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Comprehensive Review

AFD-Net: Wheat Foliar Disease Multi-Classification Using Deep Learning on Plant Pathology Datasets – A Comprehensive Review

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Abstract: Wheat foliar diseases such as leaf rust, stripe rust, tan spot, and powdery mildew continue to threaten global wheat production, necessitating rapid and accurate diagnostic tools to support timely disease management. Recent advances in deep learning have enabled high-performance image-based detection systems, with AFD-Net (Attention and Feature-Distilled Network) emerging as a state-of-the-art framework for fine-grained wheat disease classification. This review synthesizes current knowledge on AFD-Net architectures, training strategies, benchmark datasets, evaluation metrics, and real-world applicability. We highlight how the integration of attention mechanisms, multi-scale feature extraction, and feature distillation enables the model to capture subtle visual differences among closely related foliar diseases. Comparative analysis with existing convolutional neural networks and transformer-based models demonstrates the superior accuracy, robustness, and computational efficiency of AFD-Net across multiple plant pathology datasets. Additionally, we discuss practical deployment pathways including mobile-based diagnosis, drone-assisted crop monitoring, breeding program integration, and disease forecasting systems along with existing challenges related to dataset quality, environmental variability, model generalization, and explainability. Finally, future research directions are proposed to enhance model interpretability, dataset diversity, multimodal fusion, and transfer learning capabilities. Overall, AFD-Net represents a significant advancement in automated wheat foliar disease detection and holds strong potential for supporting sustainable and precise crop protection.

Keywords: AFD-Net, Wheat foliar diseases, Deep learning, Attention mechanisms, Feature distillation, Image-based disease detection, Precision agriculture, multi-class classification.

Introduction

Wheat is one of the world's most important staple crops, providing nutrition for billions of people and playing a vital role in global food security. As global population and consumption patterns continue to rise, the need to maintain stable wheat production becomes increasingly urgent [1]. Ensuring sustainable wheat productivity is therefore essential for meeting future food demands.

However, wheat production is severely threatened by a range of foliar diseases, including Septoria tritici blotch (STB), stripe rust, leaf rust, powdery mildew, and tan spot. These pathogens frequently cause substantial yield losses, especially under favorable environmental conditions, and they increase production costs due to repeated fungicide applications [2,3]. In East Africa, diseases such as stripe rust and STB remain major constraints, with recurrent epidemics threatening food security and farmer livelihoods [4].

Traditional diagnosis of wheat foliar diseases relies heavily on visual inspection and field scouting, techniques that are labor-intensive, time-consuming, and dependent on the expertise of trained pathologists. Accuracy often varies due to subjective judgment, and in regions where experts are limited, misdiagnosis or delayed diagnosis is common [5]. These challenges highlight the need for efficient, scalable, and objective disease detection systems.

Recent advances in artificial intelligence particularly deep learning (DL) and computer vision have opened new possibilities for automated plant disease detection. DL-based models can process large datasets and extract complex visual features, enabling rapid and highly accurate diagnosis of multiple wheat diseases [6,7].

Hybrid and ensemble models integrating CNNs, transformers, and multi-scale feature extraction have shown exceptional classification accuracy, with some achieving over 99% precision in wheat disease detection [8,9].

To further improve accuracy and efficiency, recent studies have introduced specialized neural network architectures designed for plant pathology datasets. Among these, the Attention-based Feature Distillation Network (AFD-Net) has gained significant attention for its ability to combine attention mechanisms with feature distillation to improve recognition performance [10,11]. Although originally applied to other crops, its architecture has strong potential for multi-class wheat foliar disease classification. Combined with advances in drone and hyperspectral imaging for large-scale monitoring, such models represent a promising direction for next-generation disease surveillance [12,13].

Deep Learning in Plant Disease Detection

Deep learning has emerged as a transformative approach in plant disease detection, offering substantial improvements over classical machine-learning and manual inspection methods. The introduction of Convolutional Neural Networks (CNNs) marked a pivotal shift in the field, allowing automated extraction of complex visual patterns directly from leaf images. Early studies such as [14,15] demonstrated that CNN-based models can outperform traditional handcrafted feature techniques, establishing deep learning as a reliable tool for plant pathology applications.

Over the past decade, numerous deep learning architectures have been introduced and widely adopted in plant disease recognition tasks. Classical models such as ResNet [16], DenseNet [17], and EfficientNet [18] have been frequently applied to classify a wide range of crop diseases due to their strong feature extraction capabilities. More recently, transformer-based architectures such as Vision Transformers [19] have been adapted for agricultural image analysis, offering improved global attention modeling and enhanced performance, particularly in large-scale datasets.

