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Meta-Heuristic Enhanced Deep Learning Model for Mango Blossom and Stem Disease Classification

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Abstract

This study presents an innovative classification framework for detecting diseases affecting mango blossoms and stems by integrating deep learning techniques with a meta-heuristic optimization strategy. A dataset consisting of 3,500 images, collected directly from mango orchards across the Konkan region in Maharashtra, is used for training and evaluation. To enhance image clarity and enable effective feature extraction, Contrast-Limited Adaptive Histogram Equalization (CLAHE) is applied during preprocessing. Deep features are subsequently extracted using Convolutional Neural Networks (CNNs). To optimize the extracted feature space, a novel hybrid algorithm, Adaptive Squirrel-Grey Wolf Search Optimization (AS-GWSO) is introduced, boosting both processing efficiency and classification precision. For the final classification stage, an Enhanced Long Short-Term Memory (E-LSTM) model is employed, which utilizes the optimized features to improve generalization and minimize overfitting. Experimental results demonstrate that the proposed AS-GWSO-LSTM model outperforms existing classifiers and meta-heuristic-based models, achieving a high accuracy rate of 97.2%. The findings highlight the model's strong applicability for real-time agricultural disease monitoring systems.

Keywords: Mango Blossom and Stem Disease, CLAHE, CNN, AS-GWSO, Enhanced LSTM, Deep Learning, Agricultural Disease Detection.

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1. Introduction

Mango (Mangifera indica) is among the most widely cultivated tropical fruits and plays an important role in India's agriculture-driven economy [1]. However, fungal infections like anthracnose and powdery mildew reduce yield by 20–40% annually [2]. Manual disease identification methods are inefficient, labor-intensive, and subjective [3]. Therefore, automated detection approaches using artificial intelligence and machine learning are essential for improving precision farming practices. Deep learning (DL) has demonstrated significant potential in crop disease detection, providing high accuracy in complex classification tasks [4, 5]. However, the effectiveness of DL models depends heavily on feature quality and hyperparameter tuning [6]. To address these challenges, this study presents a novel framework that combines deep feature extraction using CNNs with a hybrid feature selection and parameter optimization method based on AS-GWSO. The optimized features are then classified using Enhanced LSTM architecture, resulting in highly accurate and efficient disease detection.

2. Related Work

Recent progress in mango disease detection has increasingly incorporated deep learning (DL) and meta-heuristic optimization techniques to boost classification precision, optimize feature selection, and enable real-time implementation. This section discusses key research developments in the field. Deep neural networks have been widely utilized for mango disease identification. Singh et al. [2] designed a multilayer CNN to detect anthracnose in mango leaves, showcasing the strength of deep feature learning in disease detection. In a related effort, Mia et al. [3] integrated neural networks with support vector machines (SVMs), achieving effective disease classification without the need for expert diagnosis. Pham et al. [1] implemented a feed-forward neural network (FNN) in combination with a hybrid meta-heuristic feature selection method, enabling improved early-stage classification by targeting lesion-specific regions. Lavanya et al. [4] proposed an advanced BIRCH-based segmentation algorithm paired with a hybrid classifier to enhance disease differentiation. Addressing lighting variation, Rajpoot et al. [5] employed brightness-preserving histogram equalization (BBHE) in tandem with CNNs, a technique extended in this study using contrast-limited adaptive histogram equalization (CLAHE). Gautam et al. [8] developed ESDNN, a stacked deep learning framework that delivered superior sensitivity and specificity in mango leaf disease classification.

Meta-heuristic algorithms have become central in refining feature spaces and tuning model parameters. Seetha et al. [6] introduced the Coyote-Grey Wolf Optimization (CGWO) algorithm to fine-tune neural networks for leaf disease classification. Veling et al. [7] applied a weighted feature selection approach based on meta-heuristics within a hybrid E-LSTM-CNN framework, achieving notable improvements in multi-class classification. Vijay and Pushpalatha et al. [11] proposed DV-PSO-Net, combining particle swarm optimization (PSO) with deep mutual learning to accelerate convergence and improve classification accuracy. Other recent meta-heuristics, including the Botox Optimization Algorithm in Hubálovská et al. [14], Archimedes Optimization (Hashim et al[16]), Red-Tailed Hawk Algorithm (Ferahtia et al., [17]), and Pufferfish Optimization (AlBaik et al. [18]), have proven effective in high-dimensional model tuning, supporting the use of hybrid optimization in the present work.

