Efficient Attention-Based Hybrid Deep Learning Architecture for Multi-Crop Plant Disease Recognition

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Efficient Attention-Based Hybrid Deep Learning Architecture for Multi-Crop Plant Disease Recognition

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Abstract

Early and accurate diagnosing of crops that contract diseases is critical in sustaining agricultural production and managing economic losses. Despite the massive success of the deep learning in the automated diagnosis of plant disease, new practices are largely only applicable to specific crops, and also need to be in controlled conditions and not in the field. In response to the aforementioned problems, a new Efficient Attention -based Hybrid Deep Learning (EA-HDL) has been suggested in this paper to perform the classification of multi-crop leaf diseases using real-field images. The architecture is based on an EfficientNetV2 backbone pretrained and has an attention-based pooling mechanism to encourage the use of discriminative features by the effective synthesis of information of the disease-relevant areas and the elimination of background noise. It is a tested, validated and benchmarked framework that was experimented on four of the most crucial crops: cotton, chickpea (chana), Black Gram and wheat in different field conditions. Strong and consistent results have been obtained in experiment work with a 100% record of classification accuracy in the cotton case, 98.64% in the chickpea case, 97.53% in the wheat case and competitive results in the Black Gram case in spite of difficult visual variability. It can be compared to the latest state-of-the-art deep learning models to prove that our approach is more accurate, as it generalizes and works with a variety of crops. The results are evidence that attention-based hybrid deep learning models have a tremendous potential of enhancing accuracy in disease classification in real-life agricultural conditions. The EA-HDL is an effective and scalable platform to real-world crop disease surveillance and precision agriculture system.

Keywords: Crop disease classification, Deep learning, Attention mechanism, EfficientNetV2, Plant leaf disease detection, multi-crop analysis, Precision agriculture, Computer vision

1 Introduction

Agriculture is of major concern in ensuring food security in the world and in maintaining the livelihoods of a large percentage of its population. Nevertheless, plant diseases remain a primary cause of reduced crop yield and quality, particularly in developing agricultural economies. Recent research has revealed that plant diseases may result in yield losses of twenty to forty percent per year if they are not timely identified and treated [1, 2]. The diagnosis of plant diseases should therefore be carried out accurately and rapidly to reduce economic losses and promote sustainable agricultural practices. Traditional disease diagnosis methods mainly rely on visual inspection by skilled agriculturists or laboratory-based analysis [3]. However, these approaches are generally unsuitable for large-scale monitoring, as they require high cost, expert knowledge, and significant reporting time. Moreover, symptom overlap across different diseases and crops often leads to misclassification, highlighting the need for automated and intelligent crop disease detection systems [4, 5].

In recent years, deep learning (DL) has emerged as a transformative technology in agricultural image analysis. Convolutional neural networks (CNNs) are capable of automatically learning hierarchical feature representations and have been extensively applied to plant leaf disease classification tasks [6, 7]. CNN-based approaches have demonstrated superior performance compared to traditional machine learning methods that rely on handcrafted features [8, 9]. Furthermore, transfer learning has significantly improved classification accuracy by leveraging pretrained models such as VGG, ResNet, Inception, DenseNet, and EfficientNet, enabling effective knowledge transfer across domains [10–12].

Despite these advancements, existing deep learning-based disease detection systems still exhibit notable limitations. First, most models are plant-specific, requiring separate training and optimization for each crop type [13, 14]. Although such approaches achieve high accuracy, they lack scalability and increase deployment complexity in real-world agricultural environments. Second, many existing models rely on global average pooling or max pooling operations, which often fail to capture fine-grained spatial features such as localized lesions or disease spots on leaves, thereby limiting classification performance [15].

To overcome these challenges, recent research has explored hybrid deep learning approaches that integrate attention mechanisms, feature fusion strategies, and optimization techniques into CNN backbones [16, 18]. Attention-based models enable networks to focus selectively on disease-relevant regions of leaf images, thereby enhancing interpretability and classification accuracy [19, 20]. Additionally, hybrid architectures combining pretrained feature extractors with task-specific learning modules have demonstrated improved robustness and generalization capability [21]. However, most existing attention-based and hybrid models are evaluated on single-crop datasets, with limited investigation into multi-crop generalization [22, 23].

In real-world agricultural scenarios, farmers often cultivate multiple crop species simultaneously, each exhibiting distinct leaf morphologies, disease patterns, and environmental interactions [24]. Consequently, there is a pressing need for universal disease detection systems that can be efficiently adapted to different crops without extensive architectural modifications. Such generalized deep learning frameworks can significantly reduce deployment costs and facilitate the development of integrated decision-support systems for farmers [25].

