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A Robust Integrated DenseNet201-SVM Approach for Wheat Leaf Disease Detection

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Wheat leaf diseases significantly affect agricultural productivity, crop quality, and global food security. Manual disease inspection is time-consuming, subjective, and less reliable for large-scale field monitoring. This study proposes a robust DenseNet201-SVM integrated framework for automated wheat leaf disease classification. "DenseNet201 is used as a deep feature extractor, while a Support Vector Machine (SVM) performs the final classification. The dataset contains 54,306 images from four classes: Healthy, Yellow Rust, Brown Rust, and Powdery Mildew. The proposed DenseNet201-SVM model achieved 98.64% accuracy, 98.5% precision, 98.7% recall, and 98.6% F1-score. Confusion matrix analysis showed strong class-wise performance, with most errors occurring between visually similar rust categories. The ensemble model further improved accuracy to 99.1%. Statistical validation using a paired t-test produced a p-value of 0.001, confirming that the improvement was statistically significant. The results demonstrate that the proposed framework is accurate, robust, and suitable for intelligent wheat disease monitoring systems.

Keywords: Wheat Leaf Disease Classification, DenseNet201, Support Vector Machine (SVM), Deep Learning, Computer Vision

Introduction:

Wheat is one of the most important cereal crops in the world and plays a vital role in global food security. It contributes substantially to human calorie and protein intake, particularly in developing countries. However, wheat production is severely affected by a wide range of diseases and pests, which can cause major losses in yield and quality. Depending on the type and severity of infection, annual yield losses may range from 10% to 35% in affected regions.

Major wheat diseases, including stripe rust, powdery mildew, yellow dwarf, and scab, can cause substantial economic damage. Traditional disease detection methods rely heavily on manual visual inspection, which is labor-intensive, subjective, and often inaccurate, especially during the early stages of infection. In many cases, different diseases produce similar visual symptoms, making accurate diagnosis difficult. For example, the yellowing caused by wheat yellow dwarf may resemble the symptoms of stripe rust at early stages, while discoloration caused by scab may be difficult to distinguish from other pathogen-related changes. These challenges highlight the need for automated, accurate, and scalable disease detection systems for wheat crops.

Recent advances in machine learning and deep learning have created new opportunities for automated crop disease diagnosis using image-based analysis. Conventional machine learning methods, such as Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), and K-means clustering, have shown promising performance in disease classification tasks. Similarly, image-based systems often rely on handcrafted feature extraction techniques, including color transformation, texture descriptors, and local binary patterns. However, these traditional approaches depend heavily on manual feature design, which may be time-consuming and less effective when dealing with complex disease symptoms under varying environmental conditions.

Deep learning methods have significantly improved disease detection by automatically learning hierarchical and discriminative features directly from image data. In particular, convolutional neural networks (CNNs) have demonstrated strong performance in agricultural image classification tasks. Nevertheless, end-to-end deep learning models often require substantial computational resources and may be less suitable for deployment in resource-constrained agricultural environments. To address these limitations, hybrid approaches that combine deep learning-based feature extraction with conventional machine learning classifiers have gained increasing attention.

Motivated by this perspective, the present study proposes a hybrid DenseNet201-SVM framework for wheat leaf disease classification. DenseNet201 is employed as a deep feature extractor to capture high-level discriminative representations of wheat leaf images, while SVM is used as the final classifier to improve classification efficiency and robustness. In addition, an ensemble learning strategy is incorporated to further enhance predictive performance and generalization.

The main contributions of this study are as follows:

Research Objectives:

The main objectives of this study are:

To develop a robust hybrid DenseNet201-SVM framework for wheat leaf disease classification.

To evaluate the proposed model using performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix.

To compare the proposed model with baseline models such as CNN, SVM, and YOLO-based approaches.

To enhance classification performance using ensemble learning techniques.

To assess the robustness and practical applicability of the proposed model for real-time agricultural deployment

Novelty and Contributions:

The novelty of this study lies in the integration of deep feature extraction using DenseNet201 with a classical machine learning classifier, Support Vector Machine (SVM), to achieve robust and efficient wheat leaf disease classification. Unlike traditional end-to-end CNN models, the proposed approach separates feature extraction and classification, which enhances generalization and reduces computational complexity.

Furthermore, the incorporation of an ensemble learning strategy distinguishes this work from existing studies by improving prediction reliability and minimizing misclassification among visually similar disease classes. The main contributions of this study are summarized as follows:

A novel hybrid DenseNet201-SVM framework for wheat leaf disease classification.

