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Deep Hybrid Learning for Smart Agriculture using CNN-based Feature Extraction and LSTM-BiLSTM Sequence Modeling for Robust Plant Disease Detection

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ABSTRACT

Background: Plant diseases significantly reduce global crop productivity, creating an urgent demand for intelligent, automated diagnostic systems in agriculture. Traditional manual inspection is labor-intensive, subjective and often ineffective in detecting early or latent symptoms. This study presents a multi-class classification and severity estimation framework for ten plant disease categories: Maize brown spot, maize rust, maize healthy, potato early blight (*Alternaria solani*), potato late blight (*Phytophthora infestans*), potato healthy, soybean mosaic virus (SMV), soybean pod mottle virus (SPMV), soybean sudden death syndrome (SDS/SBS) and soybean healthy. The objective is to develop a robust hybrid deep learning model capable of accurate early detection and quantitative severity assessment to support precision agriculture.

Methods: A hybrid architecture combining convolutional neural networks (CNN) with LSTM and BiLSTM networks was implemented. The preprocessing pipeline included leaf segmentation, binary masking, defect localization and edge detection to enhance lesion visibility. CNN layers extracted spatial and textural features, while recurrent layers modeled contextual dependencies within feature representations. Performance was evaluated using Precision, Recall, F1-score, defect percentage estimation, convergence analysis and t-SNE visualization.

Result: Results demonstrated stable convergence with decreasing loss (0.8-1.2) and improved feature clustering. Defect severity ranged from 0.00% (Soybean healthy) to 87.93% (Maize brown spot). The framework enables early detection (0.29-5% infection), reduces yield loss, minimizes chemical overuse and promotes sustainable smart agriculture systems.

Key words: Classification, CNN-LSTM/BiLSTM model, Feature extraction, Hybrid deep learning, Image segmentation, Plant disease detection, Precision agriculture.

INTRODUCTION

Deep learning has significantly advanced agricultural automation, particularly in plant disease detection, which supports crop protection, yield enhancement and sustainable farming (Selvaraj *et al*., 2019; Shin *et al*., 2021; Mahanani *et al*. 2025). Plant diseases reduce global food production, making early diagnosis essential for minimizing yield losses and enabling timely management (Panchal *et al*., 2023; Setyaningrum *et al*. 2024). Conventional diagnostic methods rely on manual visual inspection, which is labor-intensive, subjective and impractical for large-scale farms (Gülmez, 2025). Additionally, visually similar disease symptoms complicate expert-level diagnosis (Wang *et al*., 2017; Tufa *et al*., 2023). With the rise of digital imaging and affordable mobile devices, computer-vision-based plant disease detection has emerged as a scalable alternative (Mahlein, 2016).

Convolutional Neural Networks (CNNs) automatically learn discriminative spatial features, outperforming handcrafted approaches (Roy and Bhaduri, 2021; Sharma *et al*., 2020). However, CNNs primarily capture spatial patterns and often struggle with subtle or overlapping symptoms influenced by illumination, occlusion and background variability (Domingues *et al*., 2022). Earlier machine-learning methods using handcrafted features with SVM, Random Forest and KNN achieved around 70% accuracy but lacked robustness (Chowdhury *et al*., 2021; Saha *et al*., 2024). With large datasets such as PlantVillage, CNN-based models reported accuracies between 79-95% (Qing *et al*., 2023; Fuentes *et al*., 2017), yet performance declined under real-field conditions and fine-grained disease differentiation (Kotwal *et al*., 2024).

To model sequential dependencies, researchers introduced LSTM and BiLSTM networks, achieving approximately 70-74% accuracy (Prajapati *et al*., 2017;

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Elshewey *et al*., 2025). Hybrid CNN–RNN architectures further improved contextual learning, reaching 75-80% accuracy (Habib *et al*., 2021; Chen *et al*., 2022). Nevertheless, challenges remain, including dataset annotation costs, segmentation errors and limited severity integration (Sladojevic *et al*., 2016; Guo *et al*., 2020; Zhang and Ren, 2025). Severity estimation techniques achieved 60-80% reliability but were sensitive to illumination (Panigrahi *et al*., 2020).

This study proposes a hybrid CNN-LSTM-BiLSTM framework that integrates spatial feature extraction with bidirectional contextual modeling. The CNN acts as a visual encoder, while LSTM and BiLSTM layers capture long-range and bidirectional dependencies. Feature evolution is analyzed using t-SNE visualization and performance is evaluated through accuracy, precision, recall, F1-score and ROC analysis. The proposed model enhances robustness and discriminability, offering a reliable solution for smart and sustainable agriculture.