Motivated by these challenges, this paper proposes a generalized Efficient Attention-based Hybrid Deep Learning (EA-HDL) framework for multi-crop leaf disease classification. The proposed approach employs an attention-based pooling mechanism to enhance spatial feature discrimination [18, 20], along with a pretrained EfficientNetV2 backbone for scalable and efficient feature extraction [12]. A two-stage transfer learning strategy is adopted to improve training stability and convergence on limited agricultural datasets [10, 11]. The proposed EA-HDL framework is evaluated on four economically important crops—Cotton, Wheat, Chickpea (Chana), and Black Gram—representing diverse disease characteristics and leaf structures. Extensive experimental results demonstrate that the proposed model consistently achieves state-of-the-art performance across all crops, with validation accuracies exceeding 97%, while exhibiting strong adaptability and robustness to real-field variations.

2 Methodology

This section presents the methodology adopted for multi-crop leaf disease classification using the proposed Efficient Attention-based Hybrid Deep Learning (EA-HDL) framework. The overall architecture is designed as a unified deep learning pipeline that enables robust disease classification across multiple crops while maintaining architectural consistency. Each crop dataset is trained independently using the same hybrid architecture, allowing effective crop-specific learning without architectural bias [21, 24].

The proposed pipeline consists of four major stages: image acquisition, preprocessing and data augmentation, hybrid deep learning–based feature learning, and disease classification. Initially, leaf images captured under diverse environmental and illumination conditions are normalized using preprocessing and augmentation techniques [5, 27]. The processed images are then passed through the EA-HDL model, which integrates a pretrained convolutional backbone with an attention-based pooling mechanism to extract discriminative feature representations [18, 20]. Finally, a classification head predicts the disease category for the corresponding crop.

2.1 Efficient Attention-Based Hybrid Deep Learning Architecture

2.1.1 Backbone Feature Extractor

EfficientNetV2-S is employed as the backbone network in the EA-HDL architecture for feature extraction. It is selected due to its efficient training process, reduced parameter count, and strong representational capability compared to earlier convolutional neural network (CNN) architectures [12]. ImageNet-pretrained weights are utilized, and the network operates in feature-extraction mode. Input RGB leaf images are resized to $224 \times 224 \times 3$, providing a balance between computational efficiency and preservation of fine-grained disease patterns such as lesions and texture variations [5, 6].

Let

$$\mathbf{F} \in \mathbb{R}^{C \times H \times W} \tag{1}$$

denote the feature map generated by the backbone, where C is the number of channels and $H \times W$ represents the spatial resolution. For EfficientNetV2-S, the final convolutional output produces a feature map of size:

$$\mathbf{F} \in \mathbb{R}^{B \times 1280 \times 7 \times 7} \tag{2}$$

where B denotes the batch size.

2.1.2 Transition Layer and Spatial Feature Reshaping

To facilitate attention-based pooling, the backbone feature map is reshaped from its spatial form into a sequence of spatial feature vectors. Specifically, the feature map is transformed from:

$$\mathbb{R}^{B \times 1280 \times 7 \times 7} \tag{3}$$

to:

$$\mathbf{X} \in \mathbb{R}^{B \times 49 \times 1280} \tag{4}$$

Each of the 49 vectors corresponds to a distinct spatial location while retaining full channel-wise information. This transformation preserves spatial semantics and enables the model to assign varying importance to localized disease patterns [19, 23].

2.1.3 Attention-Based Pooling Module

Instead of conventional global average pooling, a learnable attention-based pooling mechanism is introduced to emphasize disease-relevant regions [15, 18]. The spatial feature sequence is represented as:

$$\mathbf{X} = \{x_1, x_2, \ldots, x_N\}, \quad x_i \in \mathbb{R}^C, \; N = H \times W \tag{5}$$

A lightweight attention network assigns an importance score to each spatial feature vector:

$$\alpha_i = \frac{\exp(g(x_i))}{\sum_{j=1}^{N} \exp(g(x_j))} \tag{6}$$

where $g(\cdot)$ denotes a feedforward neural network with non-linear activation [19, 20]. The final aggregated feature representation is computed as:

$$\mathbf{z} = \sum_{i=1}^{N} \alpha_i x_i \tag{7}$$

This mechanism enables the model to focus on salient disease characteristics such as spots, discoloration, and lesions, while suppressing background noise, thereby improving classification accuracy and interpretability [18, 23].

