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Research Paper

SmartLeafNet: An Intelligent Swin Transformer-Based Model for Crop Disease Detection

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Abstract

Agriculture plays a vital role in the economy of Andhra Pradesh, with over 60% of the population relying on it either directly or indirectly for their livelihood. However, crop diseases continue to pose serious challenges, leading to an estimated 20–30% loss in yield annually. Among the major crops cultivated in the region, corn, potato, and tomato are highly susceptible to various leaf-based diseases caused by fungal, bacterial, and viral infections. These issues significantly impact productivity, farmer income, and food security. Early and accurate detection of diseases is therefore essential to reduce crop losses and limit excessive pesticide usage. Traditionally, Crop Disease Detection (CDD) has relied on manual inspection, which is time-consuming, subjective, and prone to human error, making it unsuitable for large-scale farming. To address these limitations, this study proposes an image-based Crop Disease Detection Network (CDD-Net) using leaf images. The system begins with preprocessing techniques such as resizing and normalization to ensure consistency in input data. Feature extraction is performed using the Swin Transformer, which captures rich spatial and contextual information. For performance evaluation, models such as Logistic Regression Classifier (LRC), eXtreme Gradient Boosting (XGB), and Gaussian Naïve Bayes Classifier (GNBC) are implemented. Finally, a Stochastic Gradient Descent (SGD) Classifier is proposed to improve accuracy and robustness. Experimental results demonstrate that the proposed approach enhances disease detection performance, providing a reliable and scalable solution for precision agriculture.

Keywords: Crop Disease Detection, Crop Disease Detection Network, Swin Transformer, Stochastic Gradient Descent, Leaf Image Classification, Precision Agriculture.

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1. Introduction

Crop diseases pose a significant threat to agricultural productivity and food security around the world. Crops such as wheat, rice, maize, and potatoes are staple foods for a large portion of the world's population, and their yield and quality are heavily affected by various plant diseases. Plant diseases are responsible for an estimated 20–40% reduction in yields for major food and cash crops, causing significant economic and social consequences. Globally, the annual loss due to plant diseases is valued at approximately $220 billion. The Food and Agriculture Organization (FAO) reports that nearly 690 million people faced hunger worldwide in 2019, a figure expected to increase due to the impact of the COVID-19 pandemic. The accurate and timely detection of these diseases is crucial for implementing effective management strategies and minimising crop losses. Figure 1 illustrates the trend in corn (maize) yields in India over the period from 2015–16 to 2025–26, measured in tonnes per hectare, showing a general improvement in productivity over time. Corn yield increases from about 2.6 tonnes per hectare in 2015–16 to around 3.1 tonnes per hectare by 2017-18, followed by a slight dip in 2019-20. Thereafter, a steady rise is observed, reaching approximately 3.5 tonnes per hectare in 2022-23. Although there is a minor decline in 2023–24, the yield peaks at about 3.8 tonnes per hectare in 2024–25 before slightly decreasing to 3.7 tonnes per hectare in 2025–26. The overlaid 10-year trend line indicates an overall growth trajectory, suggesting improvements in agricultural practices, seed quality, and crop management contributing to enhanced corn productivity in India. The development of affordable and accessible plant disease detection tools has the potential to empower farmers, reduce crop losses, and enhance livelihoods. Traditionally, plant disease detection has relied on manual inspection by trained experts, a process that is time-consuming, labour-intensive, and prone to human error. With advancements in digital technologies, there is increasing interest in autonomous systems that utilises computer vision and machine learning to detect and monitor plant diseases. They offer rapid, reliable, and cost-effective solutions for large-scale agricultural applications and precision agriculture.

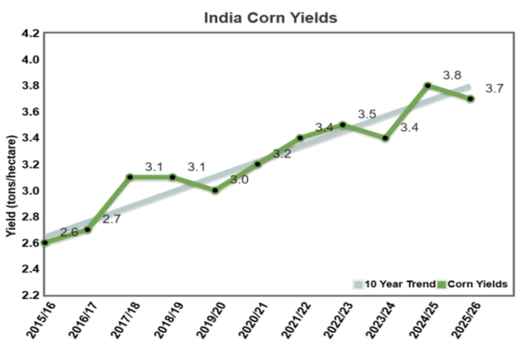

Figure. 1: Geographical distribution of corn production in India.

Plant disease analysis using leaf images focuses on identifying diseases by examining visual symptoms such as spots, colour changes, and texture variations on leaves. Image processing and machine learning techniques are applied to extract features and classify healthy and diseased crops. This approach enables early and accurate detection of crop diseases without the need for manual inspection. Timely disease analysis helps farmers reduce crop losses, minimize pesticide use, and improve overall agricultural productivity.

