EfficientNet–Fuzzy ShCNN for Multi-Level Cotton Leaf Disease Classification under Complex Environments

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ABSTRACT

Cotton diseases reduce crop yield and fiber quality, leading to significant agricultural losses. Early detection plays a key role in effective disease control and crop management. The presence of visible infection patterns on cotton leaves makes it possible to identify these diseases at an early stage. This study proposes an effective model for cotton leaf disease classification using a hybrid EfficientNet–Shepard Convolutional Neural Network (EffNet_ShCNN). The input images are first processed using a Kalman filter for noise reduction and enhancement. Subsequently, leaf segmentation is performed using Fuzzy Local Information C-Means (FLICM) clustering. Multiple features, including shape, color, texture, CNN features, Local Gabor Binary Pattern (LGBP), Spider Local Image Feature (SLIF), and Weber Local Descriptor (WLD), are then extracted. These features are used for disease detection to classify leaves into healthy and unhealthy categories. The proposed model integrates EfficientNet and ShCNN with fuzzy-enhanced layers to improve classification robustness. Finally, the model performs multi-class classification into three disease categories: aphids, bacterial blight, and target spot. Experimental results demonstrate that the proposed method achieves a maximum accuracy of 91.70%, sensitivity of 90.40%, and specificity of 92.90%, indicating its effectiveness under complex environmental conditions.

Keywords-EfficientNet; Shepard Convolutional Neural Network (ShCNN); Convolutional Neural Network (CNN); Weber Local Descriptor (WLD); Local Gabor Binary Pattern (LGBP)

I. INTRODUCTION

Agriculture is one of the primary sectors of the economy in South Asia, with nearly two-thirds of the population engaged in agricultural and allied activities. It has long been considered the backbone of India, with its origins tracing back to the Indus Valley civilization. Agriculture plays a vital role in developing countries by generating employment and contributing significantly to the Gross Domestic Product (GDP) [1].

Cotton is an important agricultural crop with substantial economic value. However, plant diseases significantly affect crop yield and fiber quality, leading to major agricultural losses. Cotton cultivation, particularly in countries such as Pakistan and India, plays a crucial role in the economy. Disease-related damage to crops adversely impacts both yield and quality, and if not detected in time, can lead to serious food security concerns. In addition, staple crops such as wheat, rice, and maize are essential for ensuring food supply, making early disease detection critical for sustainable agriculture [2]. Early diagnosis and timely intervention are essential to improve agricultural productivity and economic efficiency for farmers.

Traditional methods for detecting cotton diseases rely heavily on visual inspection by experienced farmers or agricultural experts [3]. However, this approach is labor-intensive, subjective, and often impractical for large-scale farming. In recent years, Deep Learning (DL) techniques have demonstrated significant success in plant disease classification tasks. Their ability to learn complex patterns and generalize effectively makes them well-suited for large-scale plant leaf classification problems [4].

Although recent DL approaches have shown promising results in plant disease classification, most existing methods rely primarily on end-to-end Convolutional Neural Network (CNN) architectures without explicitly addressing challenges present in real-field conditions. There is a need for a hybrid framework that combines traditional image processing techniques with DL models to enhance classification performance under complex environmental conditions. The contributions of this paper are as follows:

1. A hybrid EfficientNet–Shepard Convolutional Neural Network (EffNet_ShCNN) model is proposed for cotton leaf disease classification.
2. A Kalman filter-based preprocessing technique is used to improve image quality.
3. Fuzzy Local Information C-Means (FLICM) segmentation is employed to accurately isolate the leaf region.
4. A combination of handcrafted and deep features is used for improved representation.

II. LITERATURE REVIEW

The literature on cotton leaf disease classification has reported several machine learning and DL-based approaches.

Authors in [5] introduced S-DenseNet for cotton leaf disease spot classification. It reduced irrelevant information in images and mitigated information loss. However, it failed to preserve sufficient discriminative features for robust classification. Authors in [6] developed a Bilinear Coordinate Attention Enhancement Module (BCAEM) for cotton leaf disease identification. This improved localization and attention to diseased regions. However, it was not effective in optimizing the overall model performance.