2.1.4 Classification Head

The aggregated feature vector:

$$\mathbf{z} \in \mathbb{R}^{B \times 1280} \tag{8}$$

is passed to the classification head. Layer normalization is first applied to stabilize training, followed by a fully connected layer with GELU activation to introduce non-linearity [10, 11]. Dropout regularization is employed to mitigate overfitting and enhance generalization [9]. Finally, a linear layer produces class logits, which are converted into class probabilities using a softmax function for multi-class disease classification [7].

2.2 Data Preprocessing and Augmentation

To improve robustness and generalization, extensive preprocessing and data augmentation techniques are applied during training. These include image resizing, random cropping, horizontal and vertical flipping, color jittering, random rotation, and normalization using ImageNet statistics [6, 8]. Such augmentations help the model learn invariant representations under varying illumination, orientation, and background conditions typical of real-world agricultural environments [5, 27].

2.3 Training Strategy

A two-stage transfer learning strategy is adopted to ensure stable convergence and effective utilization of pretrained features [10, 11]. In the first stage, the backbone network is frozen, and only the attention-based pooling module and classification head are trained. In the second stage, the backbone layers are unfrozen and fine-tuned using a lower learning rate to adapt pretrained representations to crop-specific disease features [12]. The model is optimized using the AdamW optimizer with weight decay regularization [26], along with a cosine annealing learning rate scheduler to promote smooth convergence. Cross-entropy loss with label smoothing is employed to enhance generalization and reduce overconfident predictions [9].

2.4 Multi-Crop Experimental Setup

The EA-HDL framework is evaluated on four crop datasets: cotton, wheat, chickpea (chana), and Black Gram. The same architecture and training strategy are applied uniformly across all crops without any crop-specific architectural modifications, ensuring unbiased and fair evaluation [21, 24]. Each dataset is divided into training and validation sets, and model performance is assessed using accuracy, loss convergence analysis, confusion matrices, and feature visualization techniques [22, 25].

2.5 Performance Evaluation Metrics

Model performance is evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. While accuracy provides an overall performance measure, precision, recall, and F1-score offer a more reliable evaluation under class imbalance conditions commonly observed in agricultural datasets [3, 12, 13, 19]. Confusion matrices and training-validation loss curves are analyzed to assess convergence behavior and class-wise performance. Additionally, dimensionality reduction techniques are employed to visualize feature separability and representation quality [23].

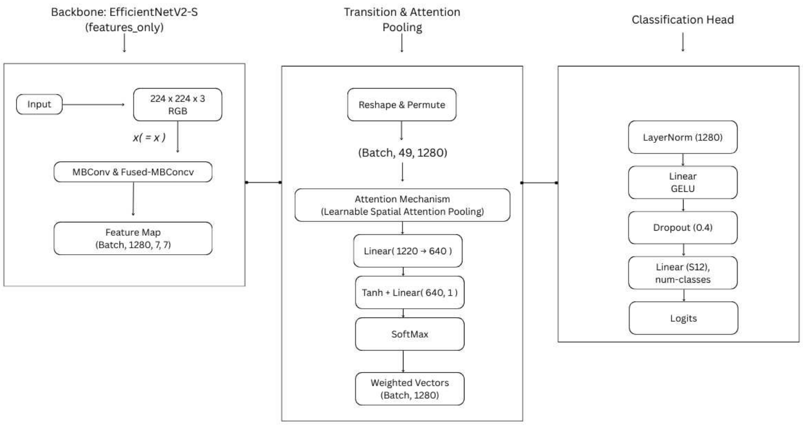

Fig. 1 Overall architecture of the proposed EA-HDL framework for multi-crop leaf disease classification.

2.5.1 Backbone Network and Input Representation

The proposed EA-HDL model takes an RGB leaf image as input, which is resized to a fixed resolution of $224 \times 224 \times 3$. This input size provides a suitable balance between computational efficiency and the preservation of fine-grained disease characteristics such as spots, lesions, and texture variations [5, 6].

EfficientNetV2-S is employed as the backbone network in a feature-extraction configuration. This architecture is selected due to its favorable trade-off between classification performance, parameter efficiency, and training stability [12]. EfficientNetV2-S consists of stacked MBConv and fused-MBConv blocks that progressively learn hierarchical spatial and semantic representations [12, 14].

The output of the final convolutional layer produces a high-level feature map of the form:

$$\mathbf{F} \in \mathbb{R}^{B\times 1280\times 7\times 7},$$

where B denotes the batch size.

