Comprehensive Analysis of a YOLO-based Deep Learning Model for Cotton Plant Leaf Disease Detection

Sailaja Madhu
Department of CSE-DS, MallaReddy Engineering College for Women (MRECW), GITAM Deemed To be University, Hyderabad, India
sailajanerella.88@gmail.com (corresponding author)

V. RaviSankar
Department of CSE, GITAM Deemed to be University, Hyderabad, India
rvadali@gitam.edu

Received: 7 September 2024 | Revised: 9 October 2024 and 6 November 2024 | Accepted: 12 December 2024

 DOI: https://doi.org/10.48084/etasr.8944

ABSTRACT

Diagnosis of cotton plant diseases is essential to maintain agricultural sustainability and output. This study proposes a YOLO-based deep learning model for leaf disease detection to maximize cotton plant leaf disease detection accuracy. This method ensures a comprehensive evaluation of cotton plant health by combining various image processing techniques, improving the accuracy of disease identification. This study provides a viable path to improve crop health monitoring and management in cotton farming systems and emphasizes the importance of utilizing cutting-edge image processing techniques in agricultural activities. ROC curve performance and classification metrics were better for YOLOv5 than for VGG16 and ResNet50, as it had the highest F1 score (99.21%), recall, and precision. Consistent performance in classification tests was demonstrated by all models, which showed balanced precision, recall, and F1 scores. ResNet50 marginally outperformed VGG16 in terms of true positive rates, F1 score (98.88% vs. 98.65%), recall, and precision. More sophisticated models, such as YOLOv5 and ResNet50, showed higher efficiency and accuracy than VGG16, which makes them more appropriate for applications demanding low false positive rates and high precision. The proposed YOLO-based method improves the accuracy of disease identification, ensuring a thorough assessment of cotton plant health using image processing techniques. The results show that the proposed approach is quite successful in correctly detecting and classifying a variety of diseases that affect cotton plants.

Keywords-cotton plant diseases; disease detection accuracy; gray scale transformation; morphological alterations; crop health monitoring;YOLOv5; ResNet50; model training

I. INTRODUCTION

Plant diseases are a major problem in modern agriculture and affect crop quality and productivity. Cotton is a major source of natural fiber, important for the world's economy, and one of the many crops that are susceptible to diseases. To sustain agricultural output and ensure the lives of millions of farmers worldwide, efficient control and mitigation of cotton plant diseases are consequently critical. Modern technology, such as image processing and machine learning, has allowed the diagnosis and detection of plant diseases, including those that afflict cotton plants [1-3].

The presented research effort summarizes a complex plan to improve the performance of conventional disease diagnosis techniques. To provide a thorough and precise evaluation of the health of cotton plants, this integrated method uses the synergistic potential of multiple modalities, such as image processing methods, machine learning algorithms, and sensor technologies [4-6]. Plant diseases are a major source of concern for farmers and other agricultural stakeholders amidst the many obstacles faced by cotton agriculture. Significant hazards to cotton crops include nematodes, bacteria, viruses, and fungi. These pathogens can reduce fiber quality, increase production costs, and cause yield losses. Cotton Leaf Curl Virus (CLCuV), Fusarium wilt, Boll rot, Alternaria leaf spot, and Verticillium wilt are among the common diseases that affect cotton. Effective management measures, including crop rotation, targeted pesticide administration, and genetic resistance breeding, depend on the timely and accurate detection of these diseases.

Modern deep-learning architectures such as YOLOv5, ResNet50, and VGG16 are used for disease identification tasks. Large-scale image datasets are used to pretrain these models to recognize intricate patterns and features typical of diseases affecting cotton plants. Models can be efficiently trained to distinguish between healthy and unhealthy cotton plants and recognize disease signs by utilizing transfer learning, which involves fine-tuning pre-trained models on domain-specific datasets [7-10]. An innovative combination of agricultural science and technology can result in an integrated multimodal strategy to improve cotton plant disease diagnosis and detection. The strategy presents a comprehensive and data-driven solution to the problems caused by cotton plant diseases by synergistically combining image processing techniques, machine learning models, and sensor data. This concept has the promise of revolutionizing disease management approaches, empowering farmers, and paving the way for a more resilient and sustainable agricultural future through experimental validation and practical implementation.