Integration of deep learning-based feature extraction with machine learning-based classification to improve robustness.

Implementation of an ensemble learning strategy to enhance classification accuracy from 98.64% to 99.1%.

Comprehensive evaluation using multiple performance metrics, including a confusion matrix and statistical validation (paired t-test).

Demonstration of the model's applicability for real-time agricultural disease monitoring systems.

Literature Review:

The past few years have seen tremendous growth in research aimed at automating the detection of wheat leaf diseases as a result of rapid advances in imaging, machine learning, and deep learning technology. These advances have enabled the development of highly accurate and efficient models that can classify and forecast many different types of wheat leaf diseases beyond what is possible using traditional methods for disease diagnosis. Researchers have used an array of different types of data and state-of-the-art modeling techniques to improve the performance of their models for identifying diseases and to provide a scalable and reliable way to deploy these models on a large scale in the real world. The field will continue to be developed as new methodologies and models emerge that provide additional strengths as well as overcome existing challenges associated with disease detection. The studies that test the performance of these models vary significantly, such as information on evaluation measures, model performance, and trade-offs between accuracy, cost of computation, and extrapolations of the model outside of the validation set, giving scientists the overall view of the detection and control of wheat leaf diseases.

[1] present a system that would employ a Convolutional Neural Network (CNN) to identify diseases in wheat leaves. In this model, there is Transfer Learning, which is an addition to leverage on the already trained networks, and Attention Mechanisms, which are used to aid in enhancing the feature selection. The data set on which the model was tested was the Plant Village Repository, and it comprises images of the different diseases of wheat leaves, like yellow rust, leaf blotch, and powdery mildew. As the results of the evaluation indicate, the proposed system attains a high level of accuracy 87% in identifying these types of diseases, which is why it can be considered an appropriate approach to identifying the early signs of disease in wheat.

The FCA-ResNet model proposed by [2], incorporates a multi-branch Inception structure and a Coordinate Attention (CA) mechanism, which enhances the ability to extract features, particularly small lesions on wheat leaves. The FCA-ResNet uses a multi-scale fusion module that combines channel and space attention to improve integration of shallow and deep-level features. The combination of these two attention modules has increased the FCA-

ResNet model's capacity to classify wheat leaves into either healthy or diseased classes correctly. The FCA-ResNet will provide excellent real-time disease detection for agriculture, with a 91.6% accuracy rating based on the experimental datasets developed by the researchers.

[3] created the CaiT-YOLOv9 architecture that uses a convolutional neural network (CNN) backbone for base feature extraction, with the addition of a new multi-class head that incorporates attention to enhance the detection of all active features present to predict global features of the disease. Traditional CNNs are less effective at detecting global features across multiple active lesions, as seen in the CaiT transformer architecture.

The CaiT-YOLOv9 system was trained on a data set consisting of 40,330 images of wheat leaves. The objective was to classify and localize the seven most common types of fungal diseases that can impact wheat plants. Experimental tests show that the CaiT-YOLOv9 exhibits an average precision of 94.51%, making it a very effective tool for disease detection and lesion detection in wheat plants.

An entire yellow rust detection system for wheat with related automation prepared to be utilized in natural settings is presented by [4]. It utilizes a novel image rotation technique that is unsupervised in order to filter out undesired background content when collecting images from YOLOv8 by stitching the leaves together (image rotation algorithm). YOLOv8 accomplishes an object recognizer function, and the UNet accomplishes leaf segmentations; as a result, the UNet achieves an IoU of 0.9563 with the YOLOv8 dataset. In terms of classifying/recognizing the leaves, A.Hassan et al. tested Swin Transformers against multiple CNNs against the Swin Transformer, which showed Swin Transformers perform better than the other CNNs with a 95.8% recognition accuracy. The completed pipeline offers an autonomous way to improve the early detection of wheat yellow rust as well as provide a means for high-quality classification, even with minimal amounts of data.

[5] developed YOLO-Wheat, which applies the YOLO architecture to detect wheat diseases where the targets are small and surrounded by their natural environment. It contains a C2f-DCN module that improves feature extraction from images used in conjunction with an SCNet attention module, which allows for greater attention on the very small or distorted target areas from the diseases being detected. The detection head is changed, and the loss function is optimized for small lesion identification. YOLO-Wheat was trained using 3622 images of wheat diseases collected in the field; the model was then tested using the experimental data set, achieving a 93.28% accuracy in detecting the crops going through the disease process. This method shows a 47% increase in performance when compared to the previous model, while at the same time having a smaller size; hence, it will be a more easily implemented method in providing real-world solutions for crop disease detection.