Segmentation plays a pivotal role in accurately identifying disease-affected regions. Alom et al [13] introduced R2U-Net, which integrates residual and recurrent components into a U-Net structure for precise segmentation, aligning with the focus of this study on critical feature localization. Nguyen et al. [19] demonstrated how Residual Attention Networks effectively emphasized significant features—conceptually similar to the enhanced LSTM structure employed in the proposed model. For real-world adoption, Rao et al. [9] applied transfer learning using lightweight architectures like MobileNet and AlexNet, creating mobile-ready systems for mango and grape leaf disease detection. Rizvee et al. [10] developed LeafNet, a customized CNN capable of recognizing seven types of mango leaf diseases with an emphasis on scalability. To overcome dataset limitations, Liu et al. [12] utilized a GAN-based semi-supervised approach for data augmentation, enhancing the robustness of DL models. Additionally, Suhasini and Balaram. [15] explored convolutional recurrent neural networks (CRNNs) augmented with meta-heuristics for fruit disease identification, effectively integrating both spatial and temporal learning.

Overall, the reviewed literature emphasizes the value of merging deep learning architectures, intelligent segmentation techniques, and meta-heuristic algorithms to attain high-performance mango disease classification. These developments form the groundwork for the proposed AS-GWSO-LSTM framework, which synergizes deep learning with hybrid optimization for superior feature selection and classification accuracy.

3. Proposed Model of Mango Blossom and Stem Disease Detection

The proposed AS-GWSO-LSTM model integrates deep learning and meta-heuristic optimization for efficient mango disease classification. It follows a five-stage pipeline, including image preprocessing, feature extraction, feature selection, classification, and evaluation. Figure 1, presents the block diagram of the model.

