

AgriHAFNet: A Dual Branch Neural Framework for Multi-Crop Disease Recognition

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Abstract

There is a substantial risk that agricultural diseases pose to the safety of food around the world. These diseases can cause large decreases in productivity and lead to greater expenses for farmers. Rapid and accurate detection of these diseases is necessary to improve agricultural output and ensure the industry's continued viability. Traditional techniques of visual examination, on the other hand, can be expensive, subjective, and imprecise at times, particularly in large-scale agricultural operations. This study presents AgriHAFNet, a dual-branch deep learning methodology for scalable multi-crop disease identification to address this challenge. The framework employs EfficientNet-B0 to encode specific lesion appearance features and ConvNeXt-V2 for its capacity to collect long-range, contextual data. An attention-based method connects these networks to increase robustness and accuracy. Training on 18,592 images from six crops with thirty disease categories yielded 99.77% accuracy on training images, 96.96% accuracy when validating with other images, 95.65% accuracy for unseen testing images and a macro F1-score of 0.94. The results suggest that AgriHAFNet has excellent generalization ability and potential for implementation in precision agriculture.

Keywords

ConvNeXt-V2, AgriHAFNet, EfficientNet-B0, Agricultural research, Hybrid framework.

1. Introduction

Agriculture is still the basis of many developing economies, where majority of it's the people rely on farming for their livelihoods. One of the factors that impacts productivity is crop health, which is important for ensuring food security, stable yields, and farmer income. Crop diseases, however, account for a significant risk to agricultural sustainability. The Food and Agriculture Organization (FAO) estimates that pests and diseases reduce food production globally by 20-40%, and crop diseases alone account for about 13% of total yield losses annually and cost billions of dollars in lost agriculture products (Alam,2025), (Suraj,2023). These lost crops not only decrease availability of food but also destabilize rural economies. Early and accurate detection of crop disease is necessary in this situation.

In the past, farmers and specialists would visually evaluate crops for diseases. This process is slow, subjective, and highly vulnerable to human error, especially when a farm is large and comprises a variety of different types of crops. Unfortunately, incorrect identification frequently results in improper application of pesticides and fungicides, which can cause damage to crop as well as the environment in the surrounding area. Deep learning (DL) has led to the creation of new approaches that are more objective and accurate in their analysis of many images. These methods have contributed to the advancement of deep learning. One of the analyses found that convolutional neural networks (CNNs) had high accuracy rates when learning complex layers of hierarchy from image characteristics in recent crop disease investigations (Alam, 2025), (Suraj, 2023). CNNs were used to train these layers. When tested with state-of-

the-art models such as EfficientNet, VGG19, AlexNet, and ResNet50, the accuracy rates that were reported for crops such as tomato, potato, and bell pepper were greater than 97%. A corporally, multistage DL systems that first identify a crop and then detect illness in the crop appear to be more natural in practical application (Jung,2023). These systems can identify diseases in the crops. To foster enhancements in robustness, scalability, and generalization across crops, this study proposes AgriHAFNet with a dual-branch deep learning framework for multi crop disease detection. ConvNeXt-V2 will serve as the branch for global contextual information, while EfficientNetB0 is tailored as the branch for fine-grained lesion feature detection. These branches will leverage an attention layer for an information-based fusion approach to multi-crop disease detection.

In section 2, the literature review has been shown. The methodology will be described in Section 3. In Section 4, the Results and Discussion has been shown. Conclusion and Future Work will be described in the last section.

2. Literature Review

In recent years, deep learning has made significant advancements that have led to improvements in agricultural disease detection. Current challenges relate to scalability, real-world adaptability, and generalization from the lab and/or model to field and/or public setting. Several studies have examined ML/DL methods for plant disease identification which produced useful information and thereby discovered some of the persistent limitations of ML/DL identification methods.

Wani et al. studied tomato, rice, potato, and apple disease detection methods which utilized the form of aleatoric uncertainty through the application of CNNs, Random Forests and SVMs, whilst concluding that all these methods had discovered the issue of dataset bias and ageing datasets as related to population diversity and real-world applications (Wani,2022). Waldamichael et al. considered cereal disease detection through CNNs and hyperspectral transfer learning, concluding that low population diversity limited model generalization and continued to impair ML methods (Waldamichael,2022). Domingues et al. focused specifically on the scalability and real time concern of ML based methods of pest and disease identification (Domingues,2022). Ouhami et al. used a similar methodology of integrating IoT with computer vision at 9598% accuracy but discovered data and identity inconsistencies and IoT integration challenges (Ouhami,2021).

Hybrid technology has sought to improve robustness and accuracy. Saleem et al. proposed AgriLeafNet (NASNetMobile + Few-Shot Learning) that achieved almost perfect accuracy for potatoes and mangoes, but struggled with variability in environmental conditions (Saleem,2024). Arshad et al. presented PLDPNet (VGG19 + Inception-V3, 98.66%) for intra-crop classification but also required more data of diverse sizes from different cropping systems (Arshad,2023). Malik et al. presented a hybrid VGG16-MobileNet (86%) that was limited to smaller datasets (Malik, 2022). Ullah et al. presented EffiMob-Net (99.92%) for tomatoes, but limited to a single crop (Ullah,2023). Islam et al. combined the structure of three models (VGG16, VGG19, and ResNet50) and termed it DeepCrop (98.59%) but struggled to scale because of the combination of a small dataset with a big architecture (Islam,2023).