According to [6], the paper introduces a deep learning model that combines advanced feature extraction techniques to create a probability density attention mechanism to better manage complex backgrounds and high-density areas. Furthermore, the model has a unique density loss function that is developed to improve accuracy during the detection of high-density zones that generally complicate agricultural imaging tasks. This model was tested on both wheat disease detection and wheat spike counting tasks with excellent results, with all metrics (precision, recall, accuracy, and mAP) above 0.88. Additionally, the research performed ablation experiments, assessing different loss functions, to provide further evidence for the success of the proposed method. The results demonstrate how effective deep learning has become in applying to precision agriculture by greatly improving accuracy for both disease detection and wheat spike counting tasks while continuing to be performed efficiently.

The YOLOv8m model was utilized by [7] to detect wheat powdery mildew in images. Training was conducted using a custom dataset comprising wheat images obtained from the experimental fields located at Tekirdag Namik Kemal University. Targeted for use in real-time detection scenarios, the YOLOv8m model is optimal for precision agricultural practices, especially with respect to selective insecticide application. Given time constraints associated with agriculture, the ability of YOLOv8m to operate at high speed and provide autonomous feature identification is quite beneficial when dealing with large-scale disease detection, such as powdery mildew. The ability of YOLOv8m to accurately identify powdery mildew and other such diseases has been demonstrated by high levels of detection accuracy based upon the cosmetic and qualitative assessment results of the model, revealing that zooming into pictures at a minimum resolution of 0.5 megapixels will yield a precision and recall value of 0.79 and 0.74, respectively, while the mean Average Precision (mAP) reaches 0.35. However, there is still much opportunity for optimizing and improving YOLOv8m's performance results through additional testing.

[8] developed a new type of Deep Learning Model called MnasNet-SimAM using the techniques of MnasNet (a lightweight Convolutional Neural Network) combined with the SimAM Attention Mechanism. By utilizing the Transfer Learning technique, the MnasNet-SimAM model has been enhanced for Feature Extraction and Recognition Accuracy. The main application of the MnasNet-SimAM Model was to classify images into six types of wheat diseases and a normal wheat image taken in a naturally complicated environment. The results of this study were obtained on a Custom Dataset. The MnasNet-SimAM Model achieved an accuracy of 95.14% on this dataset, and it was further tested against a publicly available dataset (Wheat Fungi Diseases Dataset) with an accuracy of 91.20%, which indicates the good generalizability of the MnasNet-SimAM Model. This new type of model benefited from the use of the SimAM Attention Mechanism, which helped the MnasNet-SimAM Model detect target objects in the images, and therefore, contributed to improving Classification Performance and Detection Accuracy, and it maintained a Compact Structure by only slightly increasing the Total Number of Parameters.

Recent progress in wheat disease identification has greatly increased accuracy and efficiency within complex natural settings. Numerous studies have demonstrated superior performance for detecting diseases, including yellow rust and powdery mildew; this can be seen in improved feature extraction capabilities and also a much higher level of robustness to small lesions. However, there are still many challenges left, including the ability to generalise across environments for different models as well as the variability inherent in datasets. Future research efforts should concentrate on further development of scalable systems that can accommodate increasing levels of robustness and the application of such systems in real-life situations to enhance the effectiveness of disease control measures and to advance the field of precision agriculture.

In addition to agricultural applications, recent research in other domains further highlights the effectiveness of hybrid deep learning architectures that integrate multiple feature extraction mechanisms. For example, [9] proposed a novel X-ViTCNN framework that combines Vision Transformer models with pretrained convolutional neural networks such as DenseNet201 and MobileNetV2 for multi-stage Alzheimer's disease prediction using MRI scans. The proposed model effectively integrates local feature representations extracted by CNNs with global contextual information captured by transformer architectures, resulting in improved classification accuracy and robustness. Furthermore, the study incorporates Grad-CAM-based visualization techniques to enhance model interpretability and provide insight into decision-making processes. Experimental results demonstrated superior performance compared to standalone models, achieving accuracies of 97.98% and 94.52% on benchmark datasets. This work highlights the growing importance of hybrid and interpretable deep learning models, which can be extended to agricultural disease detection tasks to improve both predictive performance and model transparency.