Recent studies (2023–2025) have continued to refine these architectures for application in real agricultural environments. For example, [7] applied modified CNNs for multi-class wheat foliar disease recognition under field conditions, while [8] combined CNNs with transformer modules to handle complex backgrounds and varying light conditions. Similarly, [9] proposed a multi-scale feature extraction framework that integrates multiple backbone networks for improved diagnostic accuracy. These advancements highlight the growing trend toward more robust, adaptable, and high-performing deep learning models tailored specifically to plant disease datasets.

One major advantage of deep learning systems is their ability to automatically learn hierarchical features directly from raw images. This eliminates the need for manual feature engineering and allows the model to capture subtle lesion patterns, color variations, and texture differences that distinguish similar disease symptoms. As noted by [20], CNN-based systems can achieve high classification accuracy across diverse disease classes, making them powerful tools for multi-disease detection in real agricultural settings. The integration of attention mechanisms and feature distillation in recent models further enhances classification precision by focusing on the most informative regions of the leaf.

Despite the significant progress, several limitations continue to challenge deep learning applications in plant disease detection. Factors such as variations in lighting, leaf orientation, background noise, and overlapping symptoms can reduce classification performance, especially in field environments where image conditions are less controlled. [21] highlighted the difficulty of distinguishing between diseases with similar visual characteristics or differentiating disease symptoms from abiotic stresses. Even modern architectures may struggle with generalization across new environments or unseen cultivars, emphasizing the need for more robust datasets, improved domain-adaptation techniques, and better integration of multimodal sensing technologies.

Wheat Foliar Diseases

Wheat foliar diseases constitute one of the most significant threats to global wheat production, with multiple pathogens capable of infecting leaves at various growth stages. These diseases often cause substantial yield reductions, and their accurate identification is essential for timely management. However, differentiating among foliar diseases remains a major challenge due to the diverse and dynamic nature of symptom expression across environmental conditions and wheat cultivars [22].

A major difficulty in disease classification arises from the substantial overlap in visual symptoms produced by different pathogens. For instance, Septoria tritici blotch (STB) and tan spot frequently exhibit similar necrotic lesions, making them hard to distinguish based solely on leaf appearance. STB typically shows elongated, dark-brown necrotic lesions with pycnidia, while tan spot produces lens-shaped tan necrotic spots yet these characteristics often overlap under field stress, leading to confusion during visual assessment [23].

Rust diseases such as stripe rust, leaf rust, and stem rust present additional classification difficulties because their symptoms vary widely depending on the pathogen species and the stage of infection.

Stripe rust produces yellow, narrow, elongated pustules, whereas leaf rust forms rounder, orange-brown uredinia. However, color intensity, pustule size, and distribution can change depending on leaf age, temperature, and pathogen development stage [24]. These variations often challenge even trained pathologists, especially under mixed infection scenarios.

Environmental conditions further complicate disease identification. Factors such as humidity, leaf wetness, solar radiation, and nutrient stress can modify symptom severity, causing lesions to appear atypical or mimic those of other diseases. For example, nutrient deficiencies, herbicide injury, and drought stress can produce chlorosis, necrosis, or leaf spotting, which closely resemble foliar disease symptoms. This overlap increases the likelihood of misclassification in field scouting and image-based disease detection systems [22].

Given these complexities, accurate classification of wheat foliar diseases using traditional visual methods is inherently limited. These challenges underscore the need for advanced computational tools capable of capturing subtle differences in lesion shape, texture, and spectral signatures. Deep learning models, especially those enhanced with attention mechanisms, multi-scale feature extraction, and hyperspectral imaging, offer significant promise in overcoming these diagnostic barriers. However, their success depends on carefully curated datasets that reflect real field variability and the diverse manifestations of wheat foliar diseases.

Architecture of AFD-Net

The Attention-based Feature Distillation Network (AFD-Net) is a specialized deep learning architecture designed to improve fine-grained classification of wheat foliar diseases. By combining attention mechanisms with feature distillation, AFD-Net can focus on the most informative regions of a leaf while compressing and transferring knowledge from a larger teacher model to a smaller, efficient student model. This approach allows the network to capture subtle differences between visually similar disease symptoms, such as the overlapping necrotic patterns of STB and tan spot [10,11].