Authors in [7] designed a Super-Resolution Convolutional Neural Network (SRCNN) for plant disease detection to improve crop productivity. It enabled end-to-end mapping from low-resolution to high-resolution images. Nevertheless, the computational cost of this approach was high. Authors in [8] introduced a Deep Convolutional Neural Network (DCNN) for disease severity level identification in cotton plants. It was capable of capturing both local and global features for disease detection. Nonetheless, it was not efficient when processing large-scale image datasets. Authors in [9] developed a DCNN for automatic classification of real-time diseased cotton leaves and plants. This method achieved accurate disease recognition.

Authors in [10] investigated DL and transfer learning approaches for cotton disease classification, evaluating multiple CNN architectures and identifying InceptionV3 as the most effective model due to its strong feature extraction capability. Their system achieved a validation accuracy of 96.95% across seven cotton disease classes, demonstrating the potential of transfer learning–based frameworks for data-driven decision-making and improved crop health monitoring in modern cotton farming.

Authors in [11] introduced a cotton leaf disease recognition framework that combines deep feature extraction with a Genetic Algorithm (GA) for feature selection, followed by a classical classifier for final prediction.

Authors in [12] presented an EfficientNet-centric cotton leaf disease classifier designed for both accuracy and interpretability under real farming constraints. Their hybrid architecture combining EfficientNet-B3 and InceptionResNetV2 achieved 98.0% accuracy, with 98.1% precision, 97.9% recall, F1-score of 98.0%, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) of approximately 0.9992.

III. METHODOLOGY

The proposed framework integrates preprocessing, segmentation, feature extraction, and classification to address the limitations of existing DL methods, as shown in Figure 1.

A. Image Acquisition and Preprocessing

The dataset used in this study is obtained from a publicly available Kaggle cotton leaf disease dataset, which contains labeled images of cotton leaves affected by different diseases [13]. The dataset includes three classes: aphids, bacterial blight, and target spot. A total of approximately 1,500 images were used, with nearly 500 images per class. The dataset was divided into training and testing sets using an 80:20 split ratio. All images were resized to a fixed resolution of 224 × 224 pixels before further processing.

Let the cotton leaf image dataset be represented as:

$$\mathcal{I} = \{I_1, I_2, \dots, I_N\} \tag{1}$$

where N denotes the total number of images.

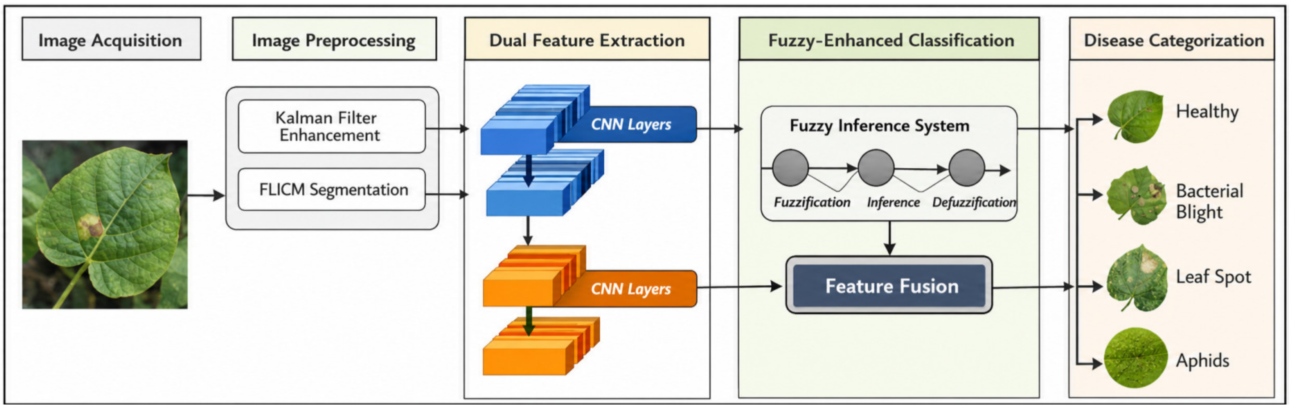

Fig. 1. Architecture of the proposed EffNet_ShCNN for multi-level cotton leaf disease classification.

Each image I_i is enhanced using an adaptive Kalman filter to suppress acquisition noise and improve feature visibility, following recent image denoising formulations that integrate recursive state estimation with spatial smoothing [14].

The Kalman state and observation models are defined in (2) and (3), respectively:

$$x_k = Ax_{k-1} + Bu_k + w_k \tag{2}$$

$$z_k = Hx_k + v_k \tag{3}$$

where w_k and v_k represent system and observation noise, respectively. The filtered output image is denoted as $I^{(p)}$.