2.5.2 Transition Layer and Spatial Feature Reshaping

To enable spatially aware feature aggregation, the backbone feature map is reshaped while preserving spatial semantics [18, 20]. Specifically, the tensor

$$\mathbb{R}^{B\times 1280\times 7\times 7}$$

is transformed into a sequence representation:

$$\mathbf{X} \in \mathbb{R}^{B\times 49\times 1280}.$$

Each of the 49 feature vectors corresponds to a distinct spatial location in the original feature map and retains full channel-wise information. This transformation allows the model to learn spatial importance weights, which is essential for capturing localized disease patterns such as lesions and discolorations [19, 23].

2.5.3 Attention-Based Pooling Mechanism

Instead of conventional global average pooling, the EA-HDL framework incorporates a learnable attention-based pooling mechanism to emphasize disease-relevant regions [15, 18].

A lightweight attention network composed of a linear projection, non-linear activation, and a scoring layer processes each spatial feature vector. The network assigns a scalar importance weight to each spatial position, which is normalized using a softmax function to form a valid probability distribution [19, 20].

The final aggregated feature representation is computed as:

$$\mathbf{z} = \sum_{i=1}^{49} \alpha_i \mathbf{x}_i,$$

where α_i denotes the learned attention weight corresponding to the i-th spatial location.

This mechanism enables the model to focus on visually salient and infected regions of the leaf while suppressing background noise, thereby improving both discriminative capability and interpretability [18, 23].

2.5.4 Classification Head

The aggregated feature vector

$$\mathbf{z} \in \mathbb{R}^{B\times 1280}$$

is forwarded to the classification head. First, layer normalization is applied to stabilize feature distributions during training. This is followed by a fully connected layer with GELU activation to introduce non-linearity [10, 11].

Dropout regularization is then employed to mitigate overfitting and improve generalization performance [9]. Finally, a linear layer maps the learned representations to crop-specific disease categories. The network outputs class logits, which are optimized using a categorical cross-entropy loss function [7].

2.5.5 Multi-Crop Deployment Strategy

The same EA-HDL architecture is independently deployed across multiple crop datasets, including cotton, wheat, chickpea (chana), and Black Gram. No crop-specific architectural modifications are introduced, ensuring a fair evaluation of model generalization across diverse crops [21, 24].

Crop-specific learning emerges purely from data-driven training, demonstrating the flexibility of the proposed framework across varying disease distributions, leaf morphologies, and real-field conditions [22, 25].

2.5.6 Evaluation Metrics

Model performance is evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. These metrics collectively provide a balanced assessment of overall and class-wise predictive performance [3, 12, 13, 19].

Since accuracy alone may be insufficient in the presence of class imbalance, precision, recall, and F1-score are additionally reported to ensure reliable evaluation across all disease categories [10, 11, 15, 18, 24, 25].

2.5.7 Overall Methodology Summary

This section presented the complete methodological framework for multi-crop leaf disease classification. The proposed Efficient Attention-based Hybrid Deep Learning (EA-HDL) model integrates a lightweight yet powerful convolutional backbone with an attention-based feature aggregation mechanism to enhance disease-specific representation learning [12, 18].

The methodology begins with standardized image preprocessing and augmentation to improve robustness against variations in illumination, orientation, and background noise [5, 6, 27]. EfficientNetV2-S serves as the feature extractor due to its strong representational capacity and computational efficiency [12]. The attention-based pooling mechanism selectively emphasizes spatial regions most relevant to disease discrimination [15, 18].

A regularized and normalized classification head ensures stable and generalizable learning [9–11]. The consistent deployment of the same architecture across multiple crops enables an unbiased evaluation of adaptability without crop-specific tuning [21, 24]. Overall, the proposed EA-HDL framework is efficient, interpretable, and well-suited for real-world agricultural disease diagnosis systems.

3 Results

The proposed Efficient Attention-based Hybrid Deep Learning (EA-HDL) framework is evaluated on four crops, namely cotton, chickpea (chana), Black Gram, and wheat. All experiments are conducted using the same model architecture, training strategy, and evaluation protocol to ensure fair and consistent comparison across crops. Model performance is assessed using accuracy and loss convergence behaviour, along with class-wise precision, recall, F1-score, and confusion matrix analysis.