Ensemble and transfer-learning approaches have also been tried. Ali et al. achieved 99.89% accuracy by leveraging deep ensembles, but they claimed that cross-crop generalization was poor (Ali,2020). Paymode and Malode utilized VGG-based transfer learning architecture for multi-crop classification, but they too stated that they needed to validate their approach in the field (Paymode,2022). Singh et al. achieved perfect accuracy using CNNs but without providing a deployment mechanism (Singh,2020). Khamparia et al. and Mohanty et al. demonstrated the presence of overfitting, while they stated that accuracy experienced drops in earlier unseen conditions. They emphasized, like others, the need to test diverse datasets (Khamparia,2020), (Mohanty,2016).

Additionally, smart phone-based CNN models researched by Picón et al. reported an accuracy of 93.6% (Picon,2019). Gangadharan et al. explored traditional ML methods, such as SVM and other classifiers, providing an accuracy of 89% (Gangadharan,2019), while Boulent et al. utilized a modification of classic ML methods and showed an accuracy of 95%. Furthermore, hybrid approaches are also beginning to show promise (Boulent,2019). Kawatra et al. [21] used AlexNet combined with SVM, reporting an accuracy of 99.99% while Javidan et al. used a K-means and SVM, achieving 98.97%. All approaches signified trade-offs in terms of accuracy, computational efficiency, and robustness in the field (Ferentinos,2018).

Comprehensive reviews by Ferentinos, Yuan et al. and Upadhyay et al. have shown that the challenges of overfitting, dataset size and difficulty in deployment are still a major barrier (Ferentinos,2023), (Yuan,2024), (Sunil,2023).

In conclusion, ML/DL methods have shown impressive benchmark accuracies for crop disease detection. But generalizability, field trialled ability, and lightweight deployment are still downsides. These challenges show need for agricultural solutions that scale reliably, such as AgriHAFNet, perform in real-world agricultural farming practices, and easily adapt to different environmental conditions.

3. Methodology

This paper proposed a deep learning hybrid framework for multi-crop disease detection that will increase reliability, scalability, and accuracy, in real-world conditions.

3.1 Data Collection

The dataset contains 18,592 images in total, with representations of six dominant crops (rice, wheat, corn, sugarcane, potato and jute) both healthy and diseased. The images included in this dataset are sourced from public agricultural datasets and were labelled into categories of diseases in a thorough manner to assure reliable labelling. Table 1 presents the number of images per crop and disease classes, as well as the average class balance. This dataset has diversity, which is crucial for an informative training and evaluation process.

Table 1. Distribution of Crop Diseases and Images

Crop	Disease	Images	Total
Rice	Bacterial Leaf Blight	438	2628
	Brown Spot	438	
	Leaf Blast	438	
	Leaf Scald	438	
	Narrow Brown Spot	438	
	Healthy	438	
Wheat	Brown Rust	1256	5597
	Loose Smut	939	
	Septoria	349	
	Yellow Rust	1395	
	Healthy	1658	
Corn	Cercospora Leaf Spot	513	3850
	Common Rust	1192	
	Northern Leaf Blight	985	
	Healthy	1160	
Sugarcane	Mosaic	462	2521
	Red Rot	518	
	Rust	514	
	Yellow	505	
	Healthy	522	
Potato	Bacteria	569	3076
	Fungi	748	
	Nematode	68	
	Pest	611	
	Phytophthora	347	
	Virus	532	
	Healthy	201	
Jute	Golden Mosaic	347	920

	Cercospora Leaf Spot	309
	Healthy	264

3.2 Data Exploration

Before the preprocessing stage, the dataset was thoroughly explored to assess the dataset structure, composition, and variability. The dataset contains multiple crops and disease categories, featuring variability in image count, symptoms patterns, the angle of the leaf, background, and lighting. This exploration confirmed that the dataset was suitable for training the proposed AgriHAFNet framework.

Visual inspections were conducted for representative samples from each class to confirm image quality and accurate annotation. After inspecting the images, it was found that the samples were correctly labeled as either healthy or diseased for each crop, as presented in Figure 1. In total, our dataset contains 18,592 images, with an average of approximately 620 images per class and a class image count ranging from 68 to 1,658 images per class. The assessment of the dataset established additional class imbalance observations, as well as confirming the dataset was adequately represented across categories.

The exploration ultimately presented contextual observations which were useful for determining preprocessing and augmentation considerations to provide a balanced, quality dataset used in the training of AgriHAFNet.