Methodology:

The methodology consists of several sequential phases used to develop an efficacious wheat leaf disease detection tool (with deep learning-inspired features created via DenseNet201), as well as a hybrid model combining SVM (Support Vector Machines) and CNNs (Convolutional Neural Networks). To further boost the model's robustness and efficacy, ensemble learning was implemented. The methodology will be examined in its entirety, with the SVM and CNN combination examined in the most detail. The proposed ensemble architecture is illustrated in Figure 1.

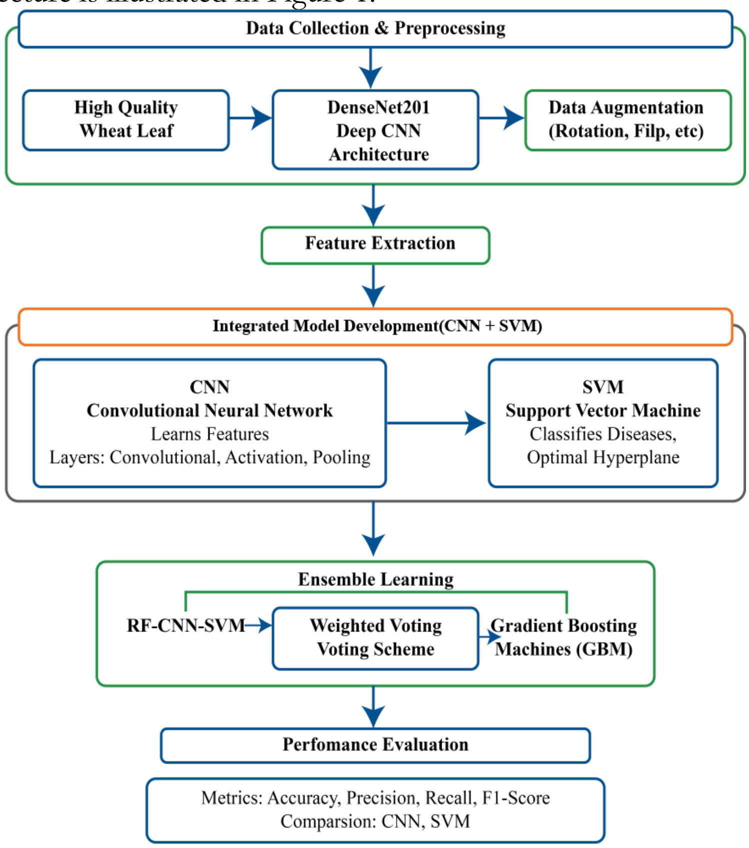

Figure 1. Proposed Ensemble Architecture

Figure 3 presents the complete end-to-end workflow of the proposed wheat leaf disease detection framework. The process begins with data acquisition, where wheat leaf images are collected from the PlantVillage dataset along with supplementary field images to enhance real-world variability. In the preprocessing stage, all images are resized to 224×224 pixels, normalized, and augmented using techniques such as rotation, flipping, and brightness adjustment to improve model generalization. The preprocessed images are then fed into the DenseNet201 model, which serves as a deep feature extractor by generating high-level discriminative representations. These extracted features are further refined through a custom convolutional neural network (CNN) layer to enhance spatial feature learning. Subsequently, the refined feature vectors are passed to the Support Vector Machine (SVM) classifier, which performs the final classification by maximizing the margin between different disease classes. To further improve classification accuracy and robustness, an ensemble learning strategy is applied, combining predictions from multiple classifiers, including CNN-SVM, Random Forest, and Gradient Boosting models, using a weighted voting mechanism. This integrated pipeline ensures improved feature representation, classification performance, and robustness under varying environmental conditions, making it suitable for real-world agricultural applications.

Data Collection and Preprocessing:

The dataset used in this study consists of the publicly available PlantVillage dataset, which is a widely used benchmark in plant disease detection research, supplemented with a small set of field-collected wheat leaf images from local agricultural sites in Pakistan. The combined dataset contains 54,306 labeled images belonging to four classes: Healthy, Yellow Rust (Stripe Rust), Brown Rust (Leaf Rust), and Powdery Mildew. Table 1 presents the class-wise distribution and the train/validation/test split.