Figure 2 illustrates the flowchart of the proposed image preprocessing algorithm.

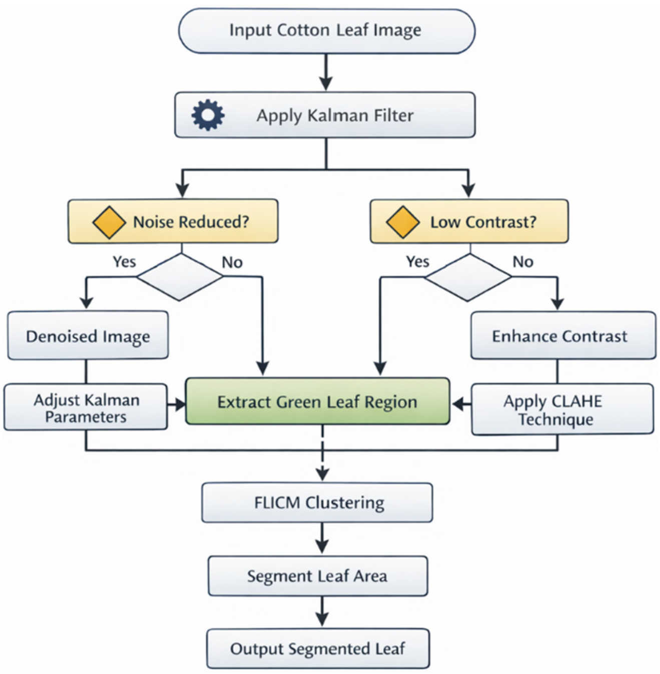

Fig. 2. Image preprocessing and segmentation pipeline.

B. Leaf Segmentation Using Fuzzy Local Information C-Means

The pre-processed image $I^{(p)}$ is segmented using FLICM to isolate the leaf region [15]. The fuzzy factor is computed as shown in (4):

$$G_{ki} = \sum_{j\in N_i} \frac{1}{d_{ij}+1}(1-u_{kj})^m \tag{4}$$

The FLICM objective function is given by (5):

$$J = \sum_{i=1}^{N}\sum_{k=1}^{C} u_{ki}^m \|x_i - v_k\|^2 + \sum_{i=1}^{N}\sum_{k=1}^{C} G_{ki} \tag{5}$$

Membership updates and cluster center updates are performed using (6) and (7):

$$u_{ki} = \frac{1}{\sum_{j=1}^{C}\left(\frac{\|x_i-v_k\|}{\|x_i-v_j\|}\right)^{\frac{2}{m-1}}} \tag{6}$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}^m x_i}{\sum_{i=1}^{N} u_{ki}^m} \tag{7}$$

Defuzzification assigns each pixel to the cluster with the highest membership value, as shown in (8):

$$\text{Class}(x_i) = \arg\max_k u_{ki} \tag{8}$$

C. Feature Extraction

From the segmented leaf image $I^{(s)}$, multiple complementary features are extracted to capture texture, shape, and color information for robust classification.

1) Texture Descriptors

Texture features are extracted to capture local spatial patterns and structural variations in the leaf surface:

- Local Gabor Binary Pattern (LGBP) using Gabor filtering followed by Local Binary Pattern (LBP) encoding.
- Spider Local Image Feature (SLIF), defined by spatial node positions:

$$(x_n, y_n) \tag{9}$$

- Weber Local Descriptor (WLD), based on differential excitation:

$$\xi = \arctan\left(\frac{\sum_{i=1}^{p}(x_i - x_c)}{x_c}\right) \tag{10}$$

and orientation:

$$\theta = \arctan\left(\frac{v^{11}}{v^{10}}\right) \tag{11}$$

2) Shape Features

Shape features are extracted to describe the geometric properties of infected and healthy leaf regions:

- Area A
- Major axis length:

$$L = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{12}$$

- Perimeter:

$$P = \sum_{i=1}^{n} d(p_i, p_{i+1}) \tag{13}$$

3) Color and Statistical Features

Color and statistical features are extracted to represent chromatic variations and intensity distributions. RGB, HSV, and LAB color space statistics are computed using mean, median, and standard deviation, where the mean is defined in (14):

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{14}$$

D. Disease Detection Using EfficientNet–Shepard Convolutional Neural Network

The feature vector F is passed to a hybrid EfficientNet-B3 with Attention (EffNet-B3_Attn2). Global average pooling [16] is defined as shown in (15):

$$y = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (15)$$

Attention-weighted feature aggregation is performed as shown in (16):

$$\alpha = \mathrm{softmax}(W_a x) \quad (16)$$

The resulting features are fused with handcrafted features and then forwarded to the Efficient fuzzy ShCNN layer [17].