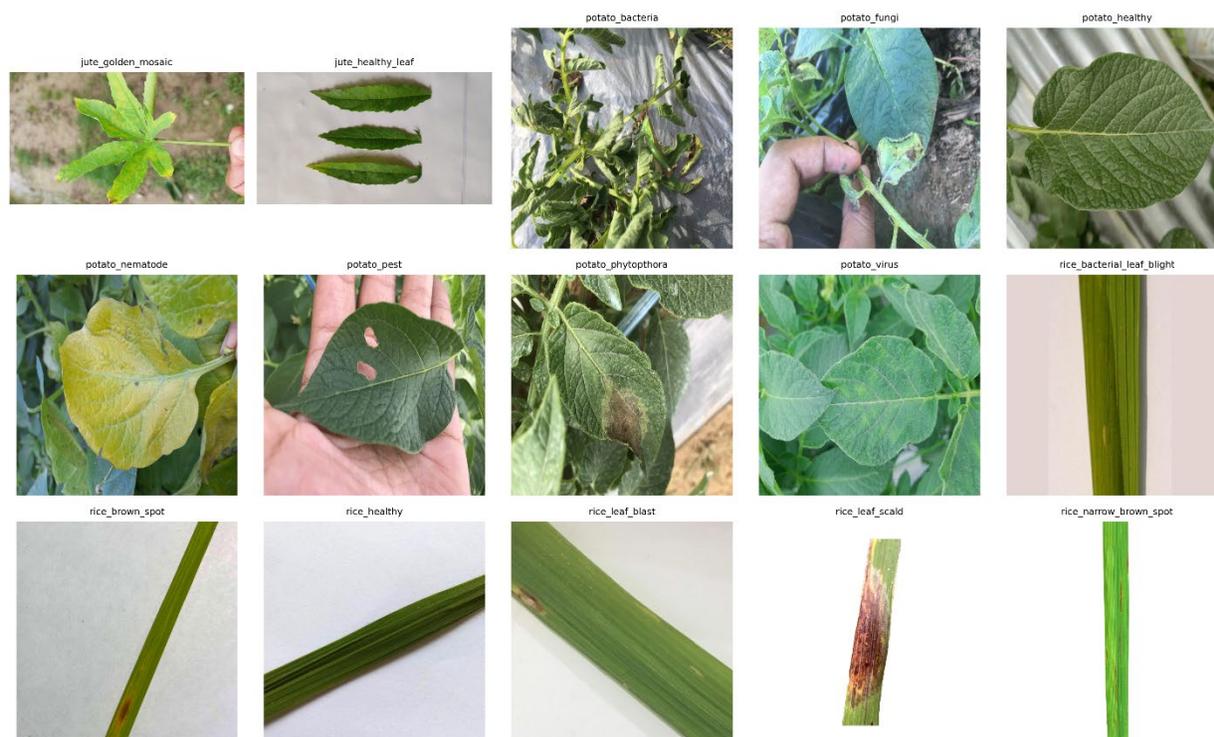


Figure 1. Representative healthy and diseased leaf samples across different crop classes.

3.3 Data Preprocessing and Augmentation

Once the dataset had been checked for errors, a comprehensive preprocessing structure was implemented to allow for a consistent dataset and potentially improve model performance. Images were resized to 224×224-pixel dimensions and normalized using the means and standard deviation from ImageNet to ensure consistency in pixel intensity distributions. Different augmentation techniques were used to help the model generalize better, including random horizontal flips, small rotations ($\pm 10^\circ$), and small adjustments on brightness, contrast, and saturation. These augmentations represent potential variations that can be expected in reality, such as lighting, leaf orientation, and background variation.

The dataset was randomly separated into training (70%), validation (15%) and testing (15%) subsets while also ensuring that class proportions remained unchanged in the proportions allocated to each subset. corresponding distributions will facilitate a representative and balanced proportion of all classes. Samples that were deemed corrupt or could not be opened for any reason were deleted, allowing for a cleaned dataset. Collectively, the preprocessing and augmentation produced a balanced, clean, and diverse dataset suitable for reliable training and evaluation of AgriHAFNet.

3.4 Framework Architecture

The AgriHAFNet (Agricultural Hybrid Attention Fusion Network) presented in Figure 2 is a two-branch hybrid framework that brings together both global contextual and local disease-specific features for effective multi-crop disease detection. AgriHAFNet reflects the foundations of the framework—agricultural applications, hybrid framework and for the attention-based feature fusion.

The overall architecture of the AgriHAFNet takes consideration of three sequential phases that enable efficient and interpretable crop disease classification. Phase 1 consists of data collection and preprocessing (resizing, normalizing, augmenting, labeling cleaning) to create a more diverse data set and handle class imbalance. Phase 2 exploits the dual feature extraction via two hybrid backbones: ConvNeXt-V2 collects wider contextual information, e.g., leaf texture, texture relationships, background patterns, etc., while EfficientNet-B0 focuses more on pinpointing finer details about leaf lesions within region of interest ROI patches (AgriHAFNet's Feature Extraction Framework). Finally, Phase 3 entails adaptively combining both feature representations through an attention-feature fusion layer that learns to create the right assigns weights to global and local feature representation for final classification.