The attention mechanism within AFD-Net enhances feature extraction by weighting spatial and channel-wise information according to its relevance for disease classification. This ensures that critical lesion regions and texture patterns contribute more strongly to the final prediction, reducing the influence of background noise and irrelevant leaf regions. AFD-Net architecture often integrates residual or dense blocks, which facilitate gradient flow and improve feature representation at multiple scales, making the model robust to variations in lighting, leaf orientation, and environmental conditions [25].

Feature distillation further strengthens the model by enabling a compact student network to learn from a more complex teacher network. Knowledge distillation transfers soft labels or intermediate feature representations, helping the student model mimic the teacher's decision-making process without the computational cost of a large network. This combination of attention and distillation not only improves classification accuracy but also allows deployment in resource-limited environments, making AFD-Net a practical solution for large-scale wheat disease monitoring [26,10].

Plant Pathology Datasets for Training AFD-Net

1. Plant Village Dataset

The PlantVillage dataset is one of the most widely used benchmarks for plant disease detection, providing high-quality, annotated images of leaves from a variety of crops, including wheat, maize, and potato [27]. This dataset has played a pivotal role in the development and evaluation of deep learning models, as it offers well-labeled images representing both healthy and diseased leaves under controlled conditions. Its structured format allows researchers to train models with consistent ground truth, facilitating reproducibility and comparative evaluation of classification architectures.

Although images in PlantVillage are primarily captured in laboratory or greenhouse environments, the dataset offers diverse disease classes and lesion patterns, enabling models to learn discriminative features for multiple diseases. The dataset's high-resolution images allow backbone networks such as ResNet-50 or EfficientNet-B3 to extract hierarchical features effectively, which can later be refined using attention modules and feature distillation in architectures like AFD-Net [14].

However, models trained solely on PlantVillage images may exhibit limited generalization when applied to field images, as controlled lighting and background conditions do not fully reflect natural variability. To address this, researchers often combine PlantVillage with field-based datasets, enhancing model robustness and real-world applicability. Despite this limitation, PlantVillage remains a foundational resource for benchmarking and pre-training deep learning models in plant pathology.

2. Wheat Disease Field Images

Field-based wheat disease datasets capture images under real-world agricultural conditions, including variable lighting, leaf orientation, soil backgrounds, and mixed infections [22].

Unlike controlled datasets, field images present natural variability that challenges models to distinguish visually similar diseases, such as STB and tan spot, across different cultivars and environmental conditions. This makes field datasets essential for improving the generalization of deep learning models.

Collecting and annotating field images requires substantial effort, as disease symptoms may be subtle or overlapping, necessitating expert pathologists for accurate labeling. Despite these challenges, the inclusion of field-based images in training datasets significantly enhances model performance under practical deployment scenarios, particularly when combined with attention mechanisms that help focus on disease-relevant regions [10].

Incorporating field images also enables models to learn variations caused by abiotic stress, nutrient deficiency, and other non-disease factors that mimic disease symptoms. This improves the model's robustness against false positives and enhances real-world applicability, making field-based wheat datasets a critical component in training AFD-Net for reliable disease detection.

3. Kaggle Wheat Disease Sets

Kaggle hosts several crowdsourced wheat disease datasets that aggregate images contributed by researchers and farmers worldwide. These datasets provide diverse samples representing multiple wheat foliar diseases captured under varying environmental conditions, from smallholder farms to experimental plots. The diversity of these datasets exposes models to a wide range of lesion shapes, colors, and backgrounds, which is particularly useful for developing robust deep learning models.

The crowd-sourced nature of Kaggle datasets presents both advantages and challenges. On one hand, these datasets increase the diversity and volume of training data, allowing models to generalize better across geographic regions and disease stages. On the other hand, variations in image quality, labeling accuracy, and inconsistent metadata require careful preprocessing and quality control before using the images for training advanced models like AFD-Net.

Despite these limitations, Kaggle wheat datasets have been successfully used to benchmark multi-class disease classification models. They complement controlled datasets and field-based images by providing additional variability, which enhances model resilience to real-world conditions and improves overall prediction accuracy.

4. Regional Ethiopian Wheat Datasets

Regional datasets, such as those collected in Ethiopia, are particularly valuable because the country is a global hotspot for wheat foliar diseases, including stripe rust and STB [28]. These datasets reflect local wheat cultivars, environmental stresses, and pathogen populations, providing context-specific information that enhances the relevance of deep learning models trained for regional disease management.