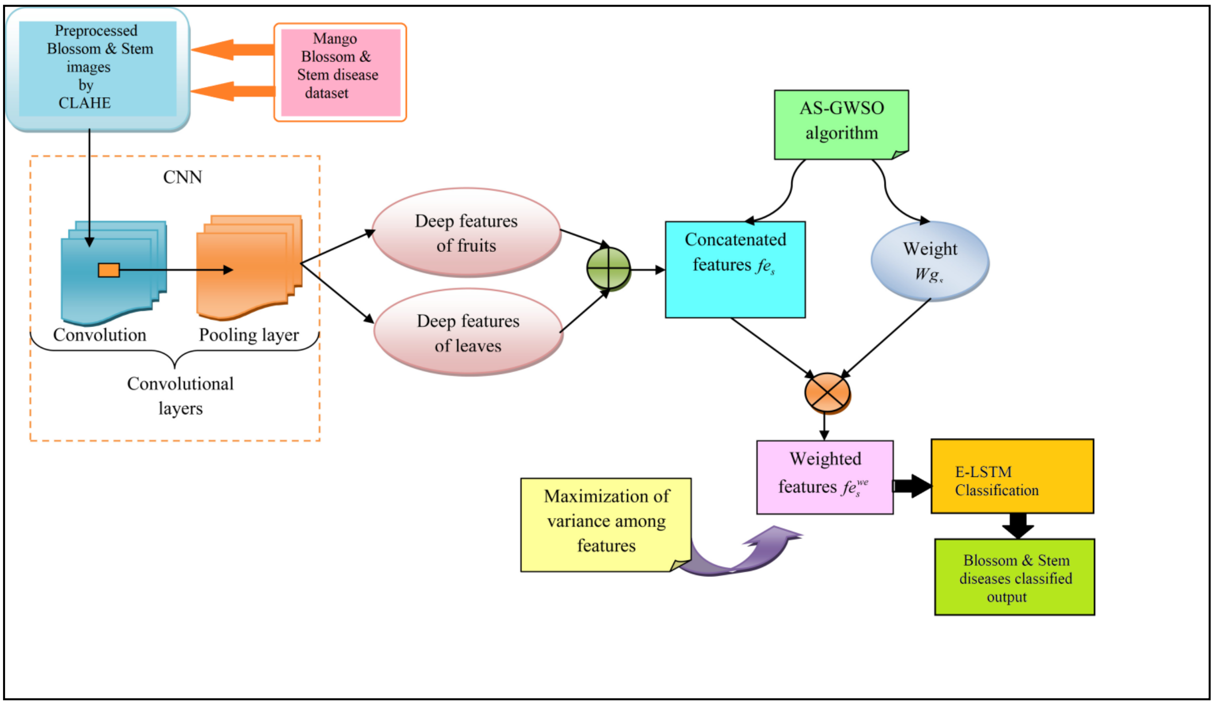

Figure 1. Block Diagram of Proposed Mango Disease Classification Model

3.1 Data Collection and Preprocessing

The dataset consists of 3,500 images of mango blossoms and stems collected from the different orchards across Konkan region in Maharashtra, India, covering both healthy and diseased samples. Mango blossom diseases included are Powdery mildew and Blossom blight, while stem diseases included are Pink disease, Black banded and Gummosis. To address inconsistencies in lighting and image quality, Contrast-Limited Adaptive Histogram Equalization (CLAHE) is applied, enhancing contrast and improving feature extraction [5, 13]. This ensures that the image inputs are optimized for CNN-based feature extraction. Figure 2 depicts the original images and CLAHE processed outputs of these mango diseases.

(a)

(b)

(c)

(d)

(e)

(f)