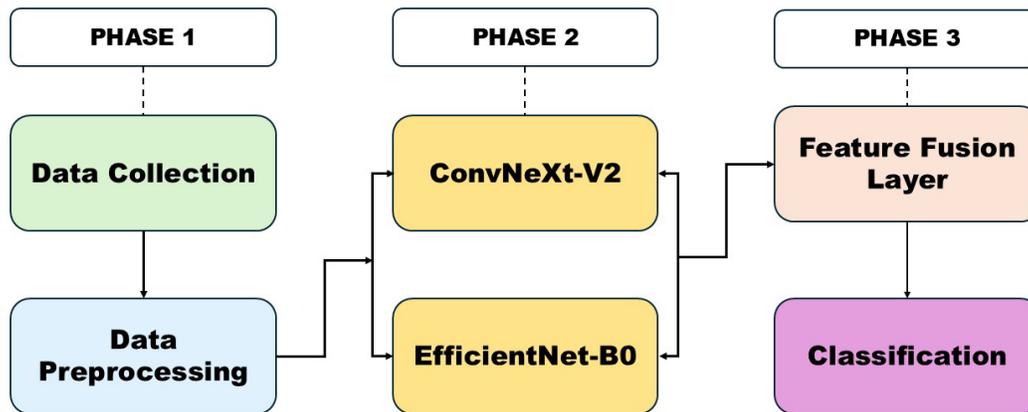


Figure 2. Dual Branch Hybrid AgriHAFNet Framework for Multi-Crop Disease Detection

This unique design allows AgriHAFNet to optimally balance both global- and localised-learning to generalise well over varying crop types and disease classes while retaining interpretability and scale in practical agricultural settings to real world use cases.

3.5 Training Procedure and Evaluation Matrices

During the training phase, the AgriHAFNet model was trained for a total of thirty epochs using a supervised learning method on the training dataset that had been created. During this time, it was made certain that the model was not exposed to either the validation or test sets. With an initial learning rate of 3×10^{-4} and a weight decay of 1×10^{-4} , the AdamW optimizer was utilized to optimize performance. This approach helped to reduce overfitting and stabilize the learning process, hence enhancing the overall performance of the system. During training, the cross-entropy loss function served as a guiding principle. This function is particularly well-suited for handling multiple numerical classes in classification tasks. In addition, Automatic Mixed Precision (AMP) was utilized to speed up the computing process and enhance the effectiveness of the training process without compromising the accuracy of the model. The model was able to fine-tune its convergence behavior thanks to a scheduling method called ReduceLROnPlateau, which

automatically dropped the learning rate by fifty percent whenever the validation loss did not improve for three consecutive epochs.

Since it is straightforward and easy to understand, accuracy was chosen as the major criterion for performance evaluation. However, the effectiveness of the model was also evaluated by using precision, recall, and F1 score. This allowed for a more comprehensive evaluation of the model's robustness, dependability, and general competence in accurately detecting and classifying the categories that were provided.

4. Results and Discussion

This section outlines the experimental results of AgriHAFNet, which include comparisons with baseline models, training behavior, and evaluations with various metrics. At the end, highlight the superiority of AgriHAFNet, in terms of the convergence patterns and performance on standard metrics, relative to different backbone models.

4.1 Training and Convergence Analysis

Figure 3 shows the activity and performance during training and validation of AgriHAFNet over 30 epochs. In sub-figure (a), the evolution of accuracy is shown. In sub-figure (b), the loss curves are shown.

Figure 3(a) shows that there is a rapid improvement in the model during the first epoch. Validation accuracy achieves 89.7% after the first epoch and 93% after the second epoch. Accuracy continues to improve and levels off at 99.77% for training accuracy, and 96.96% for validation accuracy, indicating successful learning and generalization.

The loss curves shown in Figure 3(b) support stable optimization and the performance of AgriHAFNet. The training loss drops quickly from 0.634 to 0.003, while the validation loss is low (around 0.20) with minor fluctuations. There was a close gap between training and validation losses, which indicates minimal overfitting and convergence close to the same value, which supports the reliability of the model.

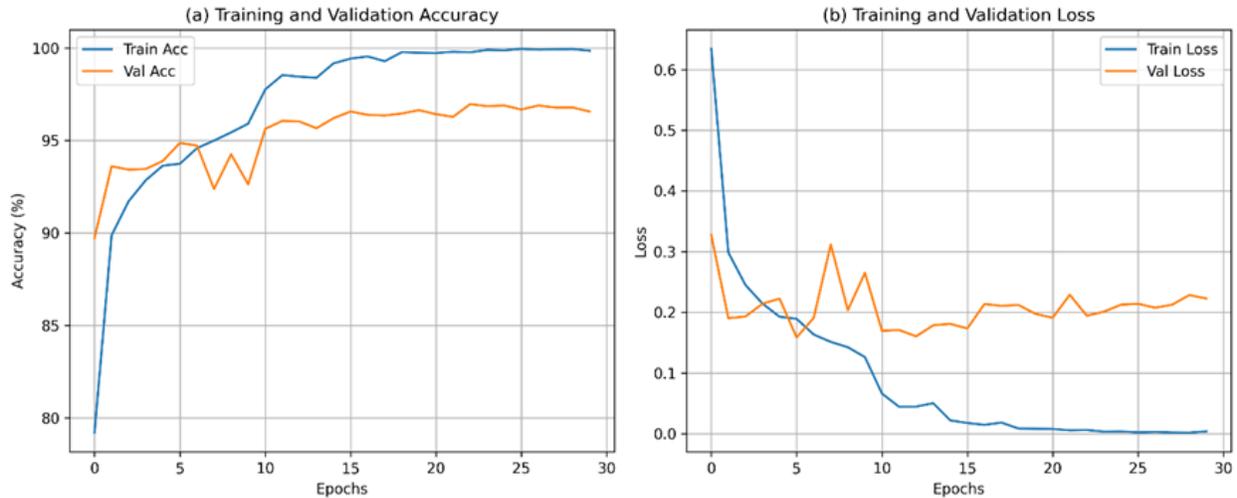


Figure 3. The training and validation performance of AgriHAFNet over 30 epochs. (a) Accuracy curves; (b) Loss curves.