E. Efficient Fuzzy Shepard Convolutional Neural Network Layer

Let the feature pattern be $x \in \mathbb{R}^d$. Using fuzzy partitioning, the Taylor-expanded activation is expressed as shown in (17):

$$f(x) \approx f(x_0) + \sum_{i=1}^{d} \frac{\partial f}{\partial x_i}(x_i - x_{0i}) \quad (17)$$

Fuzzy membership functions are defined as shown in (18):

$$\mu_{A_j}(x) = \max\left(0{,}1 - \frac{|x - c_j|}{\delta}\right) \quad (18)$$

Fuzzy rules are generated as shown in (19):

$$\text{If } x_1 \in A_1 \wedge x_2 \in A_2 \Rightarrow \text{Class } C_k \quad (19)$$

Classification of new samples is achieved using (20):

$$\hat{C} = \arg\max_k \sum_{r \in R_k} \mu_r(x) \quad (20)$$

F. Final Classification Using Shepard Convolutional Neural Network

The final classification is performed using ShCNN, defined as:

$$y = \frac{\sum_i w(d_i) x_i}{\sum_i w(d_i)} \quad (21)$$

The trainable interpolation layer is formulated as:

$$\mathrm{y}^{(l)} = \sigma\left(\frac{K^{(l)} * (\mathrm{x}^{(l-1)} \odot \mathrm{m}^{(l-1)})}{K^{(l)} * \mathrm{m}^{(l-1)}} + b^{(l)}\right) \quad (22)$$

The final model classifies cotton leaves into aphids, bacterial blight, or target spot.

IV. RESULTS

Figure 3 illustrates the image processing pipeline and intermediate outputs of the proposed EffNet–ShCNN method for cotton leaf disease classification, including the original input images, pre-processed images, segmented leaf regions, and extracted feature representations. These results demonstrate the effectiveness of the proposed preprocessing, segmentation, and feature extraction stages.

(a)

(b) (c) (d) (e)

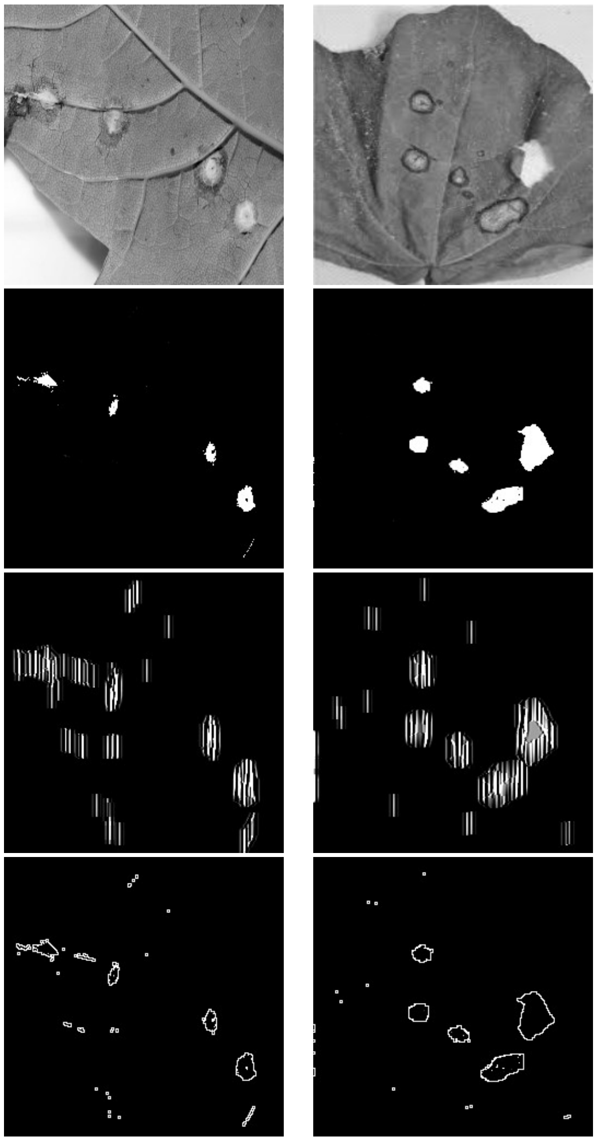

Fig. 3. Experimental outcomes: (a) input images, (b) pre-processed images, (c) segmented images, (d) LGBP features, and (e) WLD features.