In [11], the focus was on crop yield prediction, disease and weed identification in crops, and species recognition. This study also examined soil factors such as organic carbon and moisture content. Machine learning and computer vision techniques were reviewed in the classification of alternative collections of agricultural images to determine crop quality and yield. In [12], a modified version of the Spatial Pyramid Pooling (SPP) layer was proposed to efficiently extract important features at different sizes from the training data, accomplishing it by concatenating multilayer features collected from smaller to larger scales. In [13], a comprehensive summary of the deep learning methods used in agriculture was presented. This study explored the potential of deep learning models to transform agricultural methods by examining their applicability in multiple agricultural domains such as disease diagnosis, insect detection, and crop monitoring. In [14], class activation maps were shown using the Gradient Weighted Class Activation Mapping (Grad-CAM) technique to visually explain the disease detected by the model, and a heatmap was produced to indicate the region responsible for classification. This model achieved a 99 % Area Under the Curve (AUC) score, which is an indicator of almost excellent performance. In [15], a concise summary of the progress made so far in integrating crop models with pest and disease models was presented along with a discussion of scientific and technical obstacles. This study offered a five-stage roadmap to enhance the simulation of the effects caused by plant diseases and pests, enhance the quality and availability of data for model input, enhance the integration with crop models, enhance the processes for model evaluation, and foster the growth of a community of plant pest and disease modelers. The CV algorithm was also presented, showing promise for managing TBWEP more quickly and efficiently by identifying and localizing VC plants growing in the heart of corn fields.

Smart farming and precision agriculture involve methods that allow farmers to reduce their use of pesticides and chemicals while maintaining and enhancing the quality and productivity of their crops [16]. According to [17], most diseases exclusively affect the leaf sections. Identifying diseases that affect plants early has always been the main goal of disease detection to improve productivity. In [18], a method was proposed and evaluated using two public crop disease image datasets, namely the EuroSAT cotton and wheat databases. This method achieved a maximum accuracy of 98.60% and 93.90% for both crops, respectively, demonstrating better accuracy and precision compared to the results of more modern methods. According to [19], there are more opportunities and demands for agricultural systems because standard protection strategies employed in the Internet of Things or the traditional Internet may not be helpful. This study focused on open-field agriculture and reviewed state-of-the-art methods in smart agricultural security, including architecture, security concerns, key difficulties, and future objectives. Given advances in technology, agricultural development, which includes the reduction of farming losses, optimization of agricultural processes for increased yield, as well as prevention, monitoring, and early detection of plant and animal diseases, has now embraced varieties of smart sensor technologies [20].

II. PROPOSED METHOD ON PREDICTIVE ANALYSIS OF COTTON PLANT DISEASE DIAGNOSIS

The leaf images of cotton plants used in this research were collected from a public Kaggle dataset [21, 22]. Using image processing techniques to ensure a thorough assessment of cotton plant health, the proposed YOLO-based method increases the precision of disease identification. The findings show that the proposed approach was quite successful in correctly detecting and classifying a variety of diseases that affect cotton plants. Figures 1 and 2 show examples of healthy and diseased cotton plants, respectively. Preprocessing was applied to each image to ensure that it was consistent and appropriate for training the models, such as image scaling to a common size (such as 224×224 pixels) and pixel value normalization.

Fig. 1. Healthy cotton plant.

Fig. 2. Diseased cotton plants.

YOLOv5, ResNet50, and VGG16 are three prominent deep-learning architectures, each with its advantages. ResNet50 uses skip connections and residual learning to overcome the difficulties of training deep networks, and YOLOv5 excels in real-time object identification due to its single-stage design and effective inference. However, the ease of use and efficiency of VGG16 make it a flexible option for a wide range of image recognition applications, especially those involving image classification. All of these models demonstrate the ongoing creativity and progress in deep learning research, opening new avenues for the creation of more potent and effective neural network architectures.

For each model, its accuracy, precision, recall, and F1 score were calculated, using classification results and confusion matrices. Plotting ROC and precision-recall curves helps to evaluate model performance. Figures 3-6 represent the algorithm of different deep learning methods for the analysis of the images captured on different cotton plants.

Data Collection and Preprocessing

|

Model Selection

|

Model Training

|

Model Evaluation

|

Comparative Analysis

Fig. 3. Implemented method.