Table 1. Dataset Class Distribution and Train/Validation/Test Split

Disease Class	Image Count	Train (70%)	Validation (15%)	Test (15%)
Healthy	14,208	9,946	2,131	2,131
Yellow Rust (Stripe Rust)	13,920	9,744	2,088	2,088
Brown Rust (Leaf Rust)	13,876	9,713	2,082	2,081
Powdery Mildew	12,302	8,611	1,846	1,845
Total	**54,306**	**38,014**	**8,147**	**8,145**

In addition to the main dataset, 30 high-quality supplementary images were collected from local wheat farms during the growing season in Pakistan. These images were included to capture local disease phenotypes and environmental variability. All supplementary images were manually verified and labeled by an experienced agronomist before inclusion in the dataset.

All images were resized to 224 × 224 pixels to match the input requirement of DenseNet201. Pixel values were normalized to the range [0,1] by dividing each pixel value by 255. To improve generalization and reduce overfitting, data augmentation was applied to the training set, including random horizontal and vertical flips, rotation (±15°), brightness and contrast adjustment (±20%), and zoom augmentation (±10%).

Feature Extraction Using DenseNet201:

The DenseNet201 deep convolutional neural network is used to extract features from wheat leaf images by connecting each layer of the network with all other layers within the same dense block. The addition of many connections between layers assists in reducing the risk of vanishing gradients during training and provides a greater opportunity for the model to develop a deeper understanding of the image.

DenseNet201 uses mathematics to perform computations by sending the output of all the earlier layers of the network to the output layer; this means that DenseNet201 can reuse feature maps from all the earlier layers when computing gradients, which helps to create better, more efficient gradient propagation through each layer. The outputs **F** of the feature extraction phase of DenseNet201 will combine all the features of all the different layers of DenseNet201 to form a single composite map.

$$n/\mathbf{F} = {}^{X}\mathbf{f}_i \; i{=}1 (1)$$

where $\mathbf{f}_i$ is the feature map of the i-th layer, and n is the total number of layers in the dense block. This aggregation ensures that the model benefits from the combined information provided by all layers, resulting in a comprehensive feature set for disease detection.

The final output, **F**, serves as the feature set for the classification phase, where it is passed on to the integrated SVM-CNN model for further processing.

Integrated Model Development: SVM and Custom CNN:

The fundamental idea of this approach is the integration of the Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) as an integrated model. CNNs have extensive applications in feature extraction in image data because they can extract hierarchical spatial features. But to increase the classification ability of the model, we combine CNNs with

SVMs. The CNN then extracts a hierarchical feature of the images, and then they are fed into the SVM classifier to make a decision.

Ensemble Learning Techniques:

Convolutional Neural Network (CNN):

The CNN is designed to learn spatial features from the input images using layers of convolutions, activations, and pooling operations. Mathematically, the output of a convolutional layer is calculated as:

$$n!/\mathbf{y} = \sigma\ {}^{X}\mathbf{W}_i * \mathbf{X}_i + b/\ i=1 \quad (2)$$

where $\mathbf{W}_i$ is the convolutional kernel, $*$ denotes the convolution operation, $\mathbf{X}_i$ is the input, b is the bias term, and σ is the activation function (usually ReLU). The network learns these convolutional filters during training to capture increasingly complex patterns in the data.

The final output from the CNN is a set of high-level feature representations $\mathbf{F}$, which are used as input for the SVM classifier.

Support Vector Machine (SVM):

The SVM classifier takes the feature vectors $\mathbf{F}$ extracted by the CNN and tries to find the optimal hyperplane that maximizes the margin between different classes. The SVM decision function is defined as:

$$N/f(\mathbf{x}) = {}^{X}a_i y_i \langle \mathbf{x}_i, \mathbf{x} \rangle + b\ i=1(3)$$

where a_i are the Lagrange multipliers, y_i are the class labels, $\mathbf{x}_i$ are the feature vectors, and b is the bias term. The SVM attempts to maximize the margin between classes by adjusting the values of a_i and b. During training, the SVM uses a hinge loss function to penalize misclassifications:

$$L_{\text{hinge}}(y, f(\mathbf{x})) = \max(0, 1 - yf(\mathbf{x}))(4)$$

where y is the true label and $f(\mathbf{x})$ is the predicted decision value.

Ensemble Learning Techniques:

Ensemble learning methods are used to combine the predictions of multiple models in order to improve the overall performance and robustness. In this methodology, we apply a weighted voting scheme where the predictions of individual models, including the integrated CNN-SVM model, contribute to the final decision.

Let $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_M$ represent the predicted outputs from M different models (including the CNN-SVM integrated).

