



International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991



Vol. 22 No. 2(1) (2026)



ijerst.editor@gmail.com
editor@ijerst.com

Research Paper

MULTI STAGE NEURAL NETWORK BASED ON ENSEMBLE LEARNING APPROACH FOR WHEAT LEAF DISEASE CLASSIFICATION

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Abstract

Wheat leaf diseases significantly affect crop productivity and quality, making early and accurate detection crucial for sustainable agriculture. This study proposes a multi-stage neural network-based ensemble learning approach for automated wheat leaf disease classification. The framework integrates deep learning models, specifically EfficientNetB0, ResNet50, and a custom CNN with an Attention Mechanism, leveraging transfer learning for effective feature extraction.

A feature fusion (concatenation) algorithm is employed to combine outputs from these three models, followed by a fully connected layer (256 units) with a 0.5 dropout rate for regularization. The system was trained on a Kaggle wheat leaf disease dataset through the Adam optimizer and categorical cross-entropy loss. The proposed architecture achieved a validation accuracy of 95.60% and a low validation loss of 0.1185, demonstrating balanced performance and resilience against overfitting. Furthermore, a real-time prediction module was implemented for practical field deployment. These results confirm the model is robust and scalable for precision agriculture, enabling timely diagnosis and improved crop management.

KEYWORDS: Wheat Leaf Disease Classification, Ensemble Learning, Transfer Learning, Convolutional Neural Network (CNN), EfficientNetB0, ResNet50, Image Classification, Precision Agriculture, Data Augmentation, Model Generalization, Disease Detection, Softmax Classification, Computer Vision.

I. Introduction

Wheat (*Triticum aestivum*) is one of the most widely cultivated and consumed cereal crops in the world, playing a fundamental role in ensuring global food security and supporting agricultural economies. It serves as a staple food for billions of people and contributes significantly to the livelihoods of farmers, especially in developing countries like India. However, wheat production is continuously threatened by a wide range of plant diseases, particularly leaf-based diseases such as Septoria, Stripe Rust, Leaf Blight, and Tan Spot. These diseases adversely affect both the yield and quality of crops, leading to substantial economic losses. According to agricultural studies, plant diseases can reduce wheat production by up to 20–30% annually if not detected and controlled at an early stage. Therefore, timely and accurate identification of wheat

leaf diseases is critical for effective crop management and sustainable agricultural practices.

Traditionally, disease detection in crops has been performed through manual inspection by trained agricultural experts or farmers. While this method can be effective in certain cases, it suffers from several limitations. Manual inspection is time-consuming, labor-intensive, and often subjective, as it depends on the experience and expertise of the observer. In large-scale farming environments, continuous monitoring of crops becomes impractical. Moreover, early-stage symptoms of diseases are often subtle and difficult to detect with the naked eye, leading to delayed diagnosis and treatment. This delay can result in the rapid spread of diseases across fields, significantly impacting productivity. Consequently, there is a growing need for automated, efficient, and reliable disease detection systems that can assist farmers in making timely decisions.

In recent years, advancements in artificial intelligence (AI), particularly in deep learning and computer vision, have opened new possibilities for automated plant disease detection. Convolutional Neural Networks (CNNs) have emerged as one of the most powerful tools for image classification tasks due to their ability to learn hierarchical feature representations directly from raw image data. Various deep learning architectures such as EfficientNet, ResNet, MobileNet, DenseNet, and VGGNet have been successfully applied to plant disease classification problems. These models are capable of extracting both low-level features such as edges and textures, as well as high-level semantic features that represent disease patterns. Additionally, transfer learning techniques allow these pre-trained models, originally trained on large-scale datasets like ImageNet, to be fine-tuned for specific agricultural tasks with limited data availability. This significantly reduces training time and improves model performance.

II. Literature Survey

Gajanan, A., & Preetham, N. [1] 2026 Deep Learning for Smart Agriculture: A Comprehensive Review of CNN Architectures... This study reviews deep learning techniques for crop disease detection using datasets from Scopus, Web of Science, and PlantVillage. It focuses on CNN architectures, transfer learning, and explainable AI. Results highlight high accuracy but challenges like overfitting and dataset limitations. This work supports our approach by emphasizing multi-model and transfer learning strategies, aligning with our multi-stage ensemble method for robust wheat disease classification.

Ghavghave, Y., & Rewatkar, R. [2] 2026 Precise Identification of Wheat Diseases using Enhanced VGG16. This research uses a hybrid dataset (PlantVillage + field images) with 16,885 samples. It applies transfer learning on VGG16 with CBAM attention and multi-scale convolutions. The model achieves 97.17% accuracy. It relates to our project by demonstrating improved feature extraction using attention mechanisms, which supports our ensemble approach for enhancing classification performance.