4.2 Performance of AgriHAFNet

AgriHAFNet obtained a training accuracy of 99.77%, a test accuracy of 95.65%, and a validation accuracy of 96.66%. Thereby indicating its strong capability of generalization. In Table 2, precision, recall, and F1-score were used to assess class-specific performance and exhibited robustness across different crops and disease types.

AgriHAFNet's performance was primarily evaluated using accuracy (Acc), defined as:

$$Acc = \frac{TP+TN}{TP+TN+FP+FN}$$

Where TP, TN, FP, and FN donate the number of true positives, false positives, and false negatives, respectively. In addition precision (P), recall (R), and the F1-score were computed as:

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$F1-Score = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall}$$

Table 2. Class-wise Performance Metrics of AgriHAFNet

Class	Precision	Recall	F1
corn_cercospora_leaf_spot	0.935	0.935	0.935
corn_common_rust	1.000	0.989	0.994
corn_healthy	1.000	1.000	1.000
corn_northern_leaf_blight	0.966	0.973	0.970
jute_cercospora_leaf_spot	0.947	0.766	0.847
jute_golden_mosaic	0.814	0.906	0.857
jute_healthy_leaf	0.927	0.950	0.938
potato_bacteria	0.944	0.988	0.966
potato_fungi	0.829	0.814	0.821
potato_healthy	0.829	0.936	0.879
potato_nematode	0.700	0.636	0.667
potato_pest	0.784	0.750	0.767
potato_phytophthora	0.846	0.830	0.838
potato_virus	0.866	0.879	0.872
rice_bacterial_leaf_blight	0.971	1.000	0.985
rice_brown_spot	0.970	0.970	0.970
rice_healthy	0.985	1.000	0.993
rice_leaf_blast	0.954	0.939	0.947
rice_leaf_scald	1.000	1.000	1.000
rice_narrow_brown_spot	1.000	1.000	1.000
sugarcane_healthy	0.918	0.933	0.925
sugarcane_mosaic	0.956	0.942	0.949
sugarcane_redrot	0.930	0.918	0.924
sugarcane_rust	0.911	0.897	0.904
sugarcane_yellow	0.988	0.976	0.982
wheat_brown_rust	0.941	0.929	0.935
wheat_healthy	0.922	0.937	0.929
wheat_septoria	0.875	0.857	0.866
wheat_smut	0.958	0.966	0.962
wheat_yellow_rust	0.979	0.988	0.983
Accuracy	0.956		
macro avg	0.936	0.935	0.935
weighted avg	0.956	0.956	0.956

4.3 Representation of the Evaluation Matrix

The performance of the proposed AgriHAFNet model is shown in Figure 4 by class-wise, which shows normalized confusion matrices for all thirty-crop disease and healthy leaf classes. To make it clearer the Figure is separated into three different subplots; (a), (b), (c) correspond to classes 1-10, 11-20, and 21-30 respectively. Each cell shows the prediction accuracy for an individual class and is expressed as the percentage of correctly classified samples against the total for the class.

As can be seen, most of the diagonal percentages are over 90%, illustrating accurate and consistent classification relative to disease classes. Some classes achieved a recognition accuracy of 100%, such as corn_healthy, rice_narrow_brown_spot, and sugarcane_redrot. This indicates that the model can correctly extract discriminative features across a range of visual appearances. Some classes exhibited relatively low performance, such as potato_nematode and jute_cercospora_leaf_spot, yet even here the performance is reasonably consistent, except for some confusion about visually similar diseases. This is an excellent result and showcases the merging capabilities of AgriHAFNet, where the EfficientNet-B0 and ConvNeXt-V2 extract features to fine-grained textures and global contextual signals. A strong diagonal dominance of the confusion matrices confirms superior inter-class separability and generalization across heterogeneous crops and diseases, further supporting the model's reliability in agricultural diagnostics.