YOLO is a cutting-edge family of algorithms for object identification, which is renowned for its accuracy and speed. YOLO reframes object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities, in contrast to standard detection methods that apply a model to an image at different locations and scales. With this end-to-end method, YOLO can process images in real-time. The input image is divided into an $S \times S$ grid by the model, which then predicts the probabilities and bounding boxes for every cell. Due to its unified architecture, YOLO produces improved detection rates and fewer false positives by streamlining the detection workflow. Preprocessed images are fed into the model during the training phase. With a learning rate of 0.001, each model is optimized via the Adam optimizer after being trained using a predetermined loss function (such as cross-entropy loss). Iteratively updating the model parameters to minimize the loss function occurs throughout several epochs of training. Model performance on unobserved data is evaluated by tracking validation accuracy.

Through enhancements to the model architecture and training technique, YOLOv5 improves on the success of its predecessors. Due to its single-stage architecture, YOLOv5 is remarkably effective in real-time object detection. By completing both tasks simultaneously, YOLOv5 achieves faster inference times than standard two-stage detectors, which divide their work into two phases: region suggestion and object classification. A Convolutional Neural Network (CNN), such as CSPDarknet, serves as the model architecture's backbone network. Detection heads, which predict bounding boxes and class probabilities, are positioned after this CNN. With YOLOv5, deployment flexibility across a range of hardware platforms is possible thanks to its range of models suited to varying computational resources. YOLOv5's modular design also makes it simple to customize and adapt to particular detection tasks.

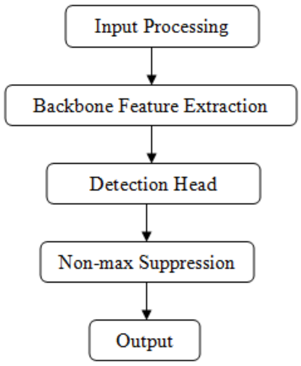

Fig. 4. YOLOv5 algorithm.

Considered a benchmark in the development of deep CNNs, ResNet50 is highly effective and profound. ResNet50 employs skip connections or shortcuts that omit specific layers to overcome the difficulty of training deep networks. These skip connections can mitigate the vanishing gradient issue and successfully train very deep architectures. The ResNet50 architecture comprises 50 layers. It utilizes a construction element, known as the residual block, which has two convolutional layers with shortcut connections. With accuracy and efficiency preserved, this approach makes it easier to train deeper networks. Pre-trained on massive datasets, such as ImageNet, ResNet50 is an effective feature extractor for a range of computer vision applications such as semantic segmentation, object recognition, and image classification. ResNet50 is considered a fundamental model in the deep learning space due to its extensive use and exceptional performance.

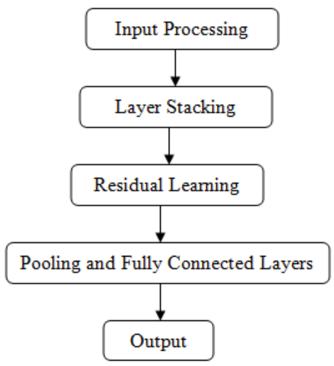

Fig. 5. ResNet50 algorithm.

VGG16 has a simple design with 16 layers, 13 convolutional layers and 3 fully connected layers. Due to its tiny filter sizes and emphasis on depth, VGG16 can learn complicated hierarchical features from input images more easily. VGG16 offers impressive results on a range of image recognition applications, particularly picture classification, despite being more straightforward than later models. The ease of implementation and interpretation is provided by its uniform architecture, which features filters of constant sizes and max-pooling layers for downsampling. In addition, transfer learning, a process where pre-trained models are improved for certain tasks with a limited amount of training data, is used in VGG16. Although VGG16's depth may make it computationally costly, its robustness and usability have led to its broad acceptance and long-lasting influence in the deep learning community.

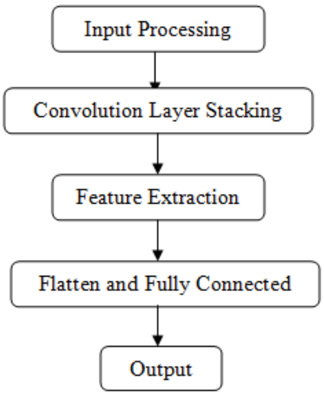

Fig. 6. VGG16 algorithm.

The most efficient method for cotton plant disease diagnosis and detection is determined by comparing the accuracies of the models during the testing phase. This study attempts to provide insights into the advantages and disadvantages of each model and suggest an integrated solution to improve disease diagnosis by combining several modalities and evaluating several models.