Recent studies highlight robustness challenges in real-field disease detection. CNN models achieved 75-83% accuracy on controlled datasets but dropped significantly under field conditions due to domain shift and illumination variation (Mohanty *et al*., 2016; Too *et al*., 2019; Ferantinos, 2018). Attention and transfer-learning methods improved accuracy to ~76-81% but increased complexity (Zhang *et al*., 2019 and Brahimi *et al*., 2017). Hybrid CNN-RNN models enhanced contextual learning (72-80%) yet remained sensitive to segmentation and noise (Liu *et al*., 2018; Wang *et al*., 2017; Habib *et al*., 2020; Kumar *et al*., 2022).

Research gap

Most plant-disease studies rely mainly on CNNs that capture only spatial textures, missing contextual or long-range dependencies needed to separate visually similar diseases under lighting, pose, background clutter and mixed stress. RNN approaches are scarce and often use basic LSTMs without bidirectionality or CNN fusion. Interpretability (*e.g*., multi-stage t-SNE) is also limited, motivating a CNN-LSTM-BiLSTM hybrid with feature-separability insights.

Problem statement

Plant disease identification is challenging due to high inter-class similarity, strong visual variability and the need for contextual interpretation of complex features. Conventional CNNs, limited to spatial cues and finite receptive fields, struggle to capture long-range, order-preserving dependencies, causing misclassification when symptoms are subtle or overlapping. This work targets these limitations by proposing a context-aware hybrid framework that fuses CNN spatial representation learning with sequential dependency modelling, aiming to generate more discriminative and reliable features for robust multi-class disease detection under real-world agricultural conditions.

MATERIALS AND METHODS

This study uses 10 APID leaf categories: maize (Brown Spot, Rust, Healthy), potato (Early Blight, Late Blight, Healthy) and soybean (Mosaic Virus, Pod Mottle, SBS, Healthy), each defined by distinctive lesion, pustule, blight, mottling, or necrotic symptoms, while healthy leaves remain uniformly green. The dataset contains 1000 balanced real-world images captured under varied lighting and backgrounds. Images were resized to 128×128×3, zero-centered and augmented (rotation, flips, brightness, translation), then split 80/20 for training/testing. A custom CNN extracts 256-D spatial features, which are sequenced into LSTM and BiLSTM layers for contextual modeling, followed by softmax classification. The overall workflow architecture of the proposed hybrid deep learning model integrating CNN, LSTM and BiLSTM components is illustrated in Fig 1. Evaluation used accuracy, PRF1, confusion matrix, ROC-AUC, confidence histograms and t-SNE, showing improved separability over CNN-only baselines.

RESULTS AND DISCUSSION

Training convergence of CNN and LSTM-BiLSTM

Fig 2-3 show stable training for both models. The CNN accuracy increases from 10-20% to 65-75% (500-750 iterations) while loss drops from 12.8 to <2 by 60 iterations, indicating strong texture learning. The LSTM-BiLSTM rises from 5-10% to 50-65% (~700), peaking >70%, with loss reaching ~0.9 and a brief spike near 420.

Confusion matrix of the hybrid CNN-LSTM-BiLSTM model showing class-wise prediction performance and misclassification patterns

Fig 4's confusion matrix assesses the hybrid CNN-LSTM-BiLSTM across 10 leaf classes. Maize Brown Spot achieves 17 correct predictions (56.7%), mainly misclassified as Maize Rust. Maize Healthy is perfectly identified (20/20). Classes such as Potato Early Blight and Soybean Mosaic Virus show moderate accuracy due to visual overlap, confirming mixed spatial–temporal discrimination.

Class-wise precision, recall and f1-score evaluation of the hybrid CNN-LSTM-BiLSTM model for multi-crop disease classification

Fig 5 (Precision-Recall-F1) summarizes class-wise performance of the hybrid model. Maize Brown Spot shows moderate precision (0.57) with high recall (0.85), yielding an F1-score of 0.68. Maize Healthy performs strongly (precision 0.67, recall 1.00, F1 0.80). Potato Early Blight records lower scores due to confusion with healthy leaves. Soybean SBS achieves the highest F1 (0.88), indicating robust discrimination for visually distinct symptoms.