2. Literature Survey

Manjunatha Shettigere Krishna et al. [1] developed CNN models (EfficientNet-B0/B3, ResNet50, DenseNet201) using a combined Plant Doc and web-sourced dataset, with enhanced augmentation like Gaussian noise. EfficientNet-B3 achieved 80.19% accuracy on combined data, with F1-scores over 90% for diseases like apple rust and grape leaf, showing strong generalization. Karan Soni et al. [2] concluded that CNN-based deep learning models offered early, accurate plant disease detection for sustainable agriculture, despite real-world challenges. Deep learning transformed image-based diagnosis, automated identification to boost crop health monitoring and productivity. The paper provided an extensive overview of CNNs, highlighting recent innovations, methods, and issues over the last half-decade, with DCNNs enabling precise detection via large-scale datasets. It charted future directions while critiquing CNNs' potential and limitations in practical contexts. Shaohua Wang et al. [3] outlined limitations of traditional approaches and discussed advancements in deep learning techniques like classification, object detection, segmentation, and change detection, plus transfer learning for better generalization. It examined challenges such as small lesion detection and dataset quality, while emphasizing opportunities for sustainable, precise agriculture.

H M Manoj et al. [4] introduced an AI-powered approach that synthesized high-resolution drone imagery with in-field IoT sensor data to improve early CDD. The model utilized a hybrid CNN-Transformer backbone and an adaptive fusion layer to extract spatial data and process time-aligned environmental evidence. Researchers collected a multimodal drone-sensor dataset and conducted experiments comparing the architecture against established models like VGG16 and ResNet50. The study demonstrated that AgroVisionNet achieved superior accuracy and provided interpretable Grad-CAM plots while remaining feasible for deployment on edge computing hardware. Karthick Mookkandi et al. [5] developed a lightweight vision transformer (MaxViT) with 814.7K parameters and 85 layers, incorporating CBAM, SE, and DW convolution plus ConvNeXt for enhanced feature representation and classification of paddy/wheat diseases. Tested on a paddy dataset (7857 images, 8 classes) and wheat dataset (5000 images, 5 classes), it achieved 99.43%/98.47% training/testing accuracy on paddy and 94%/92.8% on wheat, outperforming pre-trained networks with fewer parameters and noise immunity.

Ana-Maria Cristea et al. [6] addressed these via synthetic data, self-supervised learning, domain adaptation, and hyperspectral/thermal signals, yet many models validated on lab data failed on field images with dense vegetation or variable illumination. Federated transfer learning enabled collaborative training across environments without data sharing. This study trained a hybrid Graph–SNN model using federated learning, achieved 0.9445 accuracy on lab data and 0.6202 on field data, demonstrating FL's potential for privacy-preserving, reliable detection. Shaohuang Bian et al. [7] proposed a multi-scale feature fusion network based on an improved RT-DETR model for efficient tomato leaf disease detection, combining multi-scale extended residual modules and feature pyramid networks to enhance feature extraction while reducing complex background interference. A novel adaptive focal loss (AFL) was introduced, incorporating attenuation factors and dynamic weighting to focus on high-loss features, alleviate overfitting, and improve performance on imbalanced datasets. These innovations optimized learning, achieving 97.9% AP@0.50 for tomato diseases and 85.4% for other crops. The results provided valuable references for agricultural applications.

Chenyue Ma et al. [8] proposed MSA-UNet, an improved lightweight UNet-based model. It integrated MobileNetV3 encoder, Enhanced Atrous Spatial Pyramid Pooling (E-ASPP) for multi-scale features, and Simple Attention Module (SimAM) for boundary focus. Compared to baseline UNet, MSA-UNet improved mPA by 3.59%, mIoU by 5.32%, and F1-score by 5.75%, while reducing GFLOPs by 87% (394.50G) and parameters by 67% (16.71M). The model enhanced NCLB segmentation accuracy with lightweight efficiency for practical agriculture. Ameer Tamoor Khan et al. [9] evaluated YOLOv11-based models for automated leaf detection and segmentation across spring barley, spring wheat, winter wheat, winter rye, and winter triticale. The main objective was to assess whether a unified model trained on a combined multi-crop dataset could outperform crop-specific models. Results showed that the unified model achieved superior performance in bounding box detection, with mAP@50 exceeding 0.85 for spring crops and 0.7 for winter crops. Segmentation results exhibited mixed performance, as crop-specific models occasionally achieved higher recall for winter crops.