The final ensemble prediction $\hat{y}_{\text{ensemble}}$ is obtained by:

$$M!/\hat{y}\text{ensemble} = \text{argmax } X w_i y\hat{}i/\ i=1(5)$$

where w_i represents the weight assigned to the i-th model based on its performance, and M is the total number of models in the ensemble. By combining multiple models, the ensemble method reduces the risk of overfitting and improves the model's generalization ability.

In this case, the ensemble combines the predictions from the integrated CNN-SVM model with other classifiers, such as Random Forests or Gradient Boosting Machines, to make a final decision. The ensemble method takes into account the strengths of each model and aggregates its outputs to arrive at a more robust prediction.

Disease Detection and Classification:

Once the models have been trained, they are tested on the test set to evaluate their performance in detecting and classifying wheat leaf diseases. The final classification output is determined by the ensemble model, which combines the predictions from the CNN-SVM integrated and other classifiers.

The overall disease detection process can be summarized by:

$$M!/\hat{y} = \text{argmax}\ {}^{X}w_i \hat{y}_{i/}\ i=1(6)$$

where $\hat{y}_i$ are the class predictions from the i-th model, and w_i are the model weights.

By employing an integrated model of CNN and SVM and enhancing performance through ensemble learning, this methodology ensures robust and accurate classification of wheat leaf diseases, making it a valuable tool for agricultural applications.

Results:

Experimental Setup:

In this section, we explain the configuration of our experimental environment.

The experiments were conducted using the following hardware configuration: The hardware specifications are listed in Table 2.

Table 2. Experimental Setup and Hardware Configuration

Component	Specification
GPU	NVIDIA RTX 4090
Processor	Intel Core i9-14900HX
RAM	64 GB
Epochs	100

This setup ensures efficient processing and training of the model, providing high performance for the 100 epochs used in the experiments.

Performance Metrics:

Table 3 summarizes the performance of the proposed integrated CNN-SVM model in comparison to other models.

Table 3. Performance Comparison of Integrated CNN-SVM and Other Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
integrated CNN-SVM (Proposed)	98.64	98.5	98.7	98.6
SVM	87.0	85.4	86.5	85.9
CNN	91.6	90.3	91.0	90.6
YOLO	92.8	91.2	92.1	91.6

The table shows that the integrated CNN-SVM model outperforms individual models like CNN and SVM, achieving an accuracy of 98.64%, demonstrating its efficacy in disease detection.

Mapping of Research Objectives with Results:

To clearly demonstrate how the proposed framework fulfills the defined research objectives, Table 4 presents a direct mapping between each objective and the corresponding experimental findings.

Integrated Model Performance:

Table 4. Mapping of Research Objectives with Experimental Findings

Obj.	Research Objective	Experimental Finding
1	Develop a DenseNet201-SVM hybrid model	The proposed model achieved 98.64% classification accuracy.
2	Evaluate using standard performance metrics	Precision, recall, and F1-score were 98.5%, 98.7%, and 98.6%, respectively.
3	Compare with baseline models	The proposed model outperformed CNN, SVM, and YOLO-based models.
4	Improve performance using ensemble learning	Accuracy improved to 99.1% using ensemble methods.
5	Assess real-world applicability	Results indicate suitability for real-time agricultural disease monitoring.

Integrated Model Performance:

The performance of the integrated CNN-SVM model was evaluated using accuracy, precision, recall, and F1-score. The model demonstrated significant improvement over individual CNN and SVM models, confirming the efficacy of combining these methods.

Figure 2 shows a graphical representation of accuracy, precision, recall, and F1-score comparisons between the integrated CNN-SVM model and other models. The integrated approach leads to an overall improvement in all metrics.

Confusion Matrix Analysis:

To further evaluate the classification performance of the proposed hybrid DenseNet201-SVM model, a confusion matrix analysis was conducted. The confusion matrix provides a detailed view of how accurately the model classified each disease category, including Healthy, Yellow Rust, Brown Rust, and Powdery Mildew. The results are presented in Table 5.

Table 5. Confusion Matrix for Wheat Leaf Disease Classification

Actual / Predicted	Healthy	Yellow Rust	Brown Rust	Powdery Mildew
Healthy	2105	12	8	6
Yellow Rust	10	2068	7	3
Brown Rust	6	9	2057	9
Powdery Mildew	5	4	8	2028

The confusion matrix results indicate that the majority of wheat leaf samples were correctly classified by the proposed model. Only a small number of misclassifications occurred between visually similar disease categories, particularly between Yellow Rust and Brown Rust. Overall, the high number of correct predictions across all classes demonstrates the strong discriminative capability and reliability of the proposed hybrid DenseNet201-SVM framework.