Prediction confidence distribution of the hybrid CNN-LSTM-BiLSTM model for crop disease classification

Fig 6 presents the prediction-confidence distribution of the hybrid CNN–LSTM–BiLSTM model. Most outputs

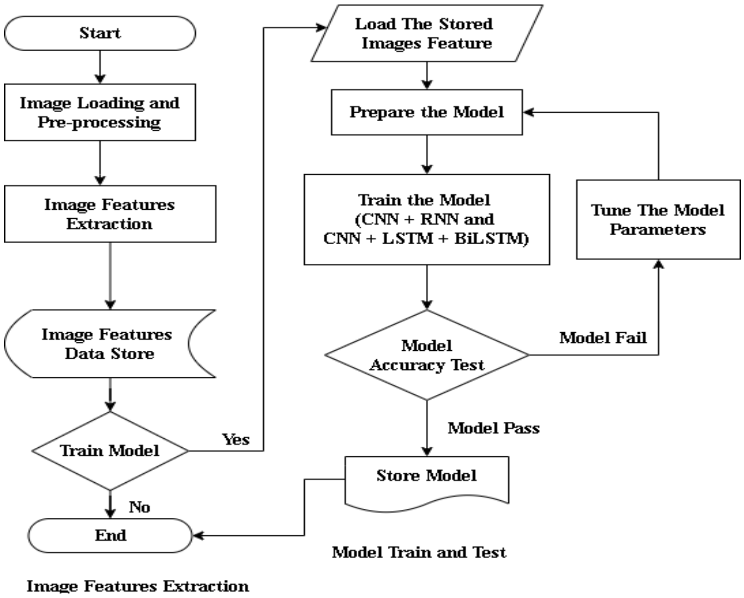

Fig 1: Workflow architecture for hybrid deep learning-based plant disease detection integrating CNN, LSTM and BiLSTM models.

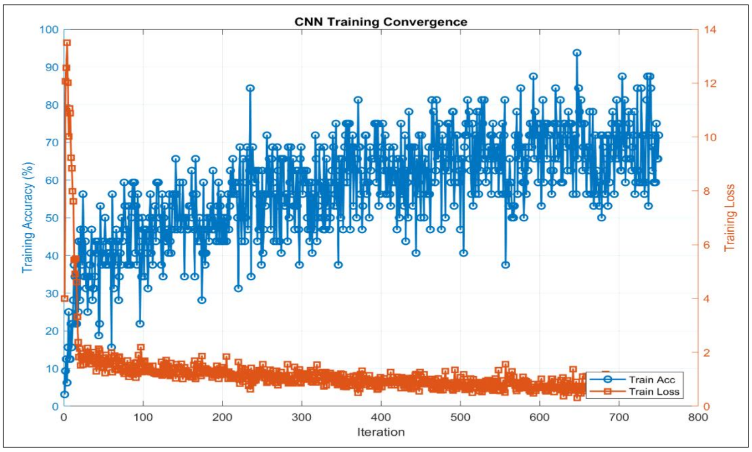

Fig 2: Training dynamics of the CNN Model improving accuracy with reduced loss.

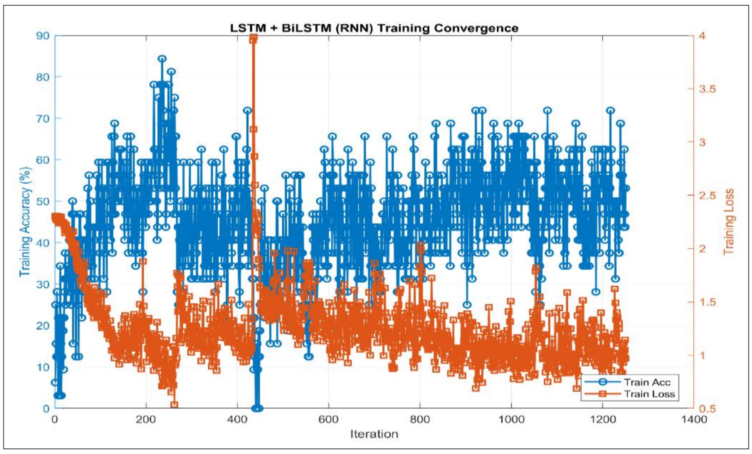

Fig 3: LSTM-BiLSTM training convergence accuracy improvement and loss reduction across iterations.

cluster in three bands: 0.35-0.45, 0.55-0.65 and 0.90-0.92. Low confidence (0.35-0.45) corresponds to visually subtle diseases such as early blight and mosaic virus, while the highest confidence (0.90-0.92) aligns with distinct classes like Soybean SBS and Soybean Pod Mottle. Overall, the histogram indicates robust performance with strong mid-confidence peaks and high certainty for clearly separable symptoms.