Ethiopian wheat datasets often include both greenhouse and field-collected images, capturing disease progression under varying agroecological zones. This allows models to learn how disease symptoms manifest under different temperature, humidity, and soil conditions. When incorporated into AFD-Net training, these datasets improve the network's ability to accurately classify wheat diseases in local settings, supporting precision agriculture and early-warning systems.

Moreover, regional datasets address the limitations of global datasets by offering unique lesion patterns, disease combinations, and infection stages that may not be represented elsewhere. Combining these datasets with benchmark datasets like PlantVillage and Kaggle improves both the generalization and specificity of models, ultimately contributing to more reliable and regionally applicable wheat disease detection systems.

Performance of AFD-Net Compared to Other Models

Attention-based deep learning models have demonstrated significant advantages in plant disease classification, particularly when dealing with fine-grained visual datasets where subtle differences in lesion morphology are critical. By focusing on the most informative regions of the input image, attention mechanisms enhance feature localization and reduce the influence of irrelevant background noise. As a result, attention-based models consistently outperform traditional CNN architectures in multi-class classification tasks [29].

AFD-Net, which integrates attention modules with feature distillation and hierarchical backbone networks, exhibits superior performance compared to classical CNNs. The combination of attention-guided refinement and distilled feature transfer allows the model to capture both low-level and high-level discriminative features effectively, making it especially suitable for distinguishing visually similar wheat foliar diseases. This capability contributes to its high classification accuracy across multiple disease classes [29,30].

Comparative evaluations of popular architectures on benchmark wheat disease datasets show the relative performance of different models. ResNet models achieve overall accuracies ranging from 90% to 94%, while DenseNet reaches 92%–96%. EfficientNet, with optimized depth and width scaling, attains 93%–97% accuracy. Vision Transformers (ViT), leveraging self-attention mechanisms, achieve 94%–98% accuracy.

AFD-Net outperforms all of these architectures, achieving classification accuracies between 95% and 99% due to its effective combination of backbone networks, attention mechanisms, and feature distillation [29,30].

These results highlight the importance of integrating attention and feature distillation in deep learning models for agricultural applications. By improving feature localization and discriminative capacity, AFD-Net not only achieves higher accuracy but also offers robustness under varying environmental conditions, leaf orientations, and mixed-infection scenarios. Consequently, it represents a state-of-the-art approach for automated wheat foliar disease detection and multi-class classification tasks in real-world agricultural environments.

Practical Applications of AFD-Net in Agriculture

Deep learning-based wheat disease detection systems, such as AFD-Net, have a wide range of practical applications in modern agriculture. One of the primary uses is in early warning systems, where timely identification of foliar diseases allows farmers and agronomists to implement targeted interventions before epidemics spread. Early detection of diseases such as Septoria tritici blotch, rusts, or powdery mildew helps reduce yield losses and minimizes unnecessary fungicide applications, improving both crop productivity and sustainability [31].

In precision agriculture, AFD-Net and other deep learning architectures enable accurate mapping of disease prevalence across large fields. By integrating with drone imagery or multispectral sensors, these models provide spatially explicit disease information, allowing site-specific management practices. Farmers can optimize pesticide use, irrigation, and fertilization, reducing costs and environmental impact while maintaining high crop performance [32]. Such precision-targeted interventions are particularly important in wheat-growing regions with limited resources or heterogeneous field conditions.

Another key application is in disease resistance breeding programs. Deep learning models can rapidly phenotype large breeding populations, identifying resistant and susceptible genotypes with high accuracy. By automating the scoring of foliar disease severity, models like AFD-Net accelerate selection cycles, enhancing breeding efficiency and supporting the development of resistant wheat cultivars [33]. This approach is especially valuable for managing diseases with overlapping symptoms or variable expression across environments.

Finally, the mobile deployment of disease detection models has transformed farmer decision-making. Lightweight deep learning models can be integrated into smartphone applications, enabling farmers to capture leaf images in the field and receive immediate diagnostic feedback. This empowers smallholder farmers and extension agents to make informed management decisions, reducing crop losses and promoting sustainable practices [34]. The combination of high accuracy, real-time feedback, and ease of use makes mobile AFD-Net applications a powerful tool for modern agriculture.

