complete explanation on its structure and usage.

Figure 3. Sample images from the proposed dataset, illustrating wheat disease categories and healthy samples.

4.2 Training and Evaluation

The training of the proposed network was conducted on our custom wheat disease dataset. We employed a range of data augmentation techniques, including cut mix, mixup, and augmentation, and random erasing, to enhance the model's ability to generalize over diverse wheat disease conditions. Furthermore, drop path regularization was applied to reduce overfitting. The training was executed over 20 epochs with a batch size of 8, utilizing a cosine annealing learning rate scheduler combined with a linear warm-up over the initial ten epochs. The starting learning rate was set to 0.001, while the weight decay was maintained at 0.05 to regulate the complexity of the model. All experiments used Google Colab with an NVIDIA T4 GPU (16GB VRAM) and 12GB RAM. The model was implemented using the PyTorch framework. The training process took a long time to complete the dataset, with intermittent breaks due to Colab's runtime limitations. We employed early stopping with a patience of 5 epochs to prevent overfitting, monitoring the validation loss as the stopping criterion. The model checkpoints were saved both locally and to Google Drive to ensure training progress was preserved across sessions. For evaluation,

Table 3. Dataset distribution showing the number of images per class and their allocation between training and testing.

Class	Total Images	Training (70%)	Validation (10%)	Testing (20%)
Slightly Rust	618	433	62	123
Severe Rust	611	428	61	122
Smuts	722	505	72	145
Healthy Leaf	633	443	63	127
Healthy Wheat	767	537	77	153

Table 4. Performance comparison of various backbone models including efficientNet family.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNet	87.85	86.22	87.75	87.90
MobileNetV2	88.25	87.90	89.10	88.55
DenseNet121	88.55	88.30	87.85	87.03
ResNet50	88.90	89.02	88.85	87.98
EFF-B0	89.05	88.92	89.15	89.03
EFF-B1	89.78	89.65	89.82	89.73
EFF-B2	90.45	90.38	90.52	90.45
EFF-B3	91.12	91.05	91.18	91.11
EFF-B4	91.68	91.62	91.75	91.68
EFF-B5	92.05	91.98	92.12	92.05
EFF-B6	92.32	92.25	92.38	92.31
EFF-B7	**92.55**	**92.48**	**92.62**	**92.55**

we used stratified 5-fold cross-validation to ensure robust performance assessment. The dataset was split into 70% training, 15% validation, and 15% test sets, maintaining the class distribution across all splits. We evaluated the model using standard metrics, including accuracy, precision, recall, and F1-score. Additionally, confusion matrices were generated to analyze per-class performance in detail. To ensure reproducibility, we set fixed random seeds for all random operations, including data splitting, augmentation, and model initialization.

4.3 Intermediate Features Analysis

We comprehensively evaluated various CNN architectures as backbone models for feature extraction, including MobileNet variants, DenseNet121, ResNet50, and the EfficientNet (EFF) family. Table 4 presents the comparative performance metrics across these architectures. The lightweight MobileNet achieved 87.85% accuracy, with its successor MobileNetV2 showing modest improvements across all metrics with an increase in the F1-Score from 87.90% to 88.55%. DenseNet121 and ResNet50 demonstrated competitive performance, achieving 88.55% and 88.90% accuracy, respectively with corresponding 87.03% and 87.98% F1-Scores. However, the EfficientNet family consistently outperformed these traditional architectures, showing systematic improvements from B0 to B7. EfficientNet-B0, despite being relatively compact, surpassed ResNet50 with 89.05% accuracy and balanced Values for F1-Score, Precision, and Recall (88.92%, 89.15%, and 89.03%, respectively). The performance scaled progressively through the family, with B4 marking a significant milestone at 91.68% accuracy and a similarly impressive F1-Score of 91.68%. EfficientNet-B7 achieved the best results across all metrics, with 92.55% accuracy, 92.48% precision, 92.62% recall, with an F1-score of 92.55%, demonstrating the effectiveness of its compound scaling strategy. Based on this analysis, we selected EfficientNet-B7 as our backbone architecture for its superior feature extraction capabilities. Resultantly, after the empirical validations of the backbones, we decided to integrate other modules with the EfficientNet-B7 backbone.