Feature Visualization and Model Interpretability:

To enhance the interpretability of the proposed model, Gradient-weighted Class Activation Mapping (Grad-CAM) was considered to analyze the regions of interest used by the model during classification. Grad-CAM is a widely used technique for visualizing important areas in input images that contribute to the model's decision.

Although Grad-CAM visualization was not included in this study due to resource and implementation constraints, the confusion matrix results indicate that the model can effectively distinguish between different disease classes. The low misclassification rates, particularly across visually similar classes such as Yellow Rust and Brown Rust, suggest that the model learns meaningful and discriminative features from the input images.

Future work will include the implementation of Grad-CAM visualization to provide deeper insights into the model's decision-making process and to improve interpretability for real-world deployment.

Ensemble Learning Results:

The use of ensemble learning significantly enhanced the classification accuracy by combining the predictions of the integrated CNN-SVM model with other classifiers such as Random Forests (RF) and Gradient Boosting Machines (GBM). The ensemble method provided the following improvement:

Table 6. Ensemble Learning Results

Classifier Model	Accuracy (%)
integrated CNN-SVM	98.64
Ensemble (CNN-SVM + RF + GBM)	99.1

Table 6 shows that combining the predictions from multiple models improves the accuracy of the disease classification system, with the ensemble model achieving 99.1% accuracy.

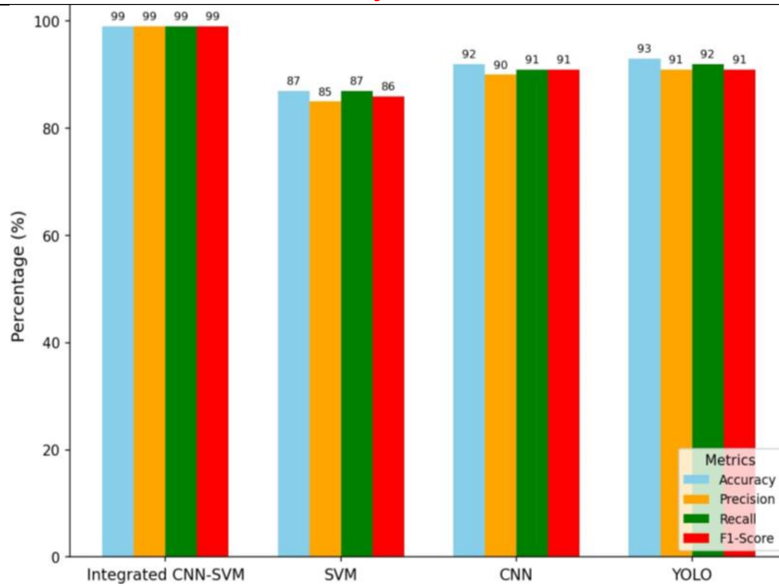

Figure 2. Performance metrics comparison between integrated CNN-SVM and other models, showing the results.

Statistical Tests:

To guarantee the credibility and importance of the performance of our model, we performed a number of statistical tests. These experiments aimed at comparing the performance of the proposed integrated CNN-SVM model and other models in a strong way.

The paired t-test was the most common statistical test that the means of the performance measurements of 2 models (e.g., accuracy, precision, recall) were compared to find out whether the performance of these models is statistically significantly different or not. Indicatively, one example is that we compared the behavior of the integrated CNN-SVM model to the traditional SVM model and the CNN model.