Limitations and Research Gaps

Despite the notable success of AFD-Net in wheat foliar disease classification, several limitations and research gaps remain that need to be addressed for broader applicability. One major challenge is dataset imbalance, where some disease classes, such as tan spot, are underrepresented compared to others like rusts. Imbalanced datasets can bias the model toward more frequent classes, reducing classification accuracy for minority diseases and limiting the generalizability of the model in diverse field conditions [35].

Another significant challenge is domain shift across regions. Models trained on datasets from one geographic area may perform poorly when applied to wheat images from different climates, soil types, or cultivars due to variations in lighting, leaf morphology, and disease expression. This limitation highlights the need for more diverse, multi-region datasets and for domain-adaptation techniques that can enhance model robustness across heterogeneous environments [35].

Finally, mixed infection scenarios present additional difficulties. Wheat leaves can simultaneously be infected by multiple pathogens, such as STB co-occurring with stripe rust. Such overlapping symptoms complicate the feature extraction and classification process, even for advanced networks like AFD-Net. Current models often struggle to distinguish individual diseases in these complex cases, indicating the need for multi-label classification approaches or enhanced feature disentanglement methods [36]. Addressing these gaps will be critical for improving automated disease detection systems and enabling reliable, large-scale deployment in precision agriculture.

Future Directions

Despite significant advances in deep learning for wheat foliar disease classification, several research avenues remain promising for enhancing model performance, interpretability, and practical applicability. One key direction is the development of transformer–CNN hybrid architectures, which combine the local feature extraction strengths of CNNs with the global attention capabilities of transformers. Such hybrid models have shown great potential in capturing both fine-grained lesion details and broader contextual information in plant images, thereby improving multi-class disease recognition [19,8].

Another promising approach is the use of Generative Adversarial Networks (GANs) for data augmentation. GANs can synthetically generate diverse leaf images that mimic real-world disease variability, including different lighting conditions, lesion shapes, and mixed infections. This technique can significantly expand training datasets, helping deep learning models generalize better to unseen field conditions and rare disease presentations [37,7]. GAN-based augmentation is especially useful in scenarios where collecting large-scale annotated plant pathology datasets is challenging.

The integration of explainable AI (XAI) techniques is also critical for improving the transparency and trustworthiness of disease detection models. Methods such as Grad-CAM allow visualization of the regions contributing most to the model's predictions, enabling pathologists and agronomists to validate and interpret automated diagnoses. Explainable models can facilitate wider adoption of AI-based disease monitoring in practical agricultural settings, as they provide actionable insights rather than black-box predictions [38].

Finally, combining deep learning models with crop disease forecasting and advisory systems can strengthen real-time decision-making in precision agriculture. Integrating predictive models that account for weather, pathogen dynamics, and host susceptibility with image-based diagnostic tools can provide timely management recommendations, optimize fungicide applications, and reduce yield losses. Such integrated systems have the potential to transform wheat disease management by bridging the gap between early detection and actionable intervention [39,13].

In summary, future research should focus on hybrid model architectures, synthetic data generation, explainability, and integration with predictive advisory tools to enhance the reliability, applicability, and impact of AI-based wheat disease management. These directions promise to advance precision agriculture and improve global wheat productivity in the face of evolving pathogen threats.

Conclusion

The Attention-based Feature Distillation Network (AFD-Net) represents a major advancement in automated wheat foliar disease diagnosis, offering a powerful combination of attention mechanisms and feature distillation to enhance fine-grained classification. By leveraging hierarchical feature extraction from backbone networks and focusing on disease-relevant regions, AFD-Net can accurately distinguish visually similar diseases such as Septoria tritici blotch, tan spot, and various rusts, even under challenging field conditions [10,11].

The high precision and robustness of AFD-Net make it suitable for practical deployment in diverse agricultural settings. Its adaptability allows integration with mobile applications, drone-based monitoring platforms, and breeding programs, enabling large-scale, rapid disease assessment. Moreover, coupling AFD-Net with decision-support and predictive advisory systems can facilitate timely interventions, optimize fungicide usage, and reduce yield losses, contributing to sustainable wheat production [7,39].

In conclusion, AFD-Net exemplifies the potential of modern deep learning architectures in plant pathology, bridging the gap between advanced AI research and real-world agricultural applications. Future work focusing on hybrid transformer–CNN designs, GAN-based data augmentation, explainable AI, and integration with forecasting models will further enhance the model's performance, interpretability, and utility in precision agriculture. Such innovations are critical to supporting global food security by enabling effective, data-driven wheat disease management strategies.

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