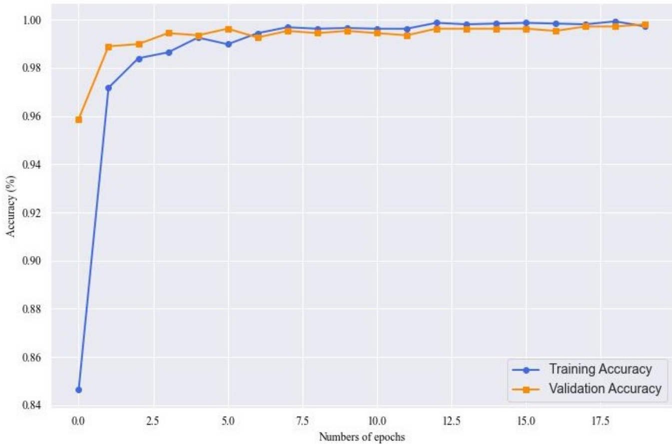

Figure 4. Training and validation accuracy curves over 20 epochs, demonstrating model convergence and absence of overfitting.

4.4 Ablation Study

We conducted comprehensive ablation experiments to validate the effectiveness of each component in our proposed network. Table 5 presents the results of our systematic investigation, where components were progressively added to analyze their contributions to the overall performance.

Table 5. Empirical analysis of the outcomes from the conducted ablation study results.

Method	Single	Multi	DCB-1	DCB-2	DCB-3	ECA	Accuracy (%)
Baseline (Single-scale)	✓						92.55
+ Multi-scale features	✓	✓					94.32
+ Dilated Conv Block-1	✓	✓	✓				95.78
+ Dilated Conv Block-2	✓	✓	✓	✓			96.45
+ Dilated Conv Block-3	✓	✓	✓	✓	✓		97.23
+ ECA Module	✓	✓	✓	✓	✓	✓	97.85
+ Residual Connections	✓	✓	✓	✓	✓	✓	98.30
+ Proposed Network	✓	✓	✓	✓	✓	✓	**98.50**

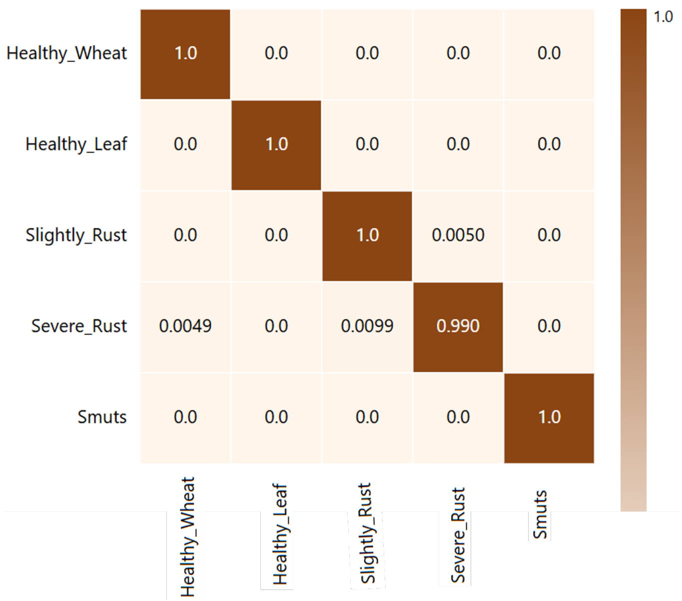

Figure 5. Normalized confusion matrix for wheat disease classification across different classes, demonstrating the classification performance and error distribution

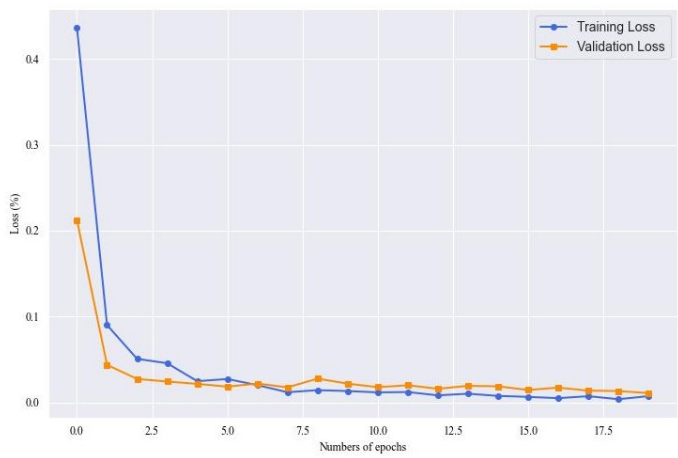

Figure 6. Evolution of training and validation loss during the training process, illustrating the model's learning dynamics and convergence behavior