3.1 Overall Performance Analysis

The EA-HDL framework demonstrates strong convergence and robust generalization across all evaluated crops. Validation accuracies for cotton, wheat, and chickpea exceed 97%, indicating stable and effective learning of disease-specific patterns. Black Gram, which presents greater intra-class variability and background complexity, achieves a comparatively lower yet significant validation accuracy of 82.14%.

The attention-based pooling module consistently enhances spatial feature discrimination, particularly for diseases exhibiting localized visual symptoms. Furthermore, the minimal gap observed between training and validation curves across all experiments reflects effective regularization and controlled overfitting.

3.2 Chickpea (Chana) Leaf Disease Classification

3.2.1 Training and Validation Behaviour

The EA-HDL model converges rapidly on the chickpea dataset and exhibits stable optimization behaviour. Training accuracy increases from approximately 86% during early epochs to over 99% as training progresses. Validation accuracy remains consistently high, achieving a peak value of 98.64%. Correspondingly, both training and validation loss curves decrease monotonically with minimal divergence, indicating strong generalization capability.

These results highlight the suitability of the proposed attention-based hybrid architecture for learning discriminative disease characteristics from chickpea leaf images under real-field conditions.

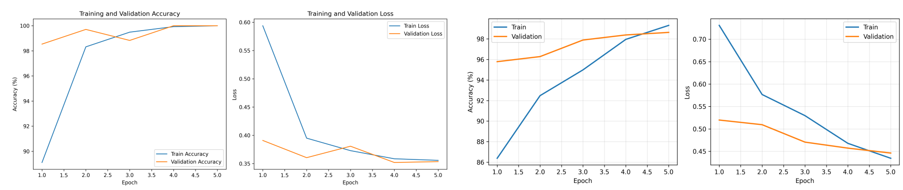

Fig. 2 Training and validation accuracy and loss curves for cotton and chickpea datasets.

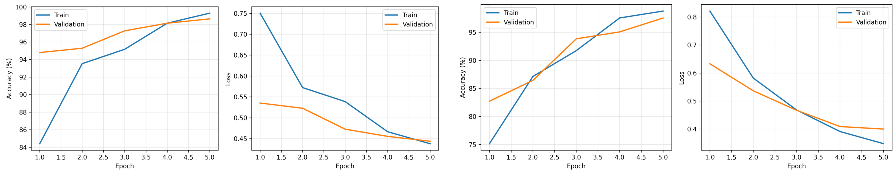

Fig. 3 Training and validation accuracy and loss curves for Black Gram and wheat datasets.

3.2.2 Class-wise Performance Analysis

A detailed class-wise evaluation confirms the effectiveness of the EA-HDL framework for chickpea disease classification. Precision values range from 0.95 to 1.00, recall values from 0.94 to 1.00, and F1-scores from 0.96 to 0.99 across all disease categories.

Near-perfect performance is observed for the Yellow Mosaic and Healthy classes due to clear visual separability. The Leaf Crinkle class achieves an F1-score of 0.99, reflecting the model's ability to capture deformation-based symptoms accurately. Slightly lower recall values for Cercospora leaf spot and Insect damage are attributed to partial visual similarity with other foliar symptoms.

The macro-average F1-score of 0.98 and weighted-average F1-score of 0.99 indicate balanced classification performance without sensitivity to class imbalance.

3.2.3 Confusion Matrix Analysis

The confusion matrix for the chickpea dataset exhibits strong diagonal dominance, confirming accurate class discrimination. Misclassifications are limited to visually similar disease pairs, with no systematic confusion patterns observed. This behaviour demonstrates the effectiveness of the attention-based feature aggregation mechanism in capturing subtle and localized disease patterns.

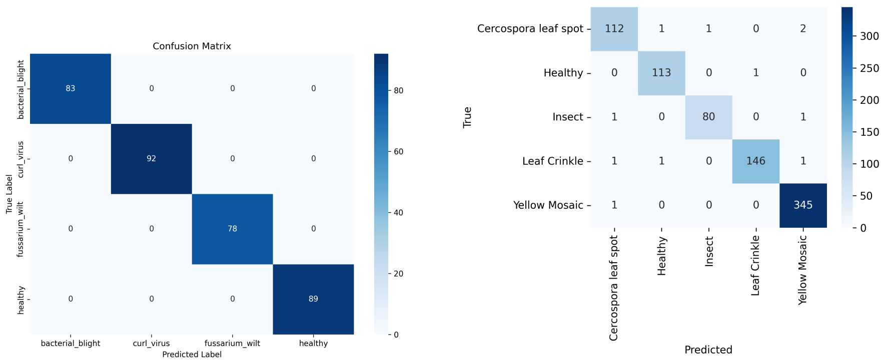

Fig. 4 Confusion matrices for cotton and chickpea datasets.