A. Performance Evaluation

The results shown in Figures 4 and 5 indicate that the proposed EffNet_ShCNN model achieves consistent performance improvements over baseline methods. For example, at 90% training data, the proposed model achieves an accuracy of 91.70%, compared to 88.20% for CNN and 86.90% for SRCNN, corresponding to an improvement of approximately 3.5%–5%.

This improvement is attributed to (i) Kalman filtering, which enhances image quality by effectively reducing noise and preserving important leaf structures, (ii) FLICM segmentation, which improves disease region localization, and (iii) feature fusion with fuzzy-enhanced ShCNN, which improves class separability under complex environmental conditions. The proposed model achieved sensitivity values of 0.865 (50% training data) and 0.904 (90% training data), compared to 0.808–0.836 and 0.843–0.873 for the baseline methods. This corresponds to an improvement of approximately 3%–6%.

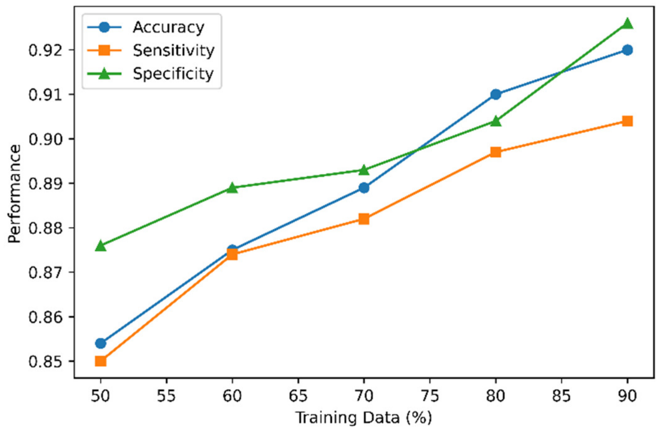

Fig. 4. Performance evaluation based on training data.

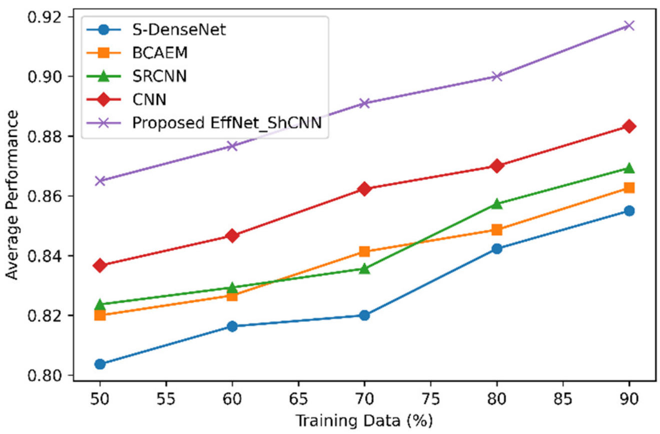

Fig. 5. Comparative performance evaluation based on training data.

1) *K-Fold Cross-Validation Analysis*

K-fold cross-validation is employed to evaluate the generalization capability of the proposed model, ensuring robustness across different data splits. For K = 5, the proposed approach achieved an accuracy of 0.865, outperforming conventional methods (0.806-0.839). For K = 9, the proposed model attained a higher accuracy of 0.917 compared to traditional approaches (0.855-0.886).

In terms of sensitivity, the proposed method achieved 0.870 (K = 5) and 0.902 (K = 9), surpassing existing models (0.800-0.839 and 0.846-0.877). Similarly, specificity improved significantly, reaching 0.862 (K = 5) and 0.929 (K = 9), compared to conventional approaches (0.799-0.836 and 0.866-0.891), as summarized in Table I.

2) *Ablation Study*

The ablation study results in Table II demonstrate the contribution of each module in the proposed framework. Starting from the EfficientNet baseline (84.50%), the inclusion of Kalman preprocessing improves accuracy to 86.20% (+1.7%), indicating the importance of noise reduction. The addition of FLICM segmentation further increases accuracy to 88.40% (+2.2%), highlighting improved region localization. Feature fusion enhances performance to 90.10% (+1.7%), whereas the complete model with fuzzy-enhanced ShCNN achieves 91.70%, confirming its effectiveness in handling uncertainty and improving classification robustness.