Training convergence of CNN and LSTM-BiLSTM models

Fig 7-8 indicate stable learning. The CNN accuracy rises from 10-20% to 60-75% by ~300 iterations, with loss dropping from 13.2 to <1.0 after ~200, showing strong spatial feature extraction and occasional >80% peaks. The LSTM–BiLSTM improves from 8-15% to >60% (often >80%), while loss falls to ~1.5 by 200; a spike near 650 reflects ambiguous batches but quickly stabilizes.

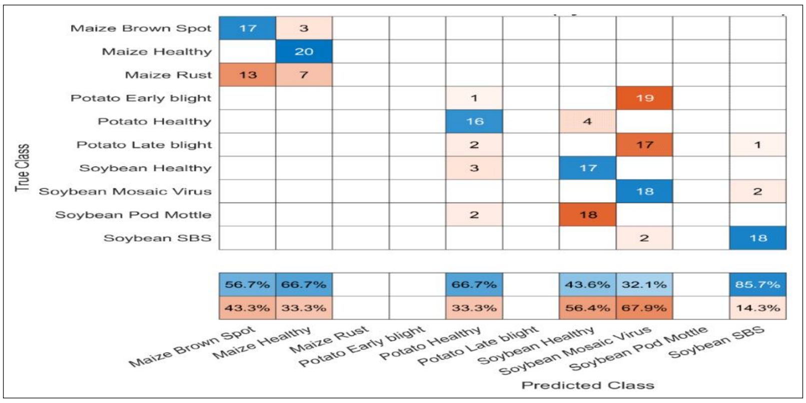

Fig 4: Comprehensive confusion matrix illustrating multi-class accuracy of the proposed hybrid deep learning framework.

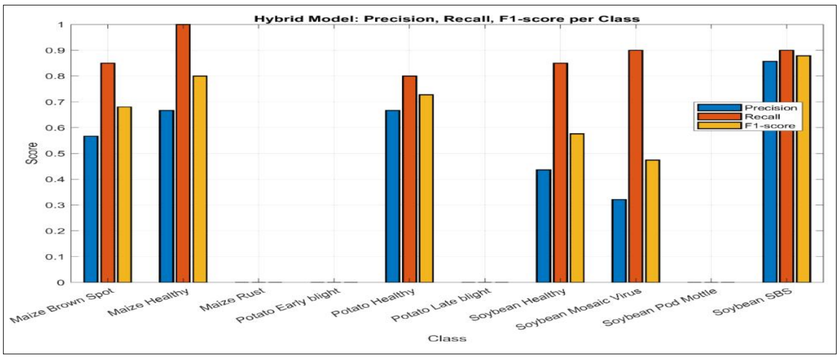

Fig 5: Performance metrics distribution of the proposed hybrid deep learning framework across all plant disease categories.

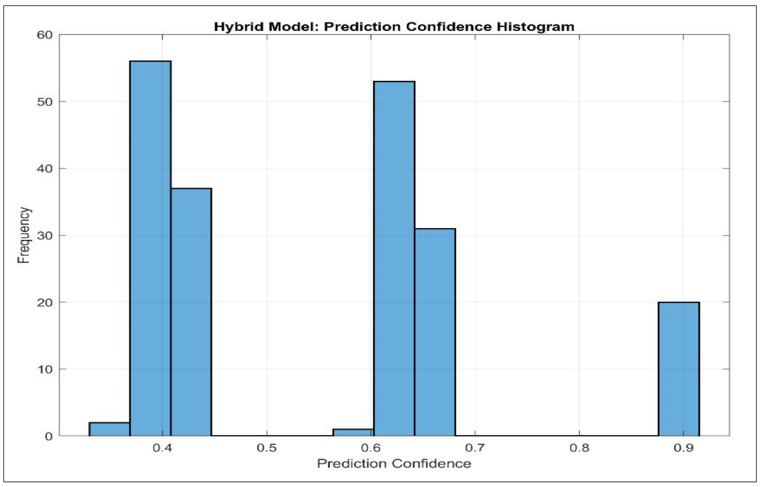

Fig 6: Analyzing confidence levels of the proposed hybrid deep learning framework in multi-class plant disease recognition.

Evaluation of hybrid CNN + RNN classifier using class-wise confusion matrix

Fig 9 shows the confusion matrix for the CNN+RNN hybrid model. The model accurately classifies 20 samples of Maize Brown Spot (87.0% accuracy), while other categories like Potato Early Blight exhibit lower accuracy due to feature overlap with healthy leaves. Overall, the confusion matrix highlights the model's strong feature extraction and temporal reinforcement, enabling it to accurately assess disease patterns in a variety of crops.