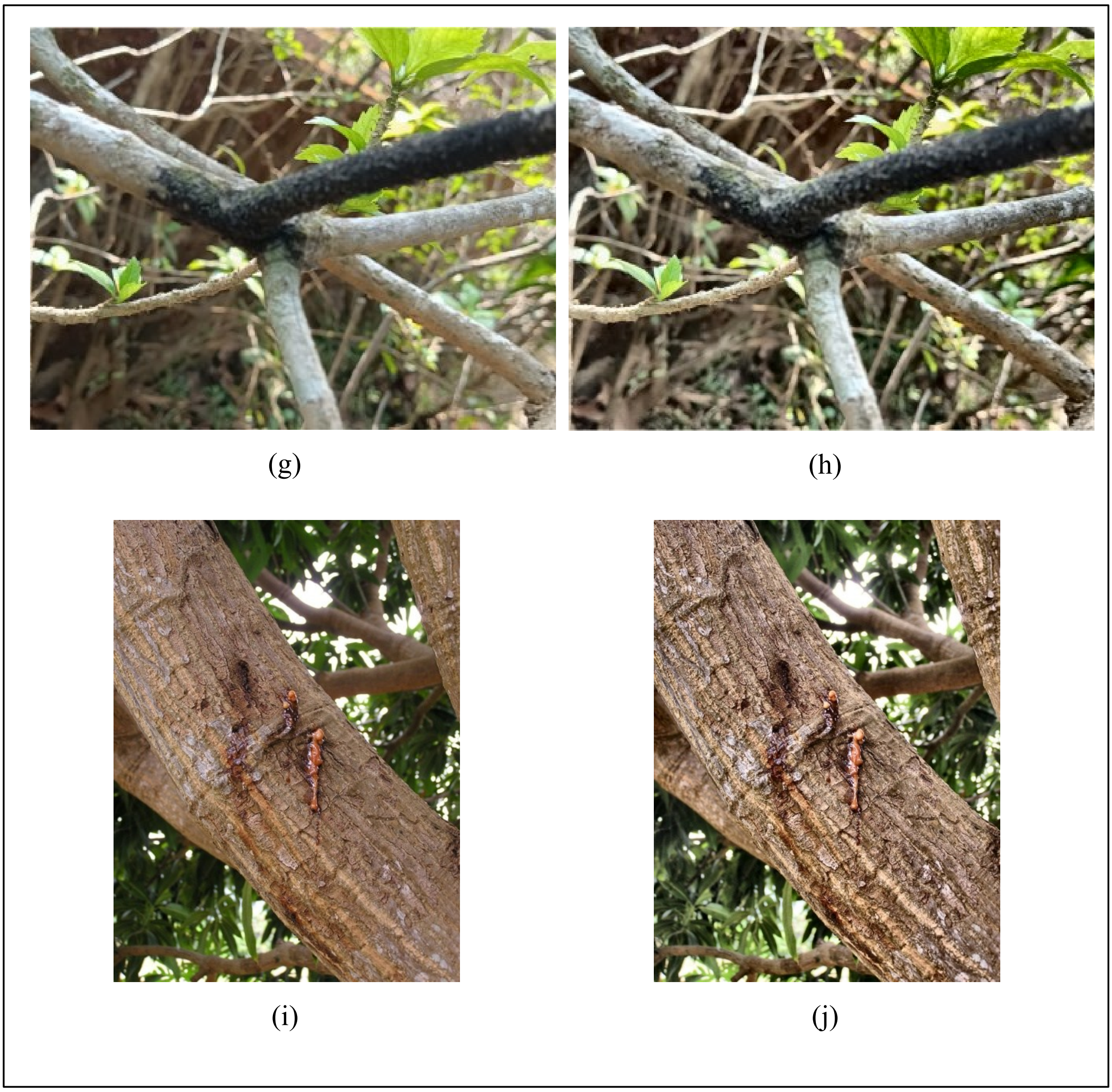

Figure 2. Original Image and CLAHE Output of (a, b) Blossom Blight, (c, d) Powdery Mildew, (e, f) Pink Disease, (g, h) Black Banded and (i, j) Gummosis Disease of Mango

3.2 Feature Extraction using CNN and Concatenation

A Convolutional Neural Network (CNN) extracts meaningful features from pre-processed images, distinguishing healthy and diseased samples. Convolution layers detect key patterns, while pooling layers reduce dimensionality, retaining important features [2]. The proposed CNN architecture features five convolutional layers (3×3 kernels, linear activation) each followed by five max-pooling (2×2), two fully connected layers, one input layer, and one output layer, extracting hierarchical disease patterns from mango blossom and stem images. Two fully-connected layers process these features, with hidden neurons dynamically adjusting between 5 - 256 units during 50 - 100 training epochs. The model fuses blossom and stem feature vectors through concatenation, enabling comprehensive disease analysis while maintaining computational efficiency through dimensionality reduction.

3.3 Feature Selection using AS-GWSO

The proposed Adaptive Squirrel-Grey Wolf Search Optimization (AS-GWSO) algorithm represents an innovative hybrid approach that synergistically combines the global exploration capabilities of the Squirrel Search Algorithm [20] with the local exploitation strengths of the Grey Wolf Optimizer [21] to enhance mango disease classification performance. This intelligent metaheuristic initiates by generating a diverse population of candidate solutions encoding both feature weights and LSTM hyperparameters, then dynamically alternates between exploration and exploitation phases based on real-time fitness evaluations through adaptive parameters ξ and η. During exploration phases ($\xi > \eta$), the algorithm mimics squirrel foraging behavior through three distinct movement patterns between solution trees while incorporating seasonal monitoring to avoid local optima, while exploitation phases ($\xi \leq \eta$) employ wolf-inspired hunting strategies following hierarchical leadership principles [15]. By simultaneously optimizing feature selection weights (0-1 range) and neural network parameters (5-256 hidden neurons, 2-20 epochs), AS-GWSO maintains an optimal balance between solution diversity and convergence speed. The algorithm demonstrates particular effectiveness in agricultural computer vision applications, efficiently identifying discriminative disease features while optimizing deep learning architectures, and terminates based on either performance thresholds or computational constraints, providing superior convergence characteristics compared to conventional optimization methods for plant disease detection tasks. Figure 3, illustrates flowchart of this process, ensuring optimized feature input for classification.