TABLE I. PERFORMANCE COMPARISON OF EXISTING METHODS AND PROPOSED MODEL

Variation	**Metric / Method**	**S-DenseNet (%)**	**BCAEM (%)**	**SRCNN (%)**	**CNN (%)**	**EffNet_ShCNN (proposed) (%)**
Training data = 90%	Accuracy	84.40	85.80	86.90	88.20	91.70
	Sensitivity	85.80	84.30	86.40	87.30	90.40
	Specificity	86.30	88.70	87.50	89.50	92.90
K-fold = 9	Accuracy	85.50	86.90	87.70	88.60	91.70
	Sensitivity	86.20	86.00	87.70	84.60	90.20
	Specificity	87.20	86.60	88.00	89.10	92.90

TABLE II. ABLATION STUDY OF THE PROPOSED EFFNET_SHCNN FRAMEWORK

Model variant	**Accuracy (%)**
EfficientNet (baseline)	84.50
EfficientNet + Kalman preprocessing	86.20
EfficientNet + Kalman + FLICM segmentation	88.40
EfficientNet + Kalman + FLICM + feature fusion	90.10
Proposed full model (EffNet_ShCNN)	91.70

3) *Comparison with State-of-the-Art Methods*

The comparative methods listed in Table III were selected based on their relevance to cotton leaf disease classification and their use of DL architectures.

TABLE III. COMPARISON WITH STATE-OF-THE-ART METHODS

Method	**Model type**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
S-DenseNet [5]	Dense CNN	84.40	83.50	85.20
BCAEM [6]	Attention-based CNN	85.80	84.30	88.70
SRCNN [7]	Super-resolution CNN	86.90	86.40	87.50
DCNN [9]	Deep CNN	88.20	87.30	89.50
[11]	CNN + GA	89.50	88.60	90.10
EffNet_ShCNN (proposed)	Hybrid DL + Fuzzy ShCNN	91.70	90.40	92.90

V. CONCLUSION

Cotton leaf diseases significantly impact agricultural productivity and crop quality, necessitating accurate and robust automated detection systems. In this study, a hybrid EfficientNet–Shepard Convolutional Neural Network (EffNet_ShCNN) framework has been proposed for multi-level cotton leaf disease classification under complex environmental conditions. The proposed approach integrates Kalman filter-based preprocessing for noise reduction, Fuzzy Local Information C-Means (FLICM)-based segmentation for precise leaf region extraction, and a comprehensive feature extraction strategy combining texture, shape, color, and deep Convolutional Neural Network (CNN) features.

Experimental results demonstrate that the proposed model outperforms conventional approaches, achieving a classification accuracy of 91.70%, sensitivity of 90.40%, and specificity of 92.90%. The performance improvements are attributed to the synergistic integration of preprocessing, segmentation, feature fusion, and fuzzy-enhanced classification, which collectively enhance feature quality and class separability. The proposed framework shows strong potential for real-world agricultural applications by providing reliable disease detection under varying environmental conditions. However, the study is limited to a relatively small dataset with three disease categories, and further validation on larger and more diverse real-field datasets is required.

VI. FUTURE WORK

In future work, the proposed EffNet_ShCNN model can be evaluated on larger and more diverse real-field datasets under varying environmental conditions. Additional disease classes and severity levels can be incorporated to enable more detailed diagnosis.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY

The dataset used in this study is publicly available in the Kaggle repository [13].

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the authors used ChatGPT and Gemini in order to improve the language, structure, and readability of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

REFERENCES

[1] M. A. Mekouar, "Food and Agriculture Organization of the United Nations (FAO)," *Yearbook of International Environmental Law*, vol. 34, no. 1, Jan. 2023, Art. no. yvae031, https://doi.org/10.1093/yiel/yvae031.

[2] P. Delfani, V. Thuraga, B. Banerjee, and A. Chawade, "Integrative approaches in modern agriculture: IoT, ML and AI for disease forecasting amidst climate change," *Precision Agriculture*, vol. 25, no. 5, pp. 2589–2613, Oct. 2024, https://doi.org/10.1007/s11119-024-10164-7.