Prabhakar, V., Misra, P., Bhatt, S., Gupta, R., & Dubey, S. K. [3] 2026 API-Based Plant Disease Detection using Vision Transformer. This paper uses the PlantVillage dataset (55,448 images) and applies transfer learning on a Swin Transformer model. It achieves near 100% training accuracy and supports API-based deployment. This

relates to our idea by highlighting transformer-based models and real-time applications, which can be integrated into our ensemble framework to improve prediction accuracy.

Begum, S., E. N., & NN, S. [4] 2026 Hybrid Model using ResNet50, PCA, and SVM for Disease Classification. This study uses the PlantVillage dataset and combines ResNet50 feature extraction with PCA and SVM. It achieves ~89.4% validation accuracy while reducing overfitting and computational complexity. This supports our project by showing the effectiveness of hybrid models, aligning with our ensemble learning strategy for improved efficiency and accuracy.

Kalejahi, B. K., Yahyayeva, S., Abdurahmanova, I., & Hasanzade, S. [5] 2026 Lightweight Deep Learning using MobileNetV2 and ResNet50. This research evaluates MobileNetV2 and ResNet50 on ~87,000 images. MobileNetV2 achieves 98.33% accuracy with lower computational cost. It highlights model efficiency and real-time deployment. This directly supports our work by suggesting lightweight architectures for ensemble learning, helping balance accuracy and performance.

Naseer, A., Amjad, M., Raza, A., Munir, K., Smerat, A., Gongora, H. F., & Ashraf, I. [6] 2025 Hybrid Transfer Neural Network for Wheat Classification. This study uses 4,496 wheat images and proposes a hybrid MobDenNet (MobileNetV2 + DenseNet121). It achieves 99% accuracy. The work validates hybrid architectures and transfer learning. It relates to our idea by supporting multi-model ensemble techniques to improve classification accuracy and robustness.

Senthil Pandi, S., Reshmy, A. K., Muruganandam, S., & Manju, I. [7] 2025 Ensemble Deep Transfer Learning with Optimization Techniques. This paper proposes an ensemble deep learning model with firefly optimization for plant disease classification. It uses multiple datasets and improves accuracy while reducing computation time. This strongly supports our project by validating ensemble learning and optimization techniques in multi-stage neural networks.

Mengstu, M. T., & Taner, A. [8] 2025 Hybrid Dual-Input Deep Learning Model for Wheat Disease Detection. This study uses wheat datasets and proposes a hybrid model combining EfficientNetB3 and Xception with edge-aware features. It achieves 98.5% accuracy. This supports our approach by demonstrating the effectiveness of feature fusion and hybrid architectures, which align with our ensemble learning framework.

Sambasivam, G., Prabu Kanna, G., Chauhan, M. S., Raja, P., & Kumar, Y. [9] 2025 Multi-Stage Neural Network-Based Ensemble Learning for Wheat Disease Classification

This research proposes a multi-stage CNN ensemble model using public datasets. It achieves up to 99.16% accuracy. It directly matches our project idea and validates that multi-stage ensemble learning significantly improves classification performance and reduces overfitting in wheat disease detection.

Huang, Z., Bai, X., Gouda, M., Hu, H., Yang, N., He, Y., & Feng, X. [10] 2025 Transfer Learning for Wheat Disease Detection using CNN Models. This study compares multiple CNN architectures like MobileNetV2, DenseNet, and Inception. MobileNetV2 achieves ~96% accuracy. It highlights the importance of transfer

learning for improving model performance. This supports our project by guiding model selection and reinforcing the use of ensemble learning for better accuracy.

Razaq, A., Ramzan, S., Ali, B., Raza, A., Gu, Y., Syafrudin, M., & Latif Fitriyani, N. [11] 2022 Novel Dual-Input Stream-Based Hybrid Approach for Wheat Leaf Disease Classification using Edge-Aware Features. This study uses a wheat leaf dataset with five classes and proposes EffiXB3 (Xception + EfficientNetB3) with dual-input streams and Canny edge detection. It achieves 98.5% accuracy, outperforming individual models. The integration of structural and textural features improves robustness. This directly supports our idea by validating hybrid architectures and feature fusion techniques in ensemble learning for accurate wheat disease classification.