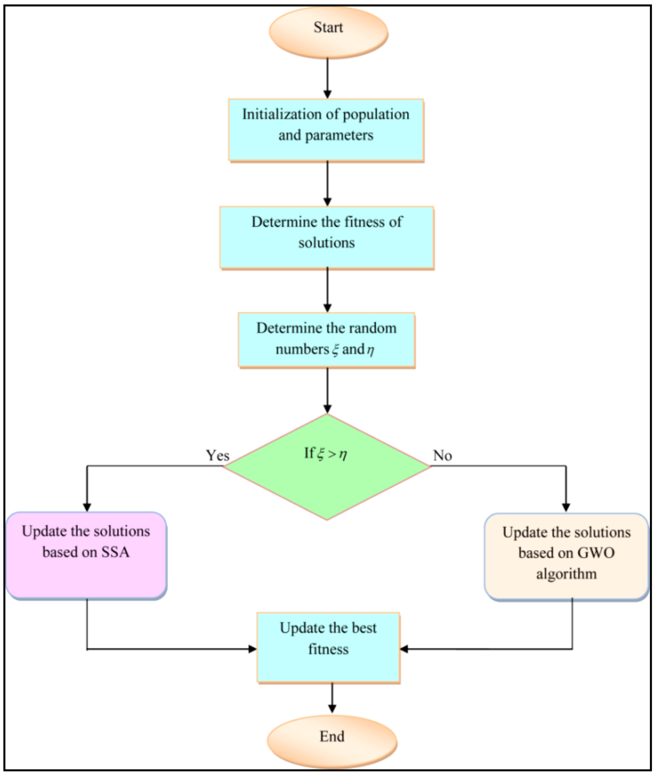

Figure 3. Flowchart of AS-GWSO Algorithm

3.4 Disease Classification using Enhanced LSTM

The Enhanced LSTM architecture incorporates AS-GWSO optimization to improve disease classification performance in mango trees. This implementation focuses on two key parameter optimizations: Hidden neuron count optimization (range: 5-255 neurons) and Training epoch optimization (range: 2-20 epochs). The optimization process follows the objective function as given in Eq. (1).

$$Fn = \underset{\{Hk,Eh\}}{\arg\min}\left(\frac{1}{Ac + Pec}\right) \tag{1}$$

Where, Hk represents the number of hidden neurons, Eh denotes the training epoch count, Ac signifies classification accuracy and Pec indicates precision metrics.

Precision is termed as that is the “ratio of positive observations that are predicted exactly to the total number of observations that are positively predicted” as shown in Eq. (2).

$$Pcs = \frac{tre^{ptv}}{tre^{ptv} + fs^{ptv}} \tag{2}$$

Accuracy is noted as , which is a "ratio of the observations of exactly predicted to the whole observations" as given in Eq. (3).

$$Acr = \frac{\left(tre^{ptv} + tre^{ntv}\right)}{\left(tre^{ptv} + tre^{ntv} + fs^{ptv} + fs^{ntv}\right)} \tag{3}$$

Here, terms like tre^{ptv}, tre^{ntv}, fs^{ptv} and fs^{ntv} denote the "true positives, true negatives, false positives, and false negatives," respectively. At last, the precise and accurate classified outcomes in terms of multi-diseases in mango trees blossoms and stems are obtained through enhanced LSTM by AS-GWSO algorithm. The framework of designed enhanced LSTM model is depicted in Figure 4.