[3] A. Haldorai, R. Babitha Lincy, M. Suriya, M. Balakrishnan, and K. S. Dhanushkumar, "Recognition of Cotton Plant Diseases Using Deep Learning Architecture," in *2024 5th International Conference on Innovative Trends in Information Technology*, Kottayam, India, 2024, pp. 1–6, https://doi.org/10.1109/ICITIIT61487.2024.10580651.

[4] S. Anwar, S. R. Soomro, S. K. Baloch, A. A. Patoli, and A. R. Kolachi, "Performance Analysis of Deep Transfer Learning Models for the Automated Detection of Cotton Plant Diseases," *Engineering, Technology & Applied Science Research*, vol. 13, no. 5, pp. 11561–11567, Oct. 2023, https://doi.org/10.48084/etasr.6187.

[5] X. Liang, "Few-shot cotton leaf spots disease classification based on metric learning," *Plant Methods*, vol. 17, no. 1, Nov. 2021, Art. no. 114, https://doi.org/10.1186/s13007-021-00813-7.

[6] M. Shao, P. He, Y. Zhang, S. Zhou, N. Zhang, and J. Zhang, "Identification Method of Cotton Leaf Diseases Based on Bilinear Coordinate Attention Enhancement Module," *Agronomy*, vol. 13, no. 1, Dec. 2022, Art. no. 88, https://doi.org/10.3390/agronomy13010088.

[7] K. Sathya and M. Rajalakshmi, "RDA- CNN: Enhanced Super Resolution Method for Rice Plant Disease Classification," *Computer Systems Science and Engineering*, vol. 42, no. 1, pp. 33–47, 2021, https://doi.org/10.32604/csse.2022.022206.

[8] T. Shi *et al.*, "Recent advances in plant disease severity assessment using convolutional neural networks," *Scientific Reports*, vol. 13, no. 1, Feb. 2023, Art. no. 2336, https://doi.org/10.1038/s41598-023-29230-7.

[9] C. K. Rai and R. Pahuja, "Classification of Diseased Cotton Leaves and Plants Using Improved Deep Convolutional Neural Network," *Multimedia Tools and Applications*, vol. 82, no. 16, pp. 25307–25325, July 2023, https://doi.org/10.1007/s11042-023-14933-w.

[10] V. R. Vangar *et al.*, "AI-Driven Agriculture: Improving Cotton Farming Through Transfer Learning-Based Disease Detection and Classification," *Cureus Journals*, vol. 2, no. 1, Sept. 2025, Art. no. es44389-024-02217–9, https://doi.org/10.7759/s44389-024-02217-9.

[11] M. Latif *et al.*, "Cotton Leaf Diseases Recognition Using Deep Learning and Genetic Algorithm," *Computers, Materials & Continua*, vol. 69, no. 3, pp. 2917–2932, 2021, https://doi.org/10.32604/cmc.2021.017364.

[12] G. Kaur, F. A. M. Al-Yarimi, S. Bharany, A. U. Rehman, and S. Hussen, "Explainable AI for Cotton Leaf Disease Classification: A Metaheuristic-Optimized Deep Learning Approach," *Food Science & Nutrition*, vol. 13, no. 7, July 2025, Art. no. e70658, https://doi.org/10.1002/fsn3.70658.

[13] R. Dhamodharan, "Cotton plant disease." Kaggle. [Online]. Available: https://www.kaggle.com/datasets/dhamur/cotton-plant-disease.

[14] M. Taassori and B. Vizvári, "Enhancing Medical Image Denoising: A Hybrid Approach Incorporating Adaptive Kalman Filter and Non-Local Means with Latin Square Optimization," *Electronics*, vol. 13, no. 13, July 2024, Art. no. 2640, https://doi.org/10.3390/electronics13132640.

[15] S. Krinidis and V. Chatzis, "A Robust Fuzzy Local Information C-Means Clustering Algorithm," *IEEE Transactions on Image Processing*, vol. 19, no. 5, pp. 1328–1337, May 2010, https://doi.org/10.1109/TIP.2010.2040763.

[16] H. M. Faisal *et al.*, "Detection of cotton crops diseases using customized deep learning model," *Scientific Reports*, vol. 15, no. 1, Mar. 2025, Art. no. 10766, https://doi.org/10.1038/s41598-025-94636-4.

[17] R. N. Atole, N. B Pokale, and A. D. Patil, "Crop Leaf Segmentation and Disease Detection Based on Shepherd Wide Residual Network," *Journal of Phytopathology*, vol. 173, no. 3, June 2025, Art. no. e70080, https://doi.org/10.1111/jph.70080.