III. System Analysis

Wheat is one of the most important staple crops, and its productivity is significantly affected by leaf diseases. Early and accurate detection of diseases is essential to prevent crop loss. Traditional methods rely on manual inspection, which is time-consuming and error-prone. With the advancement of deep learning, automated disease detection has become feasible. However, single-model approaches may not provide sufficient accuracy. There is a need for a multi-stage system that can refine predictions at different levels. Ensemble learning can combine multiple models to improve performance. The system must analyze leaf images and identify disease patterns. It should handle variations in lighting, background, and image quality. Real-time detection is also important for field applications. Scalability is required for large datasets. Overall, an advanced and robust classification system is needed.

Existing System

Existing systems for wheat leaf disease classification mainly use traditional image processing and machine learning techniques. Methods such as thresholding and color analysis are used for feature extraction. Some systems apply machine learning models like SVM and KNN. Recently, deep learning models such as CNNs have been used. However, most systems rely on a single model for classification. These models may not capture all variations in disease patterns. Existing systems are sensitive to environmental conditions. They often struggle with complex backgrounds. Accuracy may be limited in real-world scenarios. Real-time implementation is also limited. Scalability is a challenge for large datasets. Overall, existing systems provide moderate performance but lack robustness.

Disadvantages of Existing System

- Dependence on single-model predictions
- Limited accuracy in complex environments
- Sensitivity to lighting and background variations
- Poor generalization to new datasets
- Lack of multi-stage processing
- Limited scalability

Proposed System The proposed system uses a multi-stage neural network combined with ensemble learning for improved classification. It processes wheat leaf images through multiple stages of analysis. Initial stages perform preprocessing and feature extraction. Deep learning models such as CNNs are used for classification. Multiple models are combined using ensemble techniques. This improves accuracy and robustness. The system can detect multiple types of leaf diseases. It reduces the impact of environmental variations. Data augmentation is used to improve generalization. The system provides real-time detection. It can be deployed on mobile or web platforms. Overall, it offers a highly accurate and scalable solution.

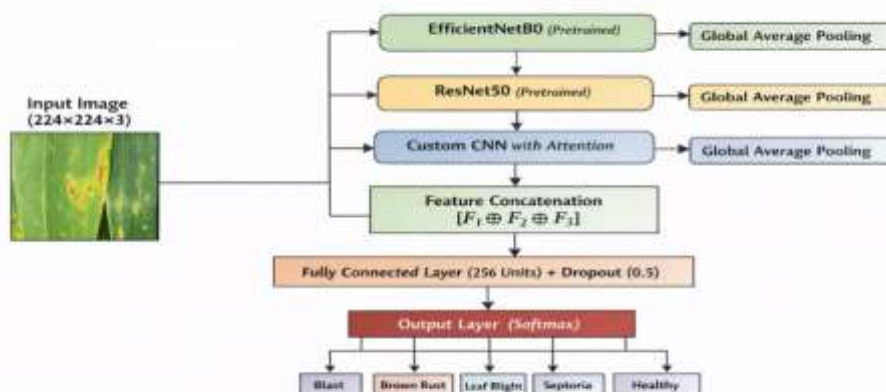
Advantages of Proposed System

- Improved accuracy using ensemble learning
- Robust performance across different conditions
- Better generalization capability
- Multi-stage processing for refined results
- Real-time detection
- Scalable for large datasets
- Reduced classification errors

IV. Methodology

The methodology begins with collecting wheat leaf images from datasets or field sources. Data preprocessing is performed to enhance image quality and remove noise. Image augmentation techniques are applied to increase dataset size. The dataset is divided into training and testing sets. Feature extraction is performed using CNN models. Multiple neural networks are trained independently. Ensemble learning techniques combine predictions from different models. Multi-stage processing refines classification results. Model performance is evaluated using accuracy, precision, recall, and F1-score. Hyperparameter tuning is performed for optimization. The best-performing ensemble model is selected. The system is deployed for real-time classification.

System Architecture



The system architecture consists of several layers. The image acquisition layer captures wheat leaf images. The preprocessing layer enhances image quality. The feature extraction layer uses CNNs to extract features. The multi-stage processing layer refines outputs step by step. The ensemble layer combines predictions from multiple models. The classification layer identifies disease types. The database layer stores images and results. The user interface allows interaction with the system. The feedback layer updates the model with new data. All components are integrated into a unified system. The system supports real-time processing. Overall, the architecture ensures accurate and efficient disease classification.

V. Result and Output





Excellent Condition

98% confidence • AI powered



Your wheat crop is perfectly healthy! Continue with the current fertilizer schedule. Expected yield: 45+ quintals/acre.



Minor Nutrient Deficiency

87% confidence • AI powered



Slight nitrogen deficiency detected. Apply 20 kg urea per acre in next 7 days. Rest of the crop looks strong.