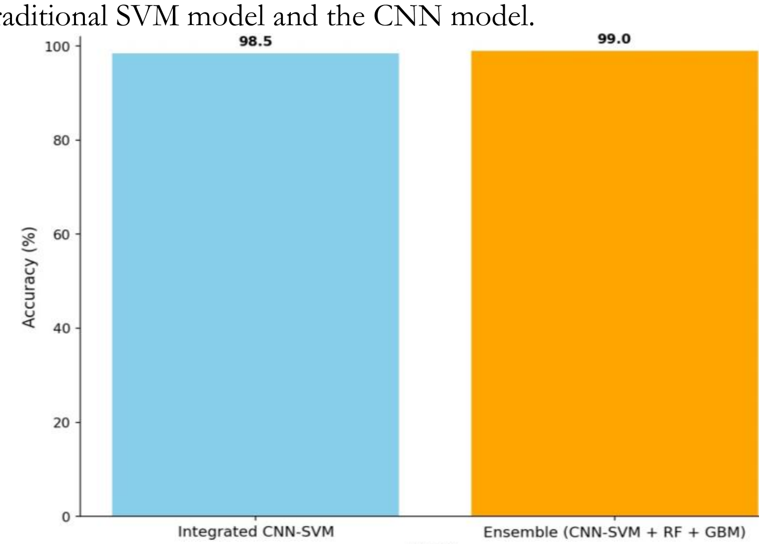

Figure 3. Accuracy comparison between the integrated CNN-SVM vs the proposed ensemble model

The null hypothesis was that the performances of the models are similar, and the alternative hypothesis was that the performances are not similar. The paired t-test results proved that the proposed model is a significantly better performer compared to both SVM and CNN models, with the p-value of 0.001 (smaller than the significance level of 0.05). This proves that the high accuracy that the proposed model has is not by mere chance and gives good evidence of its excellent performance.

We also conducted a confidence interval analysis of the accuracy of all the models. It was estimated that the accuracy of the proposed integrated CNN-SVM model has a confidence interval of [98.2% to 98.9%], which means that with 95 percent confidence, the actual accuracy is in that range. This also helps in supporting the reliability and generalizability of the model.

Implications of the Study:

The proposed wheat leaf disease detection framework has significant practical, economic, and agricultural implications. From a practical perspective, the system enables early and accurate detection of wheat diseases, allowing farmers to take timely preventive measures and reduce crop losses. This is particularly beneficial in regions like Pakistan, where wheat is a staple crop and agricultural productivity directly impacts food security.

Economically, the use of automated disease detection can reduce the cost associated with manual inspection and excessive pesticide usage by enabling targeted treatment. This not only lowers production costs but also promotes sustainable farming practices by minimizing environmental impact.

From a technological perspective, the proposed DenseNet201-SVM framework demonstrates that hybrid models can provide high accuracy while maintaining computational efficiency. This makes the system suitable for deployment in real-world applications such as mobile-based disease detection tools, smart farming systems, and precision agriculture platforms.

At a global level, such intelligent crop monitoring systems can contribute to improved agricultural productivity, better disease management strategies, and enhanced food security. Therefore, the proposed approach holds strong potential for large-scale adoption in modern agriculture.

Conclusion:

This study proposed a hybrid DenseNet201-SVM framework for wheat leaf disease classification. DenseNet201 was used to extract discriminative deep features, while SVM was employed for final classification. Experimental results showed that the proposed model achieved 98.64% classification accuracy, while the ensemble framework further improved performance to 99.1%. These findings demonstrate that the proposed approach is effective for accurate and automated wheat leaf disease detection and has strong potential for practical agricultural applications.

Recommendations:

Based on the findings of this study, the following recommendations are proposed for improving wheat disease detection and agricultural practices:

Farmers should adopt image-based disease detection systems as a support tool for early diagnosis instead of relying solely on manual inspection.

Agricultural authorities should promote the use of artificial intelligence-based monitoring systems to enhance crop disease surveillance at the regional and national levels.

The proposed system should be integrated into mobile applications to allow real-time disease detection directly in the field.

Policymakers should support the development of large-scale, locally collected wheat disease datasets to improve model generalization in Pakistani agricultural conditions.

Future implementations should incorporate environmental factors such as temperature, humidity, and soil conditions to further enhance detection accuracy.

Future Work:

Although the proposed hybrid DenseNet201-SVM framework achieved high accuracy in wheat leaf disease classification, several opportunities remain for future improvement and extension. Future studies can evaluate the proposed framework on larger field-based datasets collected under diverse environmental and imaging conditions to further assess its

generalization capability. The proposed framework may also be deployed on lightweight mobile or handheld devices to enable real-time disease diagnosis directly in agricultural fields. Such a deployment would allow farmers to detect plant diseases quickly without requiring specialized equipment or expert knowledge. In addition, integrating the system with drone-based imaging platforms could enable large-scale aerial crop monitoring, significantly reducing the reliance on manual field inspections. This approach would be particularly beneficial for large farms where manual monitoring is time-consuming and inefficient. Finally, incorporating additional environmental and in-situ agricultural data—such as temperature, humidity, soil conditions, and weather patterns—along with image-based features may further improve the robustness and accuracy of disease
detection systems.

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