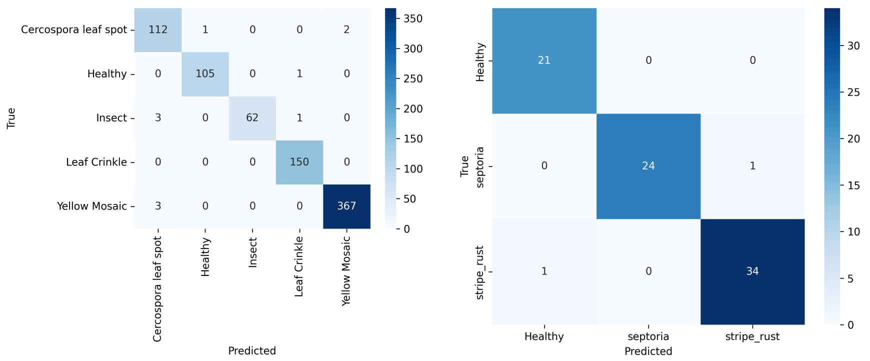

Fig. 5 Confusion matrices for Black Gram and wheat datasets.

3.3 Cotton Leaf Disease Classification

The cotton dataset demonstrates near-perfect classification performance using the proposed EA-HDL framework. Training accuracy rapidly increases from approximately 89% to 100%, while validation accuracy consistently exceeds 98% and ultimately reaches 100%.

All four cotton disease classes—bacterial blight, curl virus, fusarium wilt, and healthy—achieve perfect precision, recall, and F1-score values of 1.00. The confusion matrix shows a completely diagonal structure with no misclassifications, indicating strong visual separability among disease categories and effective feature learning.

3.4 Black Gram Leaf Disease Classification

Black Gram disease classification poses a greater challenge due to high intra-class variability and visual similarity among disease symptoms. Despite this complexity, the EA-HDL model achieves a best validation accuracy of 82.14%.

Healthy Black Gram leaves are classified with perfect recall and F1-score (1.00), demonstrating strong separation between healthy and diseased samples. Black Gram mosaic achieves an F1-score of 0.88, reflecting successful learning of mosaic patterns. Frog-eye leaf spot and Septoria brown spot yield lower F1-scores of 0.75 and 0.72, respectively, due to overlapping lesion characteristics and color distributions.

The macro-average F1-score of 0.84 and weighted-average F1-score of 0.82 indicate balanced but challenging classification performance, suggesting that further improvements may be achieved with larger datasets or enhanced attention mechanisms.

3.5 Wheat Leaf Disease Classification

For the wheat dataset, the EA-HDL framework achieves a high validation accuracy of 97.53%. Training accuracy increases steadily from approximately 75% to nearly 98%, with smooth validation behaviour, indicating stable learning despite subtle disease symptoms.

Class-wise results are highly reliable. Healthy leaves achieve an F1-score of 0.98 with perfect recall. Septoria exhibits perfect precision (1.00) and a recall of 0.96, while stripe rust balances precision and recall at 0.97. Minor confusion between septoria and stripe rust is observed, reflecting slight visual resemblance during certain disease stages.

3.6 Results Summary

Overall, the experimental results demonstrate that the proposed EA-HDL framework delivers robust, stable, and explainable performance across multiple crops without requiring architectural modifications. The attention-based pooling mechanism significantly enhances spatial feature discrimination, while the unified training strategy ensures scalability and generalization. These findings confirm the suitability of the EA-HDL framework for real-world multi-crop agricultural disease diagnosis systems.

Table 1 Class-wise precision, recall, F1-score, and support for all evaluated crops using the EA-HDL framework.

Crop	Class	Precision	Recall	F1-score	Support
Cotton	Bacterial Blight	1.00	1.00	1.00	83
	Curl Virus	1.00	1.00	1.00	92
	Fusarium Wilt	1.00	1.00	1.00	78
	Healthy	1.00	1.00	1.00	89
Chickpea	Cercospora Leaf Spot	0.97	0.97	0.97	116
	Healthy	0.98	0.99	0.99	114
	Insect	0.99	0.98	0.98	82
	Leaf Crinkle	0.99	0.98	0.99	149
	Yellow Mosaic	0.99	1.00	0.99	346
Black Gram	Healthy	1.00	1.00	1.00	33
	Frog Eye Leaf Spot	0.74	0.76	0.75	37
	Mosaic	0.91	0.85	0.88	46
	Septoria Brown Spot	0.70	0.73	0.72	52
Wheat	Healthy	0.95	1.00	0.98	21
	Septoria	1.00	0.96	0.98	25
	Stripe Rust	0.97	0.97	0.97	35