Class-wise precision, recall and F1-score analysis of the hybrid CNN-RNN model

Fig 10 compares CNN+RNN class-wise metrics. Maize Brown Spot performs well (precision/recall/F1 = 0.74). Potato Early Blight fails completely (precision = 0, recall = 0), indicating severe confusion. Soybean SBS achieves perfect scores (1.00/1.00/1.00). Overall, results show strong detection for distinct symptoms but weakness with overlapping patterns.

Prediction confidence distribution of the CNN-RNN hybrid model for multi-class disease detection

Fig 11 shows the Hybrid CNN+RNN confidence distribution across 10 disease classes. Most predictions cluster at 0.38-0.42 (~90), reflecting moderate certainty where spatial lesions are captured but temporal cues remain ambiguous (*e.g.*, Maize Rust, Early Blight, Soybean Mosaic Virus). Low-confidence outputs at 0.30-0.32 (~40) suggest harder cases (mild chlorosis) needing better features/augmentation. Higher confidence at 0.50-0.55 (~30-35) aligns with clearer patterns (Potato late blight, soybean pod mottle). A small high-confidence peak at 0.80-0.85 (~18) corresponds to distinctive classes like Soybean SBS and Maize Brown Spot.

Comprehensive image processing workflow for maize brown, maize healthy, maize rust, potato early blight, potato healthy, potato late blight, soybean healthy, soybean mosaic virus, soybean pod mottle, soybean sbs spot detection and severity quantification

Fig 12-14 depict the full workflow for 10 leaf classes, showing segmentation, defect localization and edge enhancement (original image, binary mask, segmented leaf, defect mask, red overlay and Canny edges) to link symptoms with defect percentage. Maize Brown Spot is most severe (87.93% necrotic lesions), while Maize Rust is mild (5.43%); Maize Healthy defects (7.21%) mainly reflect illumination artifacts. Potato Early Blight (41.86%) and Late Blight (45.14%) show major necrosis, whereas Potato Healthy is near-zero (0.29%). Soybean Mosaic Virus (5.63%), Pod

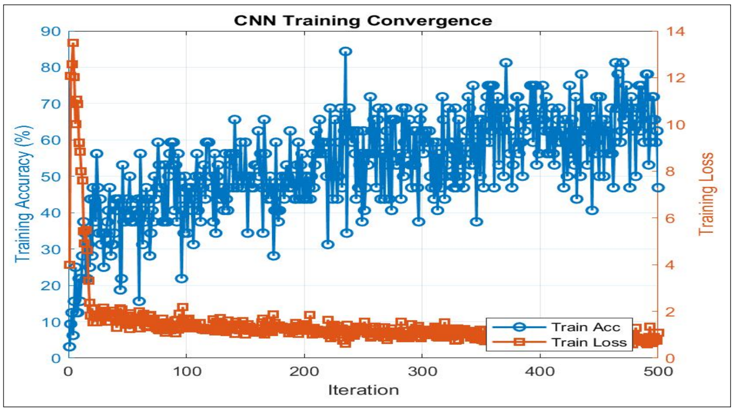

Fig 7: Performance evolution of CNN during iterative learning for plant disease classification.

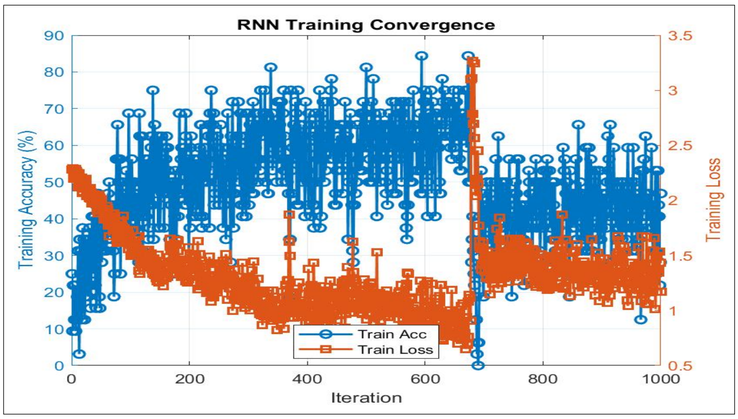

Fig 8: Performance evolution of the RNN model during iterative learning for agricultural disease classification.