Dr. Shrabani Mallick et al. [10] examined how convolutional neural networks (CNNs) and transfer learning improved disease detection across various crop species. The model was able to be precise, displaying high classification accuracy even with a small quantity of training samples through the strategic use of augmentation methods. The paper also explored real-time location using state-of-the-art object detection models such as YOLO to accurately identify infected areas for fine-grained management. Findings showed CNN-based models, especially those with transfer learning, were more accurate and efficient, pointing to the scalability of deep learning for proactive crop protection. V. Srinivas et al. [11] proposed models that leveraged transfer learning and attention mechanisms to improve accuracy, achieving hypothetical results of approximately 99.7% accuracy on the Plant Village dataset. The findings confirmed that hybrid CNN-ViT architectures yielded the best performance, enabling integration into smart farming through on-device or cloud models that alerted farmers in real-time. More information was available on the article's website.

Sajjad Saleem et al. [12] researched on agricultural productivity was critical for global food security, though crops like potato, tomato, and mango suffered yield losses from leaf diseases, with traditional visual diagnosis being labour-intensive and error-prone. This study introduced AgirLeafNet, a deep learning model combining NASNetMobile for feature extraction, Few-Shot Learning for classification, and the Excess Green Index for robust detection in low-label scenarios. It achieved 100% accuracy for potato, 92% for tomato, and 99.8% for mango leaves, outperforming existing models and advancing multi-crop detection via deep learning/IoT. The innovation set new standards for sustainable agriculture with multi-crop precision and ExG-enhanced robustness. Yimy E. Garcia-Vera et al. [13] proposed a technical review of hyperspectral applications in crops, highlighting AI algorithms like ML/DL, with a 10-year systematic literature analysis. Findings emphasized cereals/citrus, key fruits/vegetables, wavelength ranges, and AI for detection/classification, serving as a reference for sustainable agriculture research.

Youssef Lebrini et al. [14] researched agriculture faced challenges in increasing production while minimizing harmful chemical inputs. Optimizing input use required new precision agriculture technologies. Machine learning and remote sensing had shown progress in detecting crop diseases at the leaf level in controlled environments. Limited progress had been made in detection at the complex field scale for most crops. Diana-Carmen Rodríguez-Lira et al. [15] explored the use of machine learning (ML) techniques for detecting pests and diseases in crops, highlighting the significant challenge of global yield losses. The study focused on the integration of ML models, particularly CNNs, which had shown promise in accurately identifying and classifying plant diseases from images. By analysing studies published from 2019 to 2025, the work summarized common methodologies and indicated that advanced image processing and ML algorithms significantly enhanced disease detection capabilities. The findings confirmed that the incorporation of these techniques led to early and precise diagnoses, thereby improving crop yield and quality while contributing to more sustainable agricultural practices.

3. Proposed System

The proposed CDD-Net system utilizes leaf images from corn, potato, and tomato plants to automatically identify and classify multiple disease conditions and healthy states. The system integrates image preprocessing, machine learning classifiers, and an advanced Swin Transformer–based feature extraction framework optimized using SGD. By learning both local and global visual patterns from leaf images, the proposed approach improves disease discrimination compared to traditional machine learning models, as shown in figure 2. The system evaluates multiple existing classifiers and selects the best-performing model to deliver accurate and reliable disease predictions, supporting early detection and improved crop management.

Dataset: In this step, the input consists of raw leaf images collected from corn, potato, and tomato crops. These images are organized into predefined classes including Corn-Cercosporin Leaf Spot, Corn-Common Rust, Corn-Healthy, Corn-Northern Leaf Blight, Potato-Early Blight, Potato-Healthy, Potato-Late Blight, Tomato-Bacterial Spot, Tomato-Healthy, Tomato-Late Blight, Tomato-Septoria Leaf

Spot, and Tomato-Yellow Leaf Curl Virus. The images are labelled according to disease type and crop category. The output of this step is a structured multi-class dataset suitable for supervised learning.

Image Preprocessing: In this step, the labelled leaf images are prepared to ensure consistency and suitability for deep feature learning. The input images are resized to a uniform resolution and undergo colour normalization to handle illumination differences while preserving disease-related colour patterns. These preprocessing operations ensure that important visual information is retained and consistently represented. The output of this step is a standardized set of leaf images ready for feature extraction.