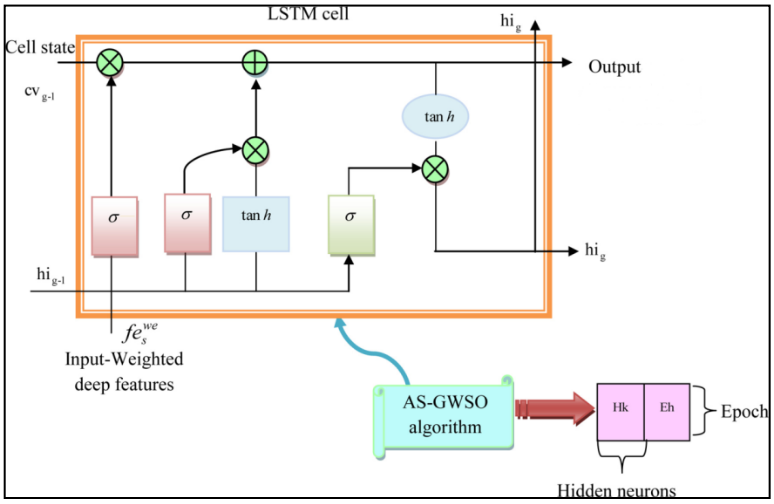

Figure 4. Proposed Enhanced LSTM Architecture

4. Results and Discussion

The AS-GWSO-LSTM framework was developed using Python's TensorFlow platform, demonstrated exceptional performance in mango disease classification. Using a standard 75-25 training-testing split, the system achieved 97.2% accuracy, outperforming both conventional machine learning approaches (SVM, MCNN, ANN, LSTM) and other metaheuristic-optimized models (PSO-LSTM, WOA-LSTM, SSA-LSTM, GWO-LSTM) as given in table 1. The framework showed balanced diagnostic performance with 97.3% sensitivity and 97.0% specificity, while maintaining high precision (83.1%) and low error rates (FPR: 2.7%, FNR: 2.3%). Composite evaluation metrics further validated the model's effectiveness, including an 89.3% F1-score and 87.5% MCC, indicating robust classification capability. Particularly noteworthy were the model's strong negative predictive value (99.85%)

and reduced false discovery rate (21.6%), making it especially reliable for real-world agricultural applications where accurate disease identification directly impacts crop management decisions. These results confirm that the proposed AS-GWSO optimization successfully enhances LSTM's pattern recognition capabilities while effectively controlling both false positive and false negative errors.

The AS-GWSO-LSTM framework's superior performance can be attributed to its innovative combination of adaptive switching and grey wolf optimization techniques, which synergistically enhance the LSTM's ability to capture complex temporal patterns in mango disease manifestation. This optimized approach enables the model to effectively navigate the high-dimensional feature space of plant disease indicators, resulting in more accurate and reliable classifications compared to traditional methods. The framework's robust performance across various evaluation metrics suggests its potential for broader applications in agricultural disease detection, potentially extending beyond mango crops to other fruit or crop species with similar disease progression patterns. The performance comparison for classification across different classifiers and varied meta-heuristic-based methods is shown in the Table 1 below.

Table 1. Performance Comparison for Classification across Different Classifiers and Varied Meta-Heuristic-based Methods

Metrics (%)	**SVM**	**MCNN**	**ANN**	**LSTM**	**PSO-LSTM**	**WOA-LSTM**	**SSA-LSTM**	**GWO-LSTM**	**AS-GWSO-LSTM**
Accuracy	94.0	93.9	93.1	95.3	93.6	93.3	95.2	93.8	97.2
Sensitivity	94.1	93.9	93.2	95.1	93.5	93.2	95.3	93.9	97.3
Specificity	93.95	93.85	93.0	95.2	93.55	93.25	95.1	93.75	97.0
Precision	74.2	72.9	70.2	76.9	74.2	72.9	70.2	76.9	83.1
FPR	2.8	3.1	4.1	3.5	2.9	3.0	4.0	3.4	2.7
FNR	2.7	3.1	3.85	3.2	2.75	3.0	3.8	3.1	2.3
NPV	99.6	99.48	99.38	99.5	99.65	99.50	99.40	99.55	99.85
FDR	25.8	27.1	29.5	26.9	25.7	27.0	29.3	26.8	21.6
F1-Score	84.2	82.8	80.1	85.3	84.1	82.9	80.3	85.2	89.3
MCC	83.0	81.5	78.6	82.1	82.9	81.6	78.7	82.0	87.5

5. Conclusion

This study presents the novel AS-GWSO-LSTM framework for accurate classification of mango blossom and stem diseases, combining advanced image enhancement through CLAHE, deep feature extraction using CNNs, and optimized classification through metaheuristic-enhanced LSTM networks. The proposed model demonstrates exceptional performance with 97.2% accuracy and 83.1% precision, while maintaining balanced sensitivity (97.3%) and specificity (97.0%) with low error rates (FPR: 2.7%, FNR: 2.3%). These results represent significant improvements over conventional approaches, as evidenced by robust metrics including an 89.3% F1-score and 87.5% MCC, along with a 21.6% reduction in false discovery rates. While the framework shows great promise for agricultural diagnostics, current challenges include scalability with large datasets and performance in complex field conditions involving multiple diseases. Future development will focus on expanding the training dataset, enhancing real-time field adaptability through IoT integration, and extending the model's capability for multi-organ disease detection. Implementation partnerships with agricultural agencies are planned to facilitate large-scale testing and deployment, with the ultimate goal of creating an intelligent monitoring system to support precision farming and automated disease diagnosis. These advancements will address existing limitations while maximizing the framework's practical applicability in real-world agricultural settings.

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