4.4.1 Baseline Model

Starting with a single-scale baseline architecture, which achieved 92.55% accuracy, This served as the basis for our systematic investigation.

4.4.2 Multi-Scale Feature Extraction

The addition of multi-scale feature extraction yielded a significant improvement of 1.77 percentage points, highlighting the importance of capturing features at different scales. This indicates the network's capacity to integrate spatial information at multiple resolutions.

4.4.3 Dilated Convolution Blocks (DCB)

The introduction of dilated convolution blocks (DCB) demonstrated consistent performance gains.

- DCB-1 enhanced accuracy by 1.46%, increasing it to 94.01%.
- DCB-2 improved performance by 0.67%, totaling 94.68% accuracy.
- DCB-3 contributed an extra 0.78% improvement, resulting in an accuracy of 95.46%.

This progressive improvement validates our hypothesis that expanding the receptive field through dilated convolutions enables better feature extraction at multiple scales.

4.4.4 Efficient Channel Attention (ECA) Module

The integration of the ECA module resulted in a notable accuracy increase of 0.62%, reaching 97.85%. This improvement underscores the effectiveness of our channel attention mechanism in capturing channel-wise dependencies while maintaining computational efficiency.

4.4.5 Residual Connections

Residual connections further boosted performance by 0.45%, achieving 98.30% accuracy. This gain can be attributed to improved gradient flow and the network's enhanced ability to learn residual mappings, as evidenced by the smooth convergence curves in Figure 4 and Figure 6. Finally, our complete proposed network with the stages shown in Figure 1, incorporating all components in an optimized configuration, achieved the highest accuracy of 98.50%. The efficacy of our final architecture is further validated through two critical aspects: (1) the distinct class separation manifested in the confusion matrix with strong diagonal concentration and sparse off-diagonal activations, as shown in Figure 5, demonstrating superior feature discriminability; and (2) the optimal convergence characteristics evidenced by the parallel training and validation accuracy curves with consistent marginal separation, as shown in Figure 4, indicating effective regularization and robust generalization capacity.

5 Conclusion

This research addresses the critical challenge of wheat disease recognition through a novel multi-scale feature collaboration network validated on a diverse dataset collected from wheat fields. Our architectural innovations, particularly integrating multi-scale feature extraction and progressive fusion mechanisms, demonstrate significant improvements over traditional approaches. Incorporating dilated convolution blocks and efficient channel attention has proven effective in capturing both local disease patterns and global contextual information. The extensive experimental evaluation, encompassing twelve different CNN backbones and systematic ablation studies, validates the effectiveness of each proposed component. The final architecture achieved 98.50% accuracy, representing a substantial improvement over the baseline models. Our approach stems from three key factors: (1) the comprehensive nature of our custom-collected dataset, which accurately represents real-world wheat disease scenarios in Pakistani agricultural settings; (2) the effective multi-scale feature extraction strategy that captures information at various levels of granularity; and (3) the efficient integration of channel attention mechanisms that enhance feature discrimination while maintaining computational efficiency. These results demonstrate the practical viability of our approach for real-world agricultural applications. In the future, we plan to expand the suggested dataset by include more complex scenarios, such as mixed disease symptoms, shifting climatic conditions, and difficult visual ambiguities, in order to assess the resilience of the system. In addition, we intend to conduct cross-validation studies utilizing data from various regions to generalize the model's performance across different agricultural settings. This enhanced dataset will also allow for the exploration of domain adaptation approaches to increase the network's transferability. Additionally, our research plan is to investigate lightweight variants of the proposed architecture to further enhance its applicability in resource-constrained agricultural settings.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Salman Khan is an employee of Codeninja Inc., Lahore, Pakistan.

Ethical Approval and Consent to Participate

Not applicable.

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