III. RESULTS AND DISCUSSIONS

As shown in Figure 7, the accuracy of YOLOv5, ResNet50, and VGG16 models in recognizing infected plants in the context of cotton plant disease detection shows their effectiveness in this task. Insights into the models' performance at various phases are offered by the training, validation, and testing accuracies. With training, validation, and testing accuracy of 98.51%, 96.74%, and 93.98%, respectively, YOLOv5 stands out in terms of accuracy throughout all phases, demonstrating its ability to differentiate between healthy and unhealthy cotton plants. ResNet50 demonstrates its efficacy in disease identification with testing, validation, and training accuracies of 95.56%, 92.47%, and 96.65%, respectively. VGG16 achieved training, validation, and testing accuracies of 93.25%, 92.54%, and 90.34%, respectively, which is a respectable performance, although it was marginally less accurate than YOLOv5 and ResNet50. Based on these findings, deep learning models can identify cotton plant diseases with high accuracy. YOLOv5 appears to be the most promising model for obtaining high accuracy in practical applications.

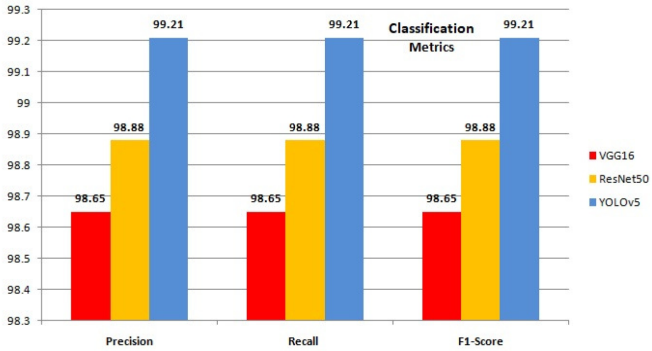

Fig. 7. Cotton plant disease diagnosis accuracy.

The VGG16, ResNet50, and YOLOv5 models demonstrated remarkable accuracy in classifying diseased cotton plants, as evidenced by their precision, recall, and F1 scores in Figure 8. The three models exhibit resilience and dependability in differentiating between healthy and diseased plants, with precision, recall, and F1 score metrics continuously exceeding 98%. With remarkable recall, F1 score, and precision values of 98.65%, VGG16 demonstrates its ability to accurately detect diseased plants with a low number of false positives. Similarly, high F1 scores of 99.21% and 98.88% for ResNet50 and YOLOv5, respectively, highlight their efficacy in identifying true positives and reducing false negatives. Concerning early disease identification and crop management, these strong classification metrics demonstrate the potential of deep learning models, especially YOLOv5, to support farmers and agricultural specialists, ultimately leading to higher crop yields and sustainability.

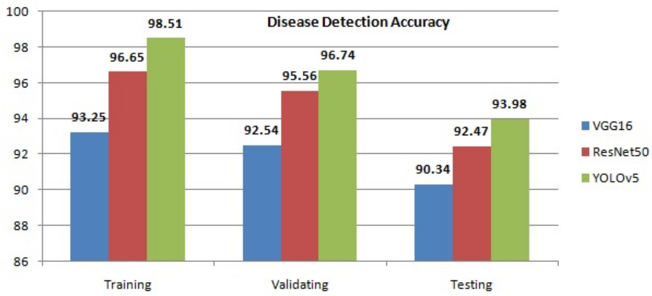

Fig. 8. Results of cotton plant disease diagnosis.

The true positive rate (sensitivity) versus the true negative rate (specificity) for various classification thresholds is shown graphically in the Receiver Operating Characteristic (ROC) curve in Figure 9. With increasing specificity values, the models demonstrate a greater capacity to accurately classify healthy plants as true negatives while reducing false positives. ROC curves were created by graphing specificity values against corresponding sensitivity values at various thresholds. When it comes to differentiating between healthy and unhealthy cotton plants across different thresholds, models with a larger area under the ROC curve perform better overall.