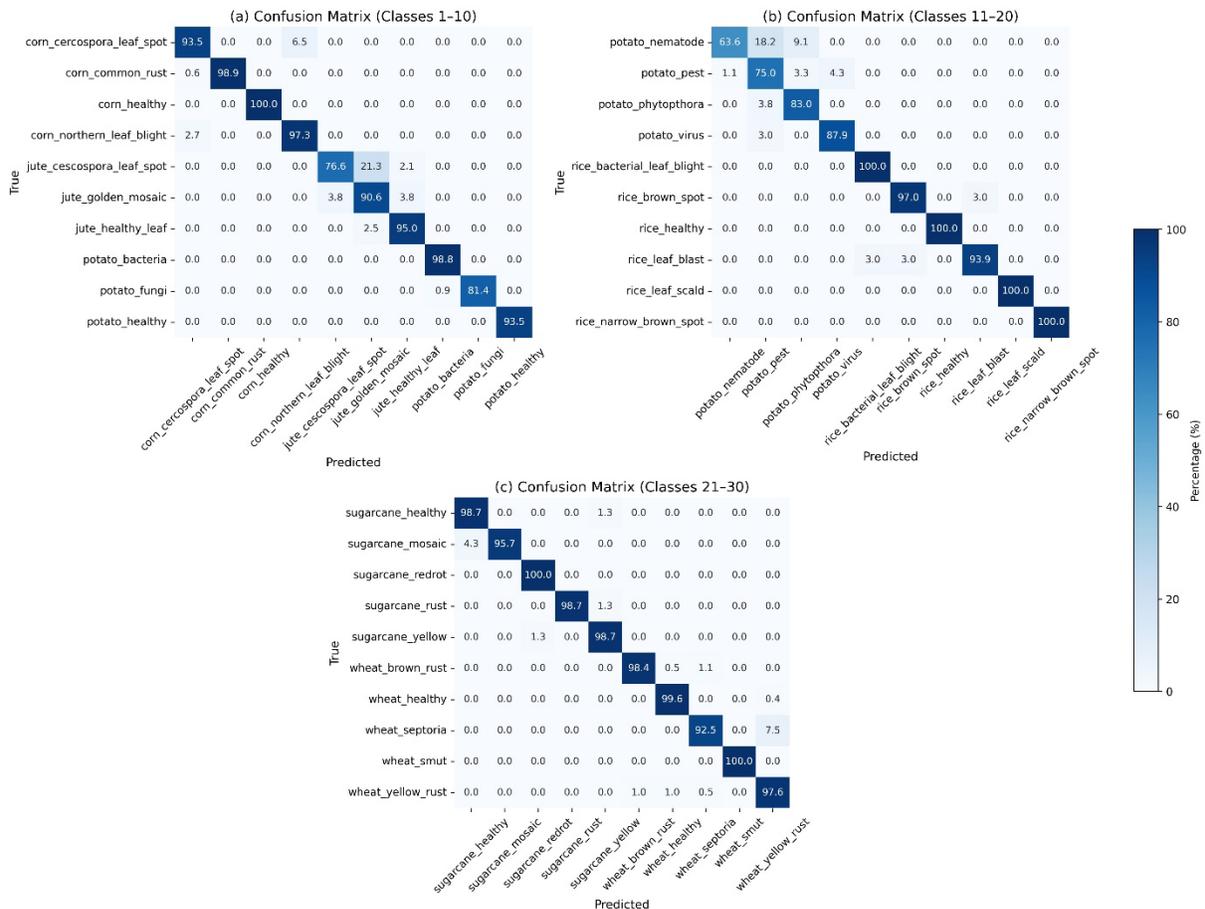


Figure 4. Normalized confusion matrices of AgriHAFNet for thirty crop disease and healthy leaf classes.

4.4 Comparative Evaluation of Proposed Model

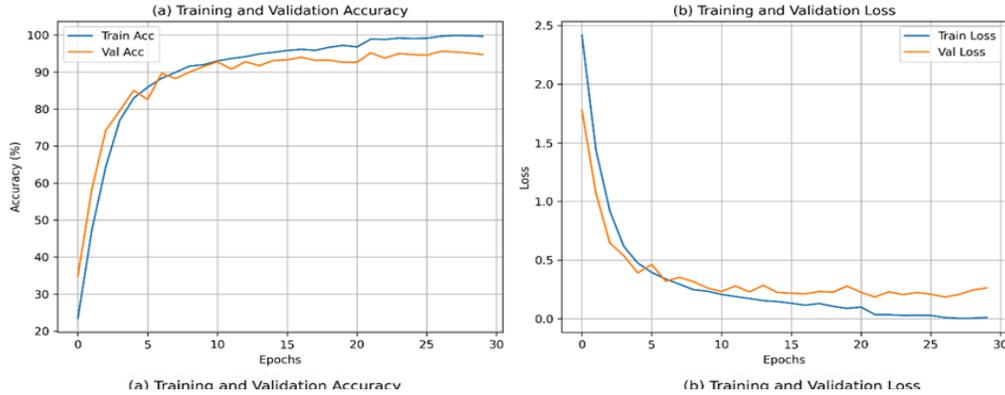


Figure 5. The training and validation accuracy and loss of ConvNeXt-V2 over 30 epochs