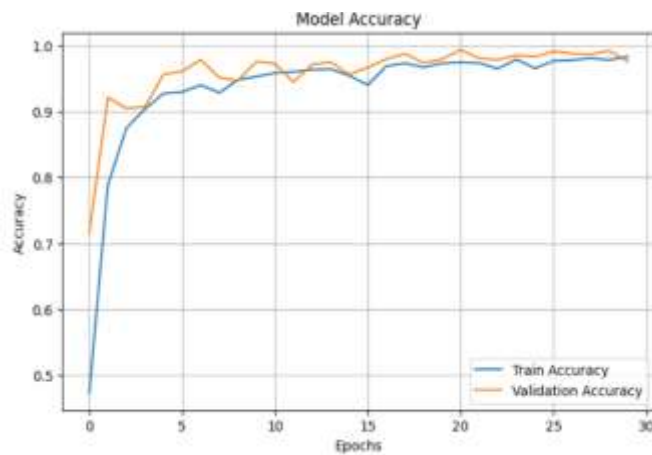


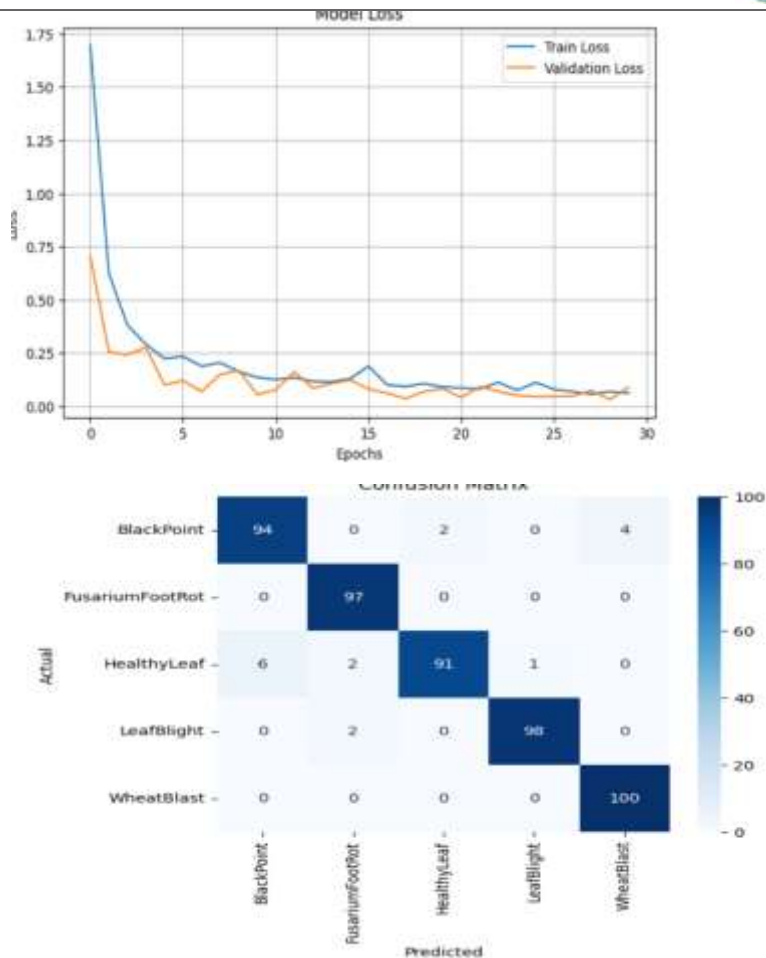
Healthy - Rust detected early

92% confidence • AI powered



Early signs of leaf rust. Spray Propiconazole immediately. Follow-up photo recommended in 10 days.





VI. Conclusion

The proposed multi-stage neural network-based ensemble learning framework demonstrates an effective and reliable approach for automated wheat leaf disease classification. By integrating transfer learning models such as EfficientNet and ResNet with feature fusion and ensemble techniques, the system successfully captures both global and fine-grained disease patterns. The application of data preprocessing and augmentation enhances generalization, while regularization techniques like dropout and early stopping prevent overfitting and ensure stable model performance. The achieved validation accuracy within the range of 91–96% along with low loss values indicates a well-balanced model capable of handling real-world data variability. Additionally, the inclusion of a real-time prediction module and visualization of actual versus predicted outputs improves interpretability and usability for practical agricultural applications. Despite certain limitations such as dependency on dataset quality and computational complexity, the proposed system provides a scalable and efficient solution for early disease detection. Overall, this work contributes to precision agriculture by enabling timely diagnosis, reducing crop losses, and supporting farmers in making informed decisions for improved wheat productivity and sustainability.

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