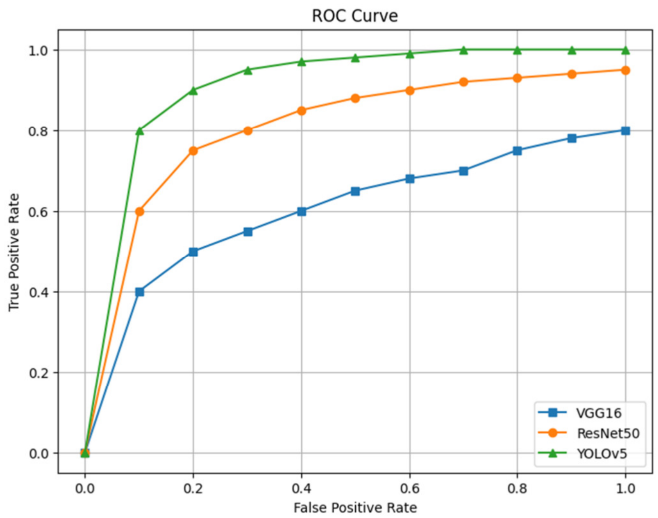

Fig. 9. ROC curve of the methods implemented.

YOLOv5 demonstrated exceptional performance in cotton disease detection, as seen in the results, which show good recall and precision values across a range of thresholds. Therefore, YOLOv5 is a good fit for precisely detecting diseased cotton plants, which is important for farmers and agricultural specialists to carry out prompt interventions to minimize crop loss and ensure maximum production. Overall, the results highlight the potential of deep learning models, especially YOLOv5, to transform the methods used to diagnose and treat cotton diseases, promoting food security and sustainable agriculture.

IV. CONCLUSION

In the field of cotton plant disease diagnosis and detection, a data-driven strategy to address concerns about cotton plant diseases uses image processing methods and machine learning algorithms. The proposed approach shows promise in transforming agricultural disease management techniques by methodically processing digital images of cotton plants and utilizing the processing capacity of deep learning models such as YOLOv5, ResNet50, and VGG16. The practical utility of this method in actual agricultural situations is highlighted by the validation. The integrated approach effectively assists farmers and agricultural specialists in making well-informed decisions about disease management by accurately identifying and diagnosing a variety of diseases that affect cotton plants. The application of cutting-edge technologies in agriculture can improve disease control procedures, encourage sustainable agriculture, and increase resilience to climate change. To efficiently transfer cutting-edge technologies from the laboratory to the field and ensure their broad acceptance, cooperation is essential between researchers, technologists, and agricultural stakeholders.

The results of this study confirm the efficacy of the integrated multimodal technique in the identification and diagnosis of diseases of cotton plants. This method has the potential to greatly improve crop health, increase production, and support sustainable agriculture techniques to create a more resilient and successful agricultural future by encouraging cooperation and creativity. It also marks a significant improvement in the management of agricultural diseases.

REFERENCES

[1] M. M. Adnan *et al.*, "Automated Image Annotation With Novel Features Based on Deep ResNet50-SLT," *IEEE Access*, vol. 11, pp. 40258–40277, 2023, https://doi.org/10.1109/ACCESS.2023.3266296.

[2] W. Shafik, A. Tufail, A. Namoun, L. C. De Silva, and R. A. A. H. M. Apong, "A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends," *IEEE Access*, vol. 11, pp. 59174–59203, 2023, https://doi.org/10.1109/ACCESS.2023.3284760.

[3] K. Taji, A. Sohail, T. Shahzad, B. Shoaib Khan, M. Adnan Khan, and K. Ouahada, "An Ensemble Hybrid Framework: A Comparative Analysis of Metaheuristic Algorithms for Ensemble Hybrid CNN Features for Plants Disease Classification," *IEEE Access*, vol. 12, pp. 61886–61906, 2024, https://doi.org/10.1109/ACCESS.2024.3389648.

[4] R. Rani, J. Sahoo, S. Bellamkonda, S. Kumar, and S. K. Pippal, "Role of Artificial Intelligence in Agriculture: An Analysis and Advancements With Focus on Plant Diseases," *IEEE Access*, vol. 11, pp. 137999–138019, 2023, https://doi.org/10.1109/ACCESS.2023.3339375.

[5] S. Abinaya, K. U. Kumar, and A. S. Alphonse, "Cascading Autoencoder With Attention Residual U-Net for Multi-Class Plant Leaf Disease Segmentation and Classification," *IEEE Access*, vol. 11, pp. 98153–98170, 2023, https://doi.org/10.1109/ACCESS.2023.3312718.

[6] S. Allaoua Chelloug, R. Alkanhel, M. S. A. Muthanna, A. Aziz, and A. Muthanna, "MULTINET: A Multi-Agent DRL and EfficientNet Assisted Framework for 3D Plant Leaf Disease Identification and Severity Quantification," *IEEE Access*, vol. 11, pp. 86770–86789, 2023, https://doi.org/10.1109/ACCESS.2023.3303868.