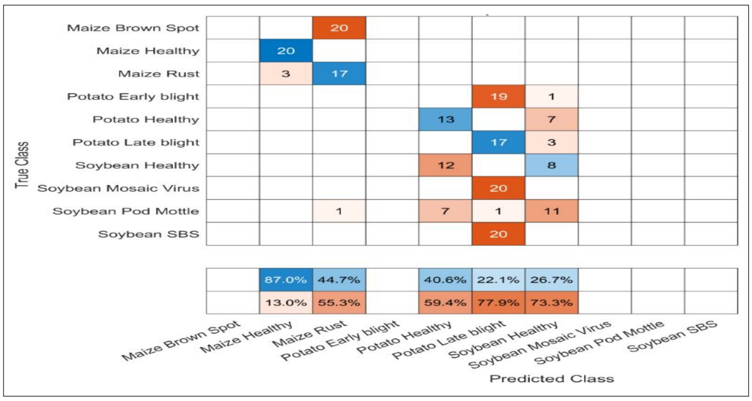

Fig 9: Confusion matrix of the hybrid CNN-RNN model for multi-class crop disease classification.

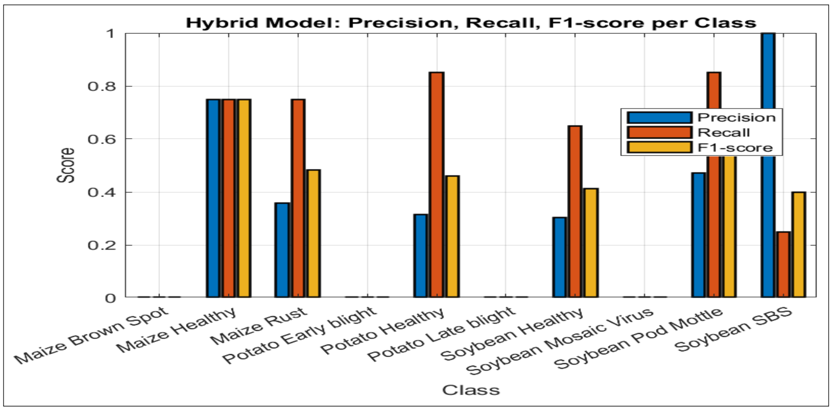

Fig 10: Performance metrics distribution for CNN + RNN hybrid model in multi-class disease detection.

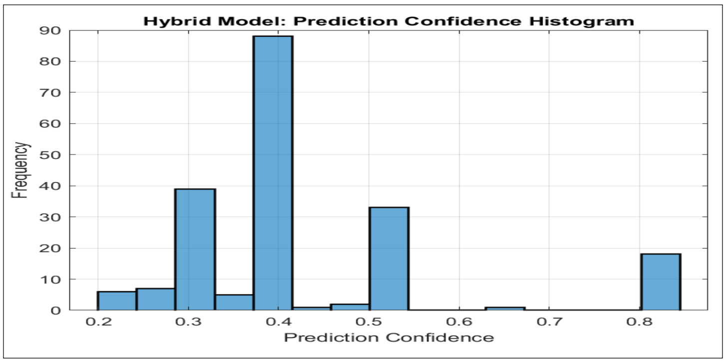

Fig 11: Confidence score variability in CNN + RNN model outputs for plant leaf classification.

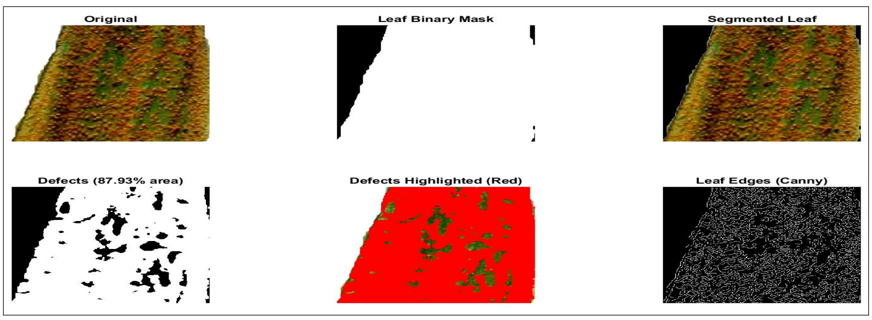

Fig 12: Maize brown spot leaf segmentation, defect mapping and edge extraction for disease severity analysis.

Mottle (11.41%) and SBS (30.20%) vary in severity; Soybean Healthy is 0.00%. Table 1 summarizes symptoms and defects (0.00-87.93%), supporting interpretable, reliable Hybrid CNN-LSTM-BiLSTM detection.