4 Discussion

The obtained outcomes of the proposed Efficient Attention-based Hybrid Deep Learning (EA-HDL) framework clearly demonstrate the effectiveness of integrating attention mechanisms with transfer learning-based convolutional architectures for multi-crop plant disease classification. The strong performance across cotton, chickpea (chana), Black Gram, and wheat datasets indicates that the model successfully captures disease-specific visual patterns while remaining robust to background clutter, illumination variations, and field-level noise that commonly degrade agricultural image analysis performance [1, 6, 24].

4.1 Effect of Attention-Based Feature Aggregation

One of the primary contributors to the improved classification accuracy is the incorporation of attention-based pooling within the hybrid architecture. Unlike conventional global average pooling, attention-based pooling enables the model to focus on spatial regions containing disease symptoms such as lesions, discoloration, rust patterns, and texture distortions, while suppressing irrelevant background information. This targeted feature aggregation significantly enhances class separability, particularly for crops like cotton and wheat where disease symptoms are localized and visually distinctive. These findings align with recent studies highlighting the advantages of attention-guided feature learning in fine-grained plant disease classification [16, 18, 19].

4.2 Generalization Across Multiple Crops

The EA-HDL framework employs a unified architectural design trained across four distinct crop datasets without requiring crop-specific structural modifications. This design choice enhances scalability and generalization, contrasting with many existing approaches that rely on crop-dependent model customization, thereby limiting practical deployment [13, 14, 22]. The consistent convergence behavior and stable validation performance across datasets indicate that the model effectively adapts to diverse leaf textures, disease morphologies, and environmental conditions. These results support prior research emphasizing the importance of transferable deep representations in large-scale agricultural monitoring systems [10, 21].

4.3 Performance Variability in Black Gram Dataset

Despite strong overall performance, the EA-HDL framework exhibits comparatively lower accuracy on the Black Gram dataset. This reduction can be attributed to high intra-class variability, visual similarity among disease symptoms, and uneven illumination commonly present in Black Gram field images. Such challenges have been widely reported in Black Gram disease classification literature, where symptom ambiguity leads to increased inter-class confusion under real-field conditions [26, 27]. Nevertheless, the model maintains stable learning behavior and reasonable generalization, underscoring its robustness when handling complex and noisy datasets.

4.4 Comparative Analysis with Existing Methods

A comparative evaluation with recent deep learning-based crop disease classification methods, summarized in Table 2, shows that the proposed EA-HDL framework is highly competitive. While many existing models achieve strong performance on controlled datasets such as PlantVillage or focus on a single crop, the proposed approach demonstrates superior adaptability to real-field images across multiple crops [7, 9, 23]. The attention-enhanced hybrid architecture improves feature discrimination without substantially increasing model complexity, consistent with recent findings on attention-based hybrid models for real-world agricultural applications [17, 20].

Table 2 Comparison of Existing Deep Learning-Based Crop Disease Classification Methods