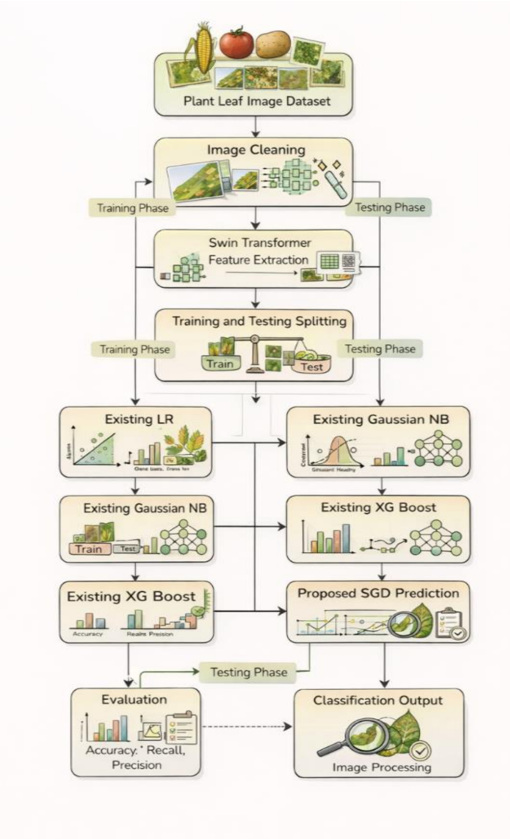

Figure. 2: System architecture.

Swin Transformer Feature Extraction: The pre-processed leaf images are given as input to the Swin Transformer-based feature extraction module. The model divides each image into hierarchical patches and learns multi-scale representations by capturing both local details and global contextual information present in disease-affected regions. Through attention-based learning, the transformer focuses on discriminative patterns such as texture irregularities, shape distortions, and colour variations associated with different crop diseases. The output of this step is a rich and high-dimensional feature representation for each leaf image.

Train &Test Splitting: The pre-processed dataset is divided into training and testing sets. The input is the complete set of processed images with labels, and a fixed ratio is applied to ensure balanced representation of all disease classes in both subsets. The training set is used to learn disease patterns, while the testing set is reserved for unbiased evaluation. The output of this step is two independent datasets that support reliable performance assessment.

Existing LRC: This step applies LRC to the extracted feature vectors obtained from leaf images. The model learns linear decision boundaries by analysing relationships between image features and disease classes. It estimates class probabilities and assigns the most likely disease label to each image. The output is a trained LRC model used as a baseline for performance comparison.

Existing GNBC: In this step, GNBC is employed using the same feature representations. The method assumes feature independence and models each feature using a Gaussian distribution for every disease class. Probabilistic inference is used to classify leaf images into disease categories. The output is a trained GNBC that provides fast and simple disease prediction.

Existing XGB: This step utilizes XGB to classify leaf images based on structured feature inputs. The model builds an ensemble of decision trees in a sequential manner, capturing complex and non-linear relationships between leaf characteristics and disease types. Error correction through boosting improves classification performance. The output is a powerful ensemble model with enhanced predictive capability.

SGD: In the proposed method, pre-processed leaf images are directly fed into a Swin Transformer-based feature extractor. The model divides images into hierarchical patches and learns rich contextual representations of disease symptoms such as lesion spread, texture irregularities, and colour variations. SGD is used to optimize the model parameters by minimizing classification loss. The output of this step is a highly discriminative feature set and an optimized classification model that outperforms existing approaches.

Evaluation: The trained models are evaluated using the test dataset as input. Performance is measured using accuracy to assess overall correctness, recall to evaluate the ability to detect diseased leaves, and precision to measure the reliability of positive predictions. This step provides a comparative analysis of existing and proposed models. The output is a set of quantitative performance metrics.

Prediction: In the final step, unseen leaf images are given as input to the best-performing model identified during evaluation. The model processes the image, extracts relevant features, and predicts the corresponding disease or healthy class. The output is the final disease prediction, enabling timely and informed decision-making in agricultural disease management.

4. Result Analysis

The results analysis section evaluates the performance and effectiveness of the proposed system in achieving accurate and reliable outcomes. It focuses on assessing the model using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure comprehensive performance measurement. The analysis also compares the proposed approach with existing methods to highlight improvements and advantages. Graphical representations and visualizations are utilized to clearly interpret the results and identify patterns or trends. Additionally, the robustness and generalization capability of the model are examined using test datasets. This section provides critical insights into the strengths and limitations of the system, ensuring its suitability for real-world applications. Figure 3 illustrates the confusion matrix of the proposed SGD-based CDD-Net model for multi-class crop disease classification across corn, potato, and tomato leaf categories. The matrix presents the relationship between true class labels and predicted class labels, highlighting the classification performance of the model across all disease and healthy classes. A strong concentration of values along the diagonal indicates that the model achieves high correct classification rates for most categories, particularly for classes such as Corn Healthy, Potato Healthy, and Tomato Yellow Leaf Curl Virus. The off-diagonal elements represent misclassifications, which are relatively minimal, demonstrating the robustness and reliability of the proposed approach. Certain closely related disease classes, such as different blight categories, show minor confusion due to similarity in visual features.

