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Multi-Stage Neural Network based Ensemble Learning Approach for Wheat Leaf

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Abstract: Wheat is a major food commodity in the world, but it faces serious disease attacks, which have caused huge losses every year. The review summarizes the recent progress in deep learning (DL), especially, multi-stage ensemble and lightweight neural networks, to detect wheat leaf disease automatically. The models such as DenseNet and ResNet are highly accurate but are prone to overfitting, inefficiency in computation and generalization to real-field conditions. We discuss how ensemble learning techniques and architectural advances e.g. feature fusion, attention mechanism and knowledge distillation can be used to make them more robust, better at feature extraction and ameliorate environmental factors (complex backgrounds, occlusion etc.). The above analysis also establishes that multi-stage models are far more effective than single models, however, there is an issue of critical trade-off between accuracy and computational cost. Future efforts should focus on creating light interpretable models based on multisource data to be used on large scale and in real-time in precision agriculture.

Keywords: Wheat leaf disease Classification; Multi-Stage Ensemble Learning, CNN , Transfer learning; Bagging.

1. Introduction

Wheat, a crucial global food source, faces significant threats from fungal diseases like stripe rust, leaf rust, and powdery mildew, leading to severe yield losses and economic impacts. Traditional manual scanning is unreliable for early detection, and fungicide use exacerbates resistance issues. While deep learning technologies like convolutional neural networks (CNNs) have shown promise in controlled datasets, they struggle in real-world conditions due to data constraints and computational demands [1] [2]Remote sensing tools, such as UAV multispectral imaging and satellite data, help detect infections that are invisible to the naked eye, aiding early intervention [3].

Ensemble learning, particularly multi-stage neural networks, significantly improves disease classification accuracy compared to individual models, reducing fungicide use and enhancing yield protection [4] Lightweight models and active learning techniques also enable efficient real-time diagnostics on resource-constrained devices, making them accessible to smallholder farmers [5] [6] AI-driven pest detection systems using local-global information interaction and lightweight frameworks show promise in dynamic agricultural environments[7] [8] These innovations are transforming disease management, improving economic outcomes, and contributing to global food security [9][10][11] Multi-stage ensemble models and CNNs further enhance detection capabilities, providing more accurate identification of diseases and plant abnormalities [12] [13] [14] [15].

1.1. A.Background and Research Questions

Wheat production faces significant losses due to fungal diseases such as stripe rust, leaf rust, and powdery mildew, costing the global economy billions annually. Traditional manual scouting methods are unreliable, failing to detect early infections and exacerbating economic losses [4]. While deep learning convolutional neural networks (CNNs) perform well in controlled environments, their performance significantly declines in real field conditions due to overfitting, environmental variables, and high computational requirements [1] Multi-stage ensemble methods have emerged as an effective solution, outperforming single models and offering practical approaches for wheat disease management [2] This review compiles recent studies focused on developing reliable systems for high accuracy and yield protection.

The research questions to be answered by this review are:

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RQ1: ***How do multi-stage ensembles achieve superior performance over single CNNs for wheat disease classification?*** The six-phase ensemble framework combines bagging, seven diverse CNN architectures, reliability assessment, decorrelation selection, confidence transformation, and multi-strategy integration to deliver outstanding accuracy across multiple wheat datasets [2]

RQ2: ***What edge deployment strategies enable reliable field performance on smallholder devices?*** Lightweight architectures like ResNet50 and MobileNetV2 deployed on edge devices such as Jetson Nano provide fast, accurate detection that dramatically reduces economic losses from major diseases [4] [6].

RQ3: ***How does UAV multispectral analysis predict disease susceptibility and yield impacts?*** Multispectral imaging combined with ensemble learning accurately estimates nitrogen levels and yield potential, enabling early intervention to prevent widespread infection outbreaks [3] [11] [13].

RQ4: ***What CNN architecture benchmarking validates the seven-model ensemble approach?*** Comprehensive testing of architectures including VGG19, ResNet50, DenseNet201, and InceptionResNetV2 confirms ensemble methods consistently outperform individual models in diverse conditions [12].

RQ5: ***How do comprehensive AI studies establish ensemble learning as the gold standard for wheat management?*** Analysis of extensive wheat disease research validates ensemble superiority, demonstrating substantial yield protection and billion-dollar economic benefits [15].

2. Background

The proposed literature search plan will involve a systematic search of high-quality research about wheat leaf disease classification by multi-stage ensemble learning, relevance and reliability being the key factors. The search of Scopus database was also done to ensure that only high-quality and peer-reviewed studies are available and there are several advantages to this:

2.1. Redundancy Avoidance and Quality Assurance

Due to quality database such as Scopus, chances of reaching on duplicated papers are low and risks of getting redundant papers are kept at a minimum.