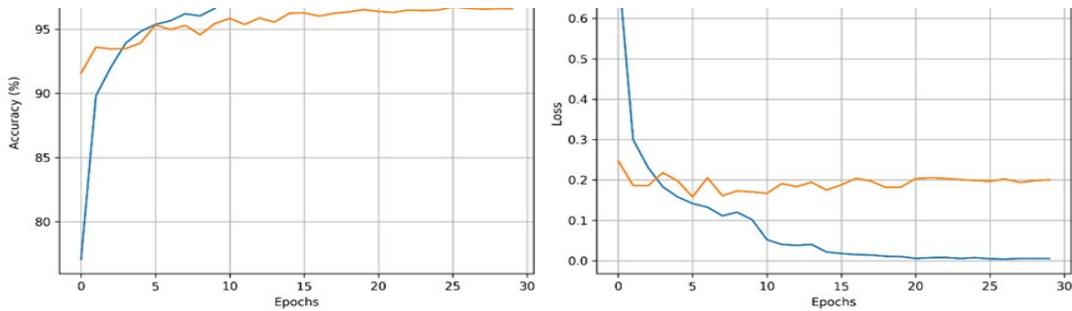


Figure 6. The training and validation accuracy and loss of EfficientNet-B0 over 30 epochs

In this subsection, AgriHAFNet is compared with its backbone networks, ConvNeXt-V2 and EfficientNet-B0, to demonstrate advantages of global and local features. ConvNeXt-V2 independently achieved an accuracy of 99.66% training, 94.71% test, and 95.59% validation accuracy (Figure 5). It effectively captures higher-level contextual features but marginally lacks similar performance related to localized disease attributes. EfficientNet-B0 independently achieved an accuracy of 99.88% training, 96.04% test, and 96.75% validation accuracy (Figure 6), effectively modelling fine-grained lesions but cannot model global context as well.

The suggested AgriHAFNet achieved training accuracy of 99.77%, test accuracy of 95.65%, and validation accuracy of 96.96%, effectively combining global and local features via its dual-branch fusion (discussed in IV-A). The hybrid solution benefited the feature representation and violated only the classification robustness of its backbones, undertaken with a global and local feature classification solution, and provided a model for improved generalization and stability in crop disease classification.

4.5 Overall Discussion

The suggested AgriHAFNet framework addresses major shortcomings of previously existing CNN and hybrid models, where an innovative due branch fusion of ConvNeXt-V2 and EfficientNet-B0 combines feature diversity, robustness, and generalization capabilities. Previous model limitations and improvements, denoted by Table 3, are summarized.

Table 3. Summary of Prior Limitations and Improvements Achieved by AgriHAFNet

Limitation (from Literature)	Improvement by AgriHAFNet
Limited generalization and dataset diversity (Wani,2022), (Waldamichael,2022), (Domingues,2022).	Achieved 95.65% test and 96.96% validation accuracy via dual-branch feature fusion.
Overfitting and poor scalability in hybrid CNNs (Arshad,2023), (Malik,2022).	Maintained minimal gap between training (99.77%) and validation (96.96%) accuracy.
Weak feature representation under real-world variations (Ouhami,2021), (Islam,2023).	Dual-branch fusion (ConvNeXtV2 + EfficientNet-B0) captured both global and local cues (F1 > 0.93).
Confusion among visually similar diseases (Kawatra,2020), (Javidan,2023).	Confusion matrix (Figure 4) shows >90% diagonal dominance, reducing misclassification.
Lack of robustness across multiple crops (Ali,2024), (Paymode,2022).	Classified 30 categories with 95.6% accuracy, confirming strong cross-crop adaptability.

AgriHAFNet remains consistently strong across thirty crop species. The dual learning context enhances discriminative learning while balanced training reduces overfitting. As evidenced by these results, generalization, stability, and cross crop performance are enhanced, thus confirming the trustworthiness of the framework for practical use in diagnosing agricultural disease across multiple crops.

5. Conclusion and Future Work

The paper proposed AgriHAFNet, a dual-branch deep learning framework, to enhance the precision and reliability of detection for multiple crop diseases. In the abstract, wide context features were applied using ConvNeXt-V2, while for fine-grained and disease-specific features, EfficientNet-B0 was employed. Further, both features are fused using an attention-based approach that may automatically weigh local and global features according to their classification potential. Robust and consistent classification performances were shown in the experiment results, i.e., a total training accuracy of 99.77%, validation accuracy of 96.96%, and test accuracy of 95.65%, while macro average F1 was equal to 0.94. In overall terms, the potential of this hybrid framework is apparent, such as robustness, scalability, and applicability in real-world agricultural settings.

Even though the results of the framework are beneficial, it is by no means perfect. In the future, we will be working on further development of feature fusion and attention modules for a more in-depth and efficient representation of features. We also intend to develop architecture that has been deployed onto real-time functionality on edge or mobile devices with an application for farmers and/or monitoring systems in agriculture. We will also investigate explainable AI methods for the development of a more trusted and explainable model for the end-user in agricultural operational settings.

In fact, AgriHAFNet will continue to be enhanced and transformed through these directions into a more intelligent, efficient, and transparent framework while bringing the benefits of artificial intelligence in the agricultural process and contributing positively to the development of sustainable precision agriculture.