[7] L. Sun, K. Liang, Y. Song, and Y. Wang, "An Improved CNN-Based Apple Appearance Quality Classification Method With Small Samples," *IEEE Access*, vol. 9, pp. 68054–68065, 2021, https://doi.org/10.1109/ACCESS.2021.3077567.

[8] S. Mousavi and G. Farahani, "A Novel Enhanced VGG16 Model to Tackle Grapevine Leaves Diseases With Automatic Method," *IEEE Access*, vol. 10, pp. 111564–111578, 2022, https://doi.org/10.1109/ACCESS.2022.3215639.

[9] C. K. Sunil, C. D. Jaidhar, and N. Patil, "Cardamom Plant Disease Detection Approach Using EfficientNetV2," *IEEE Access*, vol. 10, pp. 789–804, 2022, https://doi.org/10.1109/ACCESS.2021.3138920.

[10] E. Kristiani, C.-T. Yang, and C.-Y. Huang, "iSEC: An Optimized Deep Learning Model for Image Classification on Edge Computing," *IEEE Access*, vol. 8, pp. 27267–27276, 2020, https://doi.org/10.1109/ACCESS.2020.2971566.

[11] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine Learning Applications for Precision Agriculture: A Comprehensive Review," *IEEE Access*, vol. 9, pp. 4843–4873, 2021, https://doi.org/10.1109/ACCESS.2020.3048415.

[12] S. K. Noon, M. Amjad, M. A. Qureshi, and A. Mannan, "Handling Severity Levels of Multiple Co-Occurring Cotton Plant Diseases Using Improved YOLOX Model," *IEEE Access*, vol. 10, pp. 134811–134825, 2022, https://doi.org/10.1109/ACCESS.2022.3232751.

[13] I. Attri, L. K. Awasthi, T. P. Sharma, and P. Rathee, "A review of deep learning techniques used in agriculture," *Ecological Informatics*, vol. 77, Nov. 2023, Art. no. 102217, https://doi.org/10.1016/j.ecoinf.2023.102217.

[14] H. I. Peyal *et al.*, "Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture," *IEEE Access*, vol. 11, pp. 110627–110643, 2023, https://doi.org/10.1109/ACCESS.2023.3320686.

[15] M. Ryo, "Explainable artificial intelligence and interpretable machine learning for agricultural data analysis," *Artificial Intelligence in Agriculture*, vol. 6, pp. 257–265, Jan. 2022, https://doi.org/10.1016/j.aiia.2022.11.003.

[16] T. Domingues, T. Brandão, and J. C. Ferreira, "Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive

Survey," *Agriculture*, vol. 12, no. 9, Sep. 2022, Art. no. 1350, https://doi.org/10.3390/agriculture12091350.

[17] S. Kumar *et al.*, "A Comparative Analysis of Machine Learning Algorithms for Detection of Organic and Nonorganic Cotton Diseases," *Mathematical Problems in Engineering*, vol. 2021, no. 1, 2021, Art. no. 1790171, https://doi.org/10.1155/2021/1790171.

[18] I. Haider *et al.*, "Crops Leaf Disease Recognition From Digital and RS Imaging Using Fusion of Multi Self-Attention RBNet Deep Architectures and Modified Dragonfly Optimization," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 7260–7277, 2024, https://doi.org/10.1109/JSTARS.2024.3378298.

[19] A. Rettore de Araujo Zanella, E. da Silva, and L. C. Pessoa Albini, "Security challenges to smart agriculture: Current state, key issues, and future directions," *Array*, vol. 8, Dec. 2020, Art. no. 100048, https://doi.org/10.1016/j.array.2020.100048.

[20] A. Adesipo *et al.*, "Smart and Climate-Smart Agricultural Trends as Core Aspects of Smart Village Functions," *Sensors*, vol. 20, no. 21, Jan. 2020, Art. no. 5977, https://doi.org/10.3390/s20215977.

[21] S. Karim, "Cotton leaf disease dataset." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/seroshkarim/cotton-leaf-disease-dataset.

[22] S. K. Noon, M. Amjad, M. Ali Qureshi, and A. Mannan, "Computationally light deep learning framework to recognize cotton leaf diseases," *Journal of Intelligent & Fuzzy Systems*, vol. 40, no. 6, pp. 12383–12398, Jan. 2021, https://doi.org/10.3233/JIFS-210516.