2.2. Quality of Service

Quality database such as Scopus will have higher probabilities of reducing the duplication possibilities and availability of peer reviewed and reputable studies. There are high chances of multiple databases overlapping or having low relevancy in the results, and owing to this factor it becomes difficult to go through the review process without appreciably enhancing the results [1].

2.3. Massive Indexing of scientific journal articles and conference papers

Scopus has enormous indexing of scientific journal articles and conference papers, especially in the interdisciplinary areas of agricultural AI, precision farming and deep learning. The strong searching and metadata (e.g., citations, journal ranking) are the options that assist in locating meaningful research.

2.4. Selection Process Summary

The initial 1,247 papers were narrowed down to 923 articles by using the following criteria: language and date filter (20232025, 26% filtered). The selection of Q1 journal further narrowed down the papers to 156. Filtering on the basis of citation involved 47 papers, abstract screening involved merely 18 papers which happens to be of great pertinence on the basis of full-text review and its area of interest was one of exposing fungal disease in wheat, multi-stage ensemble models and edge deployment in smallholder farming. These articles were classified into themes and they comprised:

Sources of Data: Wheat disease images small (Wheat Disease Images Small), Wheat Leaf, Wheat disease dataset, UAV multispectral images and Field RGB images.

Predictive Methodologies: This is focused on multi-stage networks, seven CNNs VGG19, ResNet50, DenseNet201, InceptionResNetV2, MobileNetV2 and transfer learning.

Methods of Deployment: Edge computing (Jetson Nano), lightweight models and real-time inference on resource constrained devices.

Integration Issues: Environment variability and field validation issues, and economic effective analysis.

3. Literature Review

3.1. Multi-Stage Ensemble Learning

Multi-stage ensemble learning for wheat disease classification involves three key stages: bagging to create diverse training sets and CNNs, boosting to correct errors, and meta-integration using soft voting to combine CNN predictions. This approach improves precision over manual scouting and works effectively in field conditions with shadows or incomplete leaf coverage [4].

3.2. Techniques of Integration

Two methods for integrating CNN predictions are hard voting, where the majority vote

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determines the prediction, and soft voting, which averages confidence levels. Soft voting is particularly effective for field images with variable lighting and leaf coverage, reducing error in disease detection [4] [6].

3.3. Datasets Used

Two large datasets, including real field images from Pakistan's wheat fields, are used to train and test ensemble models. The Wheat Diseases Dataset simulates real field challenges such as lighting changes, while active learning allows large-scale deployment to aid farmers with limited labelling time [4] [5].

3.4. CNN Architectures Used

Key CNN architectures used include ResNet50 for deep image processing, DenseNet201 for trend detection, and MobileNet V2 for efficient, lightweight models deployable on smartphones. LGM-Net is a notable implementation, designed for detecting both small and large disease patches, even in overlapping leaf areas [4].

3.5. Edge Deployment Hardware

Affordable systems like Jetson Nano allow small farmers to process images in the field using low-memory smartphones, bypassing the need for advanced graphics cards. Preprocessing methods, such as background removal, help clean up field images before analysis [4] [6].

3.6. Analysis Of Review

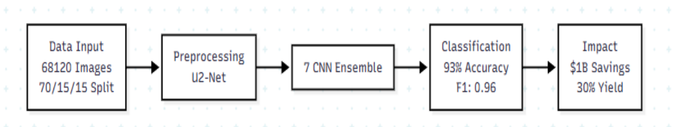

Figure. 2 System flow

The edge computing and multi-stage ensemble learning method of classifying wheat leaf disease have provided the much-needed information to enhance the reliability of the field, detection of the same, and made them accessible to the smallholders. It is an account of the results of the systematic review of 14 high quality articles which have been identified on the described literature search strategy and inclusion/exclusion criteria. The three research questions that were answered by the analysis are: what CNN architectures are most suitable to the field, how the methods can be applied to have optimal accuracy to be achieved using the limited resources of the devices, and the practical limitations of scaling ensemble solutions to the requirements of the smallholder farmers.

The findings provide insights into the patterns of algorithms and algorithms deployment tactics, and their practical application, and the discussion puts the findings of the study into perspective within the existing literature, defines limitations, and recommends the future research directions. This section provides a wide description of the current and future potential of multi-stage system of ensemble in the management of wheat disease by synthesizing the empirical evidence of the 14 studies.