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References

- Ali, A. H., Youssef, A., Abdelal, M. and Raja, M. A., An ensemble of deep learning architectures for accurate plant disease classification, *Ecological Informatics*, vol. 81, pp. 102618, 2024.
- Alam, G. M. M., Reddy, G. N., Reddy, K. S. C., Vishnu, K. S. and Vighnesh, K., Crop disease detection and classification using deep learning, 2025.
- Arshad, F., Mateen, M., Hayat, S., Wardah, M., Al-Huda, Z., Gu, Y. H. and Al-Antari, M. A., PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction, *Alexandria Engineering Journal*, vol. 78, pp. 406–418, 2023.
- Boulent, J., Foucher, S., Théau, J. and St-Charles, P. L., Convolutional neural networks for the automatic identification of plant diseases, *Frontiers in Plant Science*, vol. 10, pp. 941, 2019.
- Domingues, T., Brandão, T. and Ferreira, J. C., Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey, *Agriculture*, vol. 12, no. 9, pp. 1350, 2022.
- Ferentinos, K. P., Deep learning models for plant disease detection and diagnosis, *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
- Gangadharan, K., Kumari, G. R. N. and Dhanasekaran, D., Classification and functional analysis of major plant disease using various classifiers in leaf images, *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, no. 2, pp. 4241–4248, 2019.
- Islam, M. M., Adil, M. A., Talukder, M., Ahamed, M. K., Uddin, M. A., Hasan, M. K., Sharmin, S., Rahman, M. M. and Debnath, S. K., DeepCrop: Deep learning-based crop disease prediction with web application, *Journal of Agriculture and Food Research*, 2023.
- Javidan, S. M., Banakar, A., Vakilian, K. A. and Ampatzidis, Y., Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning, *Smart Agricultural Technology*, vol. 3, pp. 100081, 2023.
- Jung, M., Song, J. S., Shin, A. Y., Choi, B., Go, S., Kwon, S. Y. and Kim, Y. M., Construction of deep learning-based disease detection model in plants, *Scientific Reports*, vol. 13, no. 1, pp. 7331, 2023.
- Kawatra, M., Agarwal, S. and Kapur, R., Leaf disease detection using neural network hybrid models, in *Proc. IEEE 5th Int. Conf. on Computing Communication and Automation (ICCCA)*, pp. 225–230, 2020.
- Khamparia, A., Saini, G., Gupta, D., Khanna, A., Tiwari, S. and de Albuquerque, V. H. C., Seasonal crops disease prediction and classification using deep convolutional encoder network, *Circuits, Systems, and Signal Processing*, vol. 39, no. 2, pp. 818–836, 2020.
- Malik, A., Vaidya, G., Jagota, V., Eswaran, S., Sirohi, A., Batra, I. and Asenso, E., Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach, *Journal of Food Quality*, vol. 2022, pp. 9211700, 2022.
- Mohanty, S. P., Hughes, D. P. and Salathé, M., Using deep learning for image-based plant disease detection, *Frontiers in Plant Science*, vol. 7, pp. 215232, 2016.
- Ouhami, M., Hafiane, A., Es-Saady, Y., El Hajji, M. and Canals, R., Computer vision, IoT and data fusion for crop disease detection using machine learning: A survey and ongoing research, *Remote Sensing*, vol. 13, no. 13, pp. 2486, 2021.
- Paymode, A. S. and Malode, V. B., Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG, *Artificial Intelligence in Agriculture*, vol. 6, pp. 23–33, 2022.
- Picon, A., Seitz, M., Alvarez-Gila, A., Mohnke, P., Ortiz-Barredo, A. and Echazarra, J., Crop conditional convolutional neural networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions, *Computers and Electronics in Agriculture*, vol. 167, pp. 105093, 2019.
- Saleem, S., Sharif, M. I., Sharif, M. I., Sajid, M. Z. and Marinello, F., Comparison of deep learning models for multi-crop leaf disease detection with enhanced vegetative feature isolation and definition of a new hybrid architecture, *Agronomy*, vol. 14, no. 10, pp. 2230, 2024.
- Singh, A., Sharma, R. and Bharti, N., Comparative analysis of deep CNN models for plant disease classification, *Procedia Computer Science*, vol. 167, pp. 1819–1828, 2020.

- Sunil, C. K., Jaidhar, C. D. and Patil, N., Systematic study on deep learning-based plant disease detection or classification, *Artificial Intelligence Review*, vol. 56, pp. 14955–15052, 2023.
- Suraj, B., Avdesh, K. and Sharma, A., A research paper on crop disease detection using deep learning model, *International Journal for Science Technology and Engineering*, vol. 11, no. 31, pp. 399–406, 2023.
- Ullah, Z., Alsubaie, N., Jamjoom, M., Alajmani, S. H. and Saleem, F., EffiMob-Net: A deep learning-based hybrid model for detection and identification of tomato diseases using leaf images, *Agriculture*, vol. 13, no. 3, pp. 737, 2023.
- Waldamichael, F. G., Debelee, T. G., Schwenker, F., Ayano, Y. M. and Kebede, S. R., Machine learning in cereal crops disease detection: A review, *Algorithms*, vol. 15, no. 3, pp. 75, 2022.
- Wani, J. A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S. and Singh, S., Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges, *Archives of Computational Methods in Engineering*, vol. 29, no. 1, pp. 641–677, 2022.
- Yuan, Y., Sun, J. and Zhang, Q., An enhanced deep learning model for effective crop pest and disease detection, *Journal of Imaging*, vol. 10, no. 11, pp. 279, 2024.

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