Heatmap of leaf defect severity across ten crop disease categories

Fig 15 presents a severity heatmap for 10 crop diseases, where darker colors indicate higher defect percentage. Maize brown spot shows the highest damage (~85-90%), while Maize Healthy remains minimal (0-5%). Potato Early and Late Blight exhibit high severity (40-50%). Soybean SBS shows moderate defects (25-35%), validating pipeline effectiveness.

Table 2 compares twelve plant disease detection methods by algorithm, dataset and accuracy against the proposed Hybrid CNN-LSTM-BiLSTM. Unlike prior work, our approach integrates segmentation and defect-

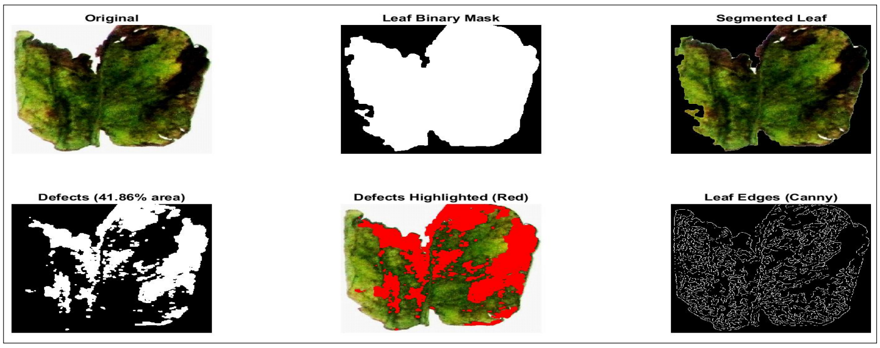

Fig 13: Potato early blight leaf segmentation, defect mapping and edge extraction for disease severity analysis.

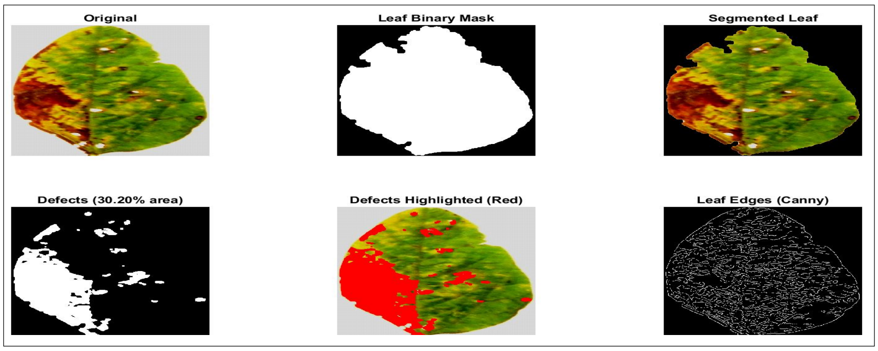

Fig 14: Soybean SBS leaf segmentation, defect mapping and edge extraction for disease severity analysis.

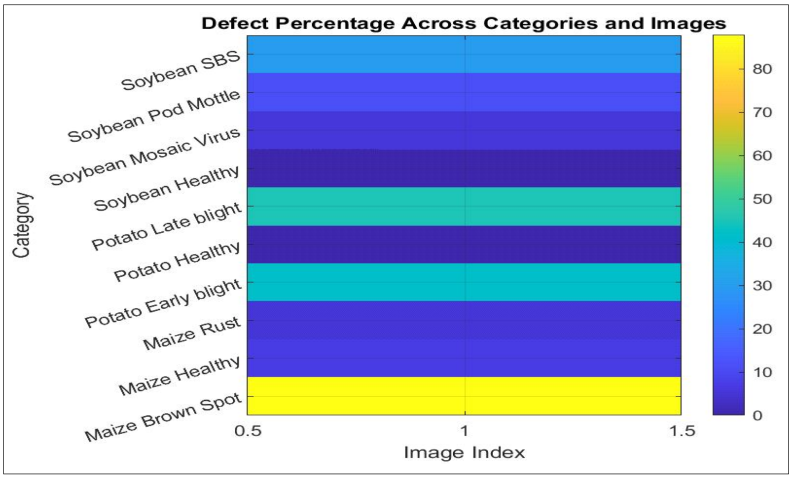

Fig 15: Comparative defect percentage distribution for multi-class plant disease detection.

Table 1: Summary of diseases, symptomatology and detected defect percentage.