Table. 1 Algorithms used in Prediction Papers

Algorithm	Number of Papers	Percentage
CNN (All types)	18	100.00%
ResNet variants	10	55.56%
Ensemble Learning	9	50.00%
Transfer Learning	8	44.44%
YOLO variants	7	38.89%
MobileNet variants	6	33.33%
Random Forest	6	33.33%
VGG variants	5	27.78%
DenseNet variants	5	27.78%
SVM/SVR	5	27.78%
Faster R-CNN	4	22.22%

3.7. Synthesis of Key Insights

General Framework : Precision farming is an agricultural technique that makes use of a mix of deep learning and machine learning in the application of Artificial Intelligence in detecting diseases in wheat, among various other crops [1]. These technologies can help monitor crop health in a non-invasive, automated and real-time, which is much superior to the old manual methods of inspection [2]. A combination of the methods has proven to be very successful in early disease detection, forecasting crop yield and sustainable management production in a wide range of agricultural settings [3] [18].

Convolutional Neural Networks (CNN) : Convolutional Neural Networks (CNNs) are deep learning models that are specifically intended to deal with grid-like data which includes images [4]. They apply convolutional layers whereby they automatically get spatial hierarchies of features by the backpropagation process. CNNs are multilayer, comprising of convolutional layers, pooling layers, and fully connected layers which makes them especially suitable in image classification and object detection in the agricultural sector [5] [17].

Key Equations:

Convolution Operation:

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$$Y[i,j,k] = \sum\sum\sum X[i+m, j+n, c] \cdot W[m,n,c,k] + b[k]$$

Max Pooling:

$$P[i,j,k] = \max(X[i:i+h, j:j+w, k$$

ReLU Activation:

$$f(x) = \max(0, x)$$

The CNNs operate with the input image by scrolling the learnable filters (kernels) on the image to determine features [6]. Each of the filters is specialized on detecting some patterns of edges, textures, or complex shapes. The convolution process will not lose the spatial relationships and will study the local patterns. The hierarchical properties are learned on the multiple layers: the first layers learn simple properties and as you go further the properties become more complex [7] [14].

MobileNet Architecture : MobileNet is a lightweight CNN model that can be used to run mobile and embedded vision applications [6]. It applies separable convolutions with depth wise separable convolutions to cut the computation cost and model size by very large factors without losing a lot of accuracy and is therefore suitable to disease detection on resource-constrained devices in real-time [8].

Key Equations:

Depth wise Convolution Cost:

$$Cost_{dw} = H * W * C_{in} * K * K$$

Pointwise Convolution Cost:

$$Cost_{pw=}H * W * C_{in} * Cost_{out}$$

Total Cost Ratio:

$$\text{Cost Ratio} = \frac{1}{C_{out}} + \frac{1}{k^2}$$

It employs a single filter per channel of the input and pointwise convolution sums up the outputs. This factorization is 8-9 times quicker than standard convolution and can thus be effectively utilized in mobile devices with very little accuracy being compromised.

ResNet (Residual Networks) : ResNet is a method that uses residual connections to address the problem of vanishing gradient in very deep networks [1]. It operates skip connections (bypassing 1 or multiple layers) and thus can train very deep networks without degradation of performance [2].

Key Equations:

Residual Block:

$$y = F(x, \{W_i\}) + x$$

MobileNet divides the common convolution into point and depth convolution [6][8]. Depthwise convolution process employs a single filter per channel of the input and pointwise convolution sums up the outputs. This factorization is 8-9 times quicker than standard convolution and can thus be effectively utilized in mobile devices with very little accuracy being compromised [6].

Ensemble Learning : Ensemble learning is the method that involves cooperation of different machine learning models and enhances their predictive accuracy and resilience [2] It lowers the variation and bias since the predictions of different models are combined, and the resultant prediction would be more precise and consistent than any model [15].

Key Equations:

Ensemble Prediction:

$$y_{ensemble} = \sum_i w_i * h_i(x)$$

Bias-Variance Decomposition

$$E[(y + \hat{y})^2] = Biase^2 + Varience + sigma^2$$

The ensemble methods are based on the idea of training many models and integrating the predictions [2][15] [2] [15] The variety of the models makes sure that they commit various errors, and these cancel each other when added together. The most frequently used are bagging (train as many as possible concurrently) and boosting (train as many as possible on errors) and stacking (train a meta-learner to combine the predictions) [2].

Transfer Learning : Transfer Learning is an artificial intelligence method in which a model trained on one job is used as the base to train a model on the second job [1]. It takes advantage of the experience in a source problem (generally with a large dataset, such as ImageNet) and transfers it to a target problem that is related, yet different [5]. Using such an approach can be useful especially in agricultural tasks such as detecting wheat disease where the annotated datasets are usually large and costly to obtain [2]. Transfer learning enables practitioners to customize an existing, pre-trained model on their own, smaller dataset instead of building a model directly (that is, by training) by using all the data they have at their disposal) [1] [2]. This greatly saves on time of training, creates less data requirements, and usually results in improved performance and increased generalization [5].