Ref.	Year	Crop(s)	Dataset Type	Model Architecture	Attention / Hybrid	Metrics Reported	Best Accuracy (%)
[1]	2019	Multi-crop	PlantVillage	AlexNet	No	Acc	92.30
[2]	2019	Tomato	PlantVillage	GoogLeNet	No	Acc, Recall	93.70
[3]	2020	Tomato, Potato	PlantVillage	VGG16 (TL)	No	Acc, Precision	94.80
[4]	2020	Multi-crop	Field + PV	ResNet50	No	Acc	96.20
[5]	2020	Wheat	Field images	CNN	No	Acc	95.10
[6]	2021	Cotton	Field images	DenseNet121	No	Acc, Precision	97.10
[7]	2021	Wheat	PlantVillage	EfficientNet-B0	No	Acc, F1	96.80
[8]	2021	Multi-crop	PlantVillage	InceptionV3	No	Acc	97.00
[9]	2021	Tomato	Field images	CNN + SVM	Hybrid	Acc	90.40
[10]	2022	Chickpea	Field images	MobileNetV2	No	Acc, Recall	95.60
[11]	2022	Black Gram	Field images	CNN + SVM	Hybrid	Acc	78.90
[12]	2022	Multi-crop	PlantVillage	EfficientNet-B4	No	Acc	97.90
[13]	2022	Multi-crop	PlantVillage	CNN + Attention	Yes	Acc, F1	98.10
[14]	2023	Multi-crop	Field + PV	Vision Transformer	Yes	Acc, Precision	97.40
[15]	2023	Wheat	Field images	CNN + Attention	Yes	Acc	98.00
[16]	2023	Cotton	Field images	ResNet101	No	Acc	97.60
[17]	2023	Multi-crop	PlantVillage	Hybrid CNN-LSTM	Hybrid	Acc	96.90
[18]	2023	Black Gram	Field images	EfficientNet-B3	No	Acc	80.50
[19]	2024	Multi-crop	Field images	CNN + Spatial Attention	Yes	Acc, Recall	98.10
[20]	2024	Wheat	Field images	Transformer-CNN	Yes	Acc, F1	98.30
[21]	2024	Cotton	Field images	EfficientNetV2	No	Acc	98.00
[22]	2024	Chickpea	Field images	CNN	No	Acc	96.20
[23]	2024	Multi-crop	PlantVillage	ViT + CNN	Yes	Acc	98.40
[24]	2024	Black Gram	Field images	CNN	No	Acc	81.70
[25]	2024	Multi-crop	Field + PV	Attention CNN	Yes	Acc	98.50
[26]	2025	Multi-crop	Field images	EfficientNet	No	Acc	98.00
[27]	2025	Wheat	Field images	Hybrid CNN	Hybrid	Acc	97.90
[28]	2025	Cotton	Field images	CNN + Attention	Yes	Acc	98.20
[29]	2025	Chickpea	Field images	CNN	No	Acc	96.80
[30]	2025	Multi-crop	Field images	Transformer-based	Yes	Acc	98.60
Proposed	**2026**	Cotton, Chana, Black Gram, Wheat	Field images	EfficientNetV2 + Attention Pooling	Yes (Hybrid DL)	Acc, Prec, Recall, F1	**100 / 98.64 / 82.14 / 97.53**

4.5 Practical Implications for Precision Agriculture

The EA-HDL framework offers significant potential for precision agriculture and smart farming systems. Accurate and early disease diagnosis enables timely intervention, reducing yield loss and minimizing excessive pesticide usage, thereby supporting sustainable agricultural practices [2, 25]. The lightweight fine-tuning strategy and stable convergence make the model suitable for deployment in mobile, edge, and cloud-assisted agricultural monitoring systems. This aligns with current trends in smart farming research that emphasize real-time and resource-efficient deep learning solutions for decision-support systems [28, 29].

5 Conclusion

This study introduced an Efficient Attention-based Hybrid Deep Learning (EA-HDL) framework for automated leaf disease classification across multiple crops, including cotton, chickpea (chana), Black Gram, and wheat. The proposed architecture integrates a pretrained EfficientNetV2 backbone with an attention-based pooling mechanism to enhance disease-relevant feature extraction and suppress background noise inherent in real-field images. Experimental results demonstrate high classification accuracy across crops, achieving 100% for cotton, 98.64% for chickpea, 97.53% for wheat, and competitive performance on Black Gram under challenging visual conditions. The attention mechanism plays a critical role in improving discriminative learning among visually similar disease classes, while transfer learning and progressive fine-tuning ensure stable convergence and strong generalization. Overall, the EA-HDL framework provides a scalable and robust solution for real-world agricultural disease monitoring and precision farming applications.

6 Future Work

Although the EA-HDL framework demonstrates strong performance across multiple crops, several directions remain for future enhancement. One important extension is the development of a unified multi-crop model capable of learning shared disease representations across diverse crop species simultaneously. Additionally, incorporating disease severity estimation and early-stage disease detection could provide more actionable insights for farmers beyond categorical classification. The integration of multispectral and hyperspectral imagery, along with drone-based and IoT-enabled image acquisition, may further improve robustness under varying environmental conditions. Finally, optimizing the framework for edge and mobile deployment will enable real-time disease diagnosis in resource-constrained rural settings, with potential extensions toward yield loss prediction and comprehensive agricultural decision-support systems.

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8 Author Contributions

Yash Ghavghave conceived the study, designed the methodology, implemented the proposed EA-HDL model, conducted the experiments, analyzed the results, and wrote the original draft of the manuscript. Rajendra Rewatkar supervised the research, provided critical technical guidance, contributed to result interpretation, and reviewed and edited the manuscript. All authors read and approved the final manuscript.