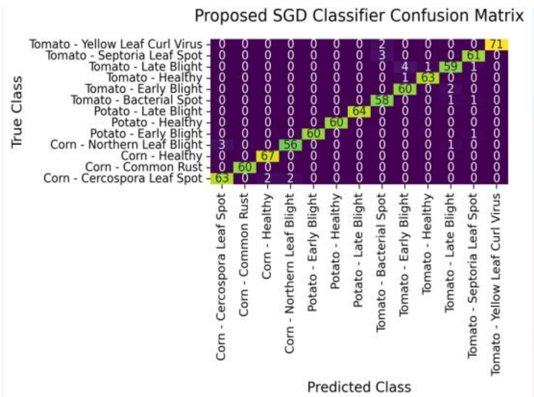

Figure. 3: Obtained confusion matrix of SGD-based CDD-Net.

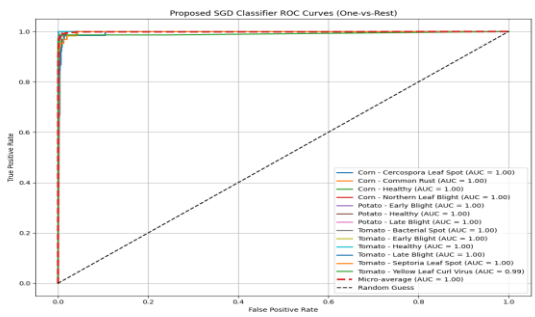

Figure. 4: Obtained ROC curve of SGD-based CDD-Net.

Table. 1: Overall comparison.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LRC	8.83	0.68	7.69	1.25
GNBC	86.70	86.62	86.66	86.56
XGB	87.79	87.63	87.75	87.61
SGD	96.98	96.99	97.00	96.98

Figure 4 illustrates the Receiver Operating Characteristic (ROC) curves of the proposed SGD-based CDD-Net model using a one-vs-rest strategy for multi-class crop disease classification. The curves represent the trade-off between true positive rate and false positive rate for each disease category across corn, potato, and tomato crops. The model demonstrates excellent discriminative ability, as most classes achieve an Area Under the Curve (AUC) value close to 1.0, indicating near-perfect classification performance. The micro-average ROC curve further confirms the overall effectiveness of the model in handling multiple classes simultaneously. The proximity of the ROC curves to the top-left corner signifies high sensitivity and specificity across all categories. Additionally, the model maintains consistent performance even among visually similar disease classes, reflecting its strong generalization capability. Table 1 presents a comparative performance analysis of multiple machine learning models used for crop disease detection, including LRC, GNBC, XGB, and the proposed SGD classifier. The results clearly indicate significant variation in model effectiveness, with LRC showing very low performance, achieving only 8.83% accuracy. In contrast, GNBC and XGB demonstrate strong and consistent performance, achieving accuracies of 86.70% and 87.79% respectively, along with balanced precision, recall, and F1-scores. Notably, the proposed SGD classifier outperforms all other models, achieving the highest accuracy of 96.98%, along with superior precision (96.99%), recall (97.00%), and F1-score (96.98%). These results highlight the robustness and efficiency of the SGD-based approach for accurate and reliable crop disease classification.

5. Conclusion

The experimental results demonstrate that the proposed CDD-Net model significantly outperforms conventional machine learning approaches for crop disease detection using leaf images. The baseline model LRC exhibits very poor performance, achieving only 8.83% accuracy, indicating its inability to effectively model complex multi-class patterns. In comparison, GNBC and XGB achieve competitive results with accuracies of 86.70% and 87.79%, respectively, showing their capability in handling probabilistic and ensemble-based learning tasks. However, the proposed CDD-Net achieves the highest performance with an accuracy of 96.98%, along with precision, recall, and F1-score values of 96.99%, 97.00%, and 96.98%, respectively. This reflects a substantial improvement of approximately 9–10% over existing methods. Furthermore, the balanced precision and recall values confirm the model's robustness with minimal false predictions, while the high F1-score indicates strong overall classification consistency. Therefore, the proposed approach proves to be an effective and reliable solution for accurate crop disease detection, making it suitable for real-time and large-scale agricultural applications.

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