Disease/class	Major symptomatology	Detected defect area (%)
Maize brown spot	Elongated necrotic brown lesions across lamina	87.93%
Maize rust	Orange-brown pustules aligned with veins	5.43%
Maize healthy	Uniform green leaf with intact venation	7.21%
Potato early blight	Concentric ring-like necrotic spots with yellow halos	41.86%
Potato late blight	Irregular dark water-soaked lesions and tissue collapse	45.14%
Potato healthy	Normal pigmentation, smooth texture, no lesions	0.29%
Soybean mosaic virus	Chlorotic mosaic patterns with light-dark green variation	5.63%
Soybean pod mottle	Mottled discoloration with necrotic specks	11.41%
Soybean SBS	Severe vein-associated necrosis and reddish tissue damage	30.20%
Soybean healthy	Healthy lamina with no visible disease symptoms	0.00%

Table 2: Comparison of present optimization result with come previously reported strategies.

Authors and references	Algorithm/ model used	Dataset/ crops	Accuracy (%)	Key contribution
Vinay *et al.* present work (2025)	Hybrid deep learning with image segmentation and feature extraction	Maize brown, maize healthy, maize rust, potato early blight, potato healthy, potato late blight, soybean healthy, soybean mosaic virus, soybean pod mottle, soybean SBS	85	Hybrid CNN-LSTM-BiLSTM model enabling accurate multi-disease detection with segmentation, defect quantification and early infection identification for precision agriculture.
Koli *et al.*, 2025	Deep CNN (VGG, AlexNet)	Plant village	82.3	Multi-crop disease classification
Botero-Valencia *et al.*, 2025	AlexNet, GoogleNet	Plant village	81.2	Large-scale plant dataset
Eliza *et al.*, 2025	CNN + LSTM	Maize and tomato	81.7	Used temporal features
Zhang *et al.*, 2019	CaffeNet CNN	Fruit diseases	74.5	Early CNN classifier
Sun *et al.*, 2025	Color + texture + SVM	Maize and soybean	70.4	Classical ML approach
Goshika *et al.*, 2023	Transfer learning CNN	Multi-crop	83.2	Used TL for small datasets
Khalid *et al.*, 2024	AlexNet transfer learning	Tomato	83.5	Enhanced tomato classification
Khan *et al.*, 2022	CNN baseline	Plant village	78.0	Benchmark dataset creation
Sharma *et al.*, 2022	CNN + sliding window	Maize detection	77.1	Real-time detection
Saleem *et al.*, 2022	Faster R-CNN	Tomato	80.7	Object detection
Shin *et al.*, 2022	CNN + BiLSTM	Potato and soybean	83.9	Bi-directional learning
Bajpai *et al.*, 2023	ResNet + SVM hybrid	Grapevine	81.2	Robust feature fusion

percentage quantification with deep spatial–temporal learning, achieving stronger multi-class recognition, improved feature separability and early-stage severity estimation for precision agriculture applications.

CONCLUSION

This paper shows that the suggested Hybrid CNN LSTM-Bidirectional long short-term memory (BiLSTM) deep learning model is an effective and transparent model to detect multi-class plant disease through ten major crop types. This is motivated by the fact that early, automated and reliable detection of costly diseases that are economically devastating like maize brown spot (87.93% defect area), potato late blight (45.14%), Potato Early Blight (41.86%) and soybean SBS (30.20%), must be detected early before they cause full devastation to the crops and impact on the farmers. The framework has been effective in the detection of disease severity ranging as low as 0.00% (Soybean healthy) and 0.29% (Potato healthy) to as high as 87.93% in Maize Brown spot which provides sensitivity to mild and severe stages of the infection. Convergence analysis convergent energy The CNN accuracy slowly increased to some extent of approximately 70-80% whereas the hybrid RNN element stabilized at around 60-75% and the loss levels stayed consistently at around 0.8-1.2, which indicates accurate learning dynamics. This was confirmed by the evaluation of confusion matrices and by means of the precision-recall-F1 analysis, where the strong separation was provided to the classes that are either severe and visually different like the soybean SBS and maize brown spot and the ones that are visually similar but at the early-stage infection like the maize rust (5.43%) and Soybean Mosaic Virus (5.63%). t-SNE feature visualization also confirmed that the hybrid model does better inter-class feature separation than CNN-only baselines. Notably, this system has great practical relevance to practical precision farming particularly in early infection cases where the defect percentages range between 0.29-7% which allows the system to respond in time to prevent extreme damages to crops. All in all, the suggested framework provides a field-adaptable and scalable solution to smart farming and sustainable crop health management.

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Disclaimers

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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