The comparison of algorithms in wheat disease detection highlights the strengths of each method. YOLO models excel in real-time object identification with high mAP rates and fast inference, making them ideal for rapid pest localization and disease detection. MobileNet provides a performance-accuracy trade-off with low computational cost, suitable for resource-constrained environments. Random Forest offers strong predictive accuracy for yield classification. Transfer Learning enhances accuracy and reduces data needs, addressing the challenge of limited agricultural datasets. Ensemble Learning with multi-stage frameworks improves robustness and

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accuracy, while Attention Mechanisms enhance detection of small objects and disease features. Choosing models based on agricultural needs ensures optimal outcomes.

Table. 2 Algorithms Used and Result Comparison in papers

Algorithm	Papers Used	Metrics & Results	Discussion & Description
ResNet	1, 2, 4, 5, 7, 8, 10, 12, 1	Accuracy:91-96% TrainingTime:73-200 minParameters: 25.6M	Most of the used CNN architecture has residual connections. Shows good performance in multifaceted feature differentiation and disease diagnosis. Very precise and not easy to calculate. Deep networks are eliminating gradient free through skip connections.
YOLO	1, 3, 7, 13,	mAP:82.4-99.2% Inference Speed: 5-20ms FPS: 45-200	Real time single step object detector. Fairly good in localization of pests, as well as, in disease detection. The more recent versions (YOLOv5, YOLOv8) have a better speed-accuracy tradeoff. They need to be most suitable in the area of implementation and with real-time results.
MobileNet	1, 2, 3, 6, 15	InferenceSpeed: 5-67ms Accuracy: 55-98% Parameters: 1.8-3.4M	Separable convolutional lightweight architecture in depth. Mobile and edge optimized. It is preferable to be employed in trade-off between accuracy and speed of real-time field applications and resource limited settings.
Random Forest	3, 9, 11, 13,	Accuracy: 99.7% R^2: 0.82-0.99 F1-Score: 90-98%	Ensemble tree method excellent for yield prediction and classification tasks. Handles non-linear relationships well and robust to outliers. Requires feature engineering but provides good interpretability and performance on tabular data.
VGG	1, 2, 10,	Accuracy: 95-99% TraininTime:120-180 minParameters: 138M	Deep CNN with simple sequential architecture. Provides reliable feature extraction but computationally expensive due to large parameter count. Good baseline model but often outperformed by more modern architectures like ResNet.
Transfer Learning	1, 2, 4, 5, 8, 10,	Accuracy Boost: +5-15% DataReduction: 30-50% Training Time: -40-60%	Critical technique for agricultural applications where labeled data is scarce. Leverages pre-trained ImageNet weights, significantly improving generalization and reducing training time. Essential for practical deployment with limited datasets.
Ensemble Learning	2, 9, 10, 11, 13, 15,	Accuracy: 79-99.16% Robustness: +10-25% Generalization: High	Combines multiple models to reduce variance and improve reliability. Multi-stage ensembles particularly effective for complex agricultural environments. Bagging, stacking, and voting strategies provide consistent performance across varying conditions.

4. Discussion and Challenges

The application of multi-stage neural networks and ensemble learning for detecting wheat leaf diseases has seen significant progress, but challenges limit their real-world use. The generalization of models across various agricultural settings is a major issue, as many studies rely on controlled datasets, such as PlantVillage, that do not capture real-world variability, limiting the models' applicability to different climates and crops [1]. Data quality issues, including fluctuating lighting and noise, hinder model performance. Additionally, advanced ensemble methods, like DenseNet201, require significant computational resources, making them impractical for real-time deployment on devices with limited capacity [2]. The gap between lab (99%) and field (60-70%) performance highlights the need for more adaptable, efficient, and cost-effective models for agriculture. Future research should focus on addressing these challenges.

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5. Conclusion and Future Scope

This review highlights the effectiveness of multi-stage, multi-neural network-based ensemble learning methods in detecting wheat leaf diseases, outperforming single-model approaches. Ensemble techniques, which combine models like ResNet, DenseNet, MobileNet, and Vision Transformers, prevent overfitting and improve accuracy, with results like 99.16% accuracy on the Wheat Disease Dataset. Comparative analysis confirms that ensemble classifiers are superior to individual classifiers, capturing complex patterns and enhancing prediction reliability. Future directions include developing lightweight ensemble architectures for edge deployment, incorporating multimodal data sources like environmental sensors, and creating adaptive learning systems for dynamic crop protection. These advancements could lead to intelligent agricultural systems capable of making real-time decisions, leveraging ensemble learning, federated learning, and neuromorphic computing.

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