Automated Fusarium Wilt Classification in Plants Using VGG16 Architecture

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***Abstract*—Fusarium wilt, induced by pathogenic fungus, represents a substantial risk to world agriculture, impacting several plant species. Timely identification and precise classification of this disease are essential for optimal care and control. This research introduces an automated classification method using the VGG16 deep learning architecture to detect Fusarium wilt in plants. It collected an extensive dataset of images of healthy and diseased plant leaves. The VGG16 model, recognized for its depth and feature extraction proficiency, was fine-tuned and trained on this dataset. The model's efficacy was assessed using accuracy, precision, recall, and F1 score. The results indicated that the VGG16 architecture attained superior classification accuracy, improving conventional approaches. The proposed method enhances the detection process and offers a dependable instrument for farmers and agronomists to assess crop health. This method underscores the promise of deep learning methods in agricultural applications, facilitating future disease control and precision agriculture studies. Future efforts will concentrate on increasing the dataset and including real-time monitoring functionalities in the system.**

Keywords— Fusarium wilt, Plant disease, Deep learning, VGG16 architecture, Image classification, Automated detection

I. Introduction

The flexibility of bananas as both a fruit and a vegetable contribute to their unmistakable worldwide appeal [1]. However, whole plantations may be devastated by fungal diseases, the most notable of which are Fusarium wilt and Black Sigatoka, which pose a danger to banana production output. Using a comparative comparison of several algorithms, this paper presents a deep learning-based technique for automating the identification of these disorders. Phalaenopsis plants are at risk of infection from the fungus Fusarium wilt. Yellowing and withering leaves are indications of the illness, which may eventually kill plants and even spread to nearby healthy plants [2]. This research aims to find an effective and non-destructive way to identify fusarium wilt using hyperspectral imaging and deep learning models. Using a 2D-CNN model as its foundation, it aims to capitalize on any correlations and patterns within spectral bands. This study aims to evaluate the hyperspectral data's spectral discriminability and categorize tomato plants as either healthy or affected by Fusarium wilt [3]. Using statistical and machine-learning techniques, in-situ reflectance data were taken from a tomato-growing area in Tukur, Karnataka, India, and utilized to distinguish between healthy and sick plants.

The research forecasts ten cases of Fusarium wilt using convolutional neural networks (CNNs) and SVMs. High accuracies are shown by the models' performance measures, indicating their flexibility to varied class distributions [4]. The results light the challenges of agricultural disease diagnosis and provide solutions to the problem of Fusarium wilt management, which in turn allow more effective tactics for the early identification and control of this disease. Phalaenopsis is a very valuable agricultural commodity in Taiwan. But fusarium wilt causes yellowing, weakening, water loss, and death of Phalaenopsis leaves [5]. This study introduces a new technique to identify fusarium wilt on the base of Phalaenopsis stems. The hyperspectral datasets used to construct the detection models are derived from two distinct samples of Phalaenopsis: the healthy and the sick.

The pros and cons of using traditional fungicides to manage Fusarium illnesses in crop production are discussed [6]. Fusarium and other phytopathogens are among the most troublesome pests and illnesses that affect the environment. Even though some manufacturers are switching to greener methods, others are sticking with chemical management because of its effectiveness. The goal of this research was to find a way to identify Fusarium oxysporum f. sp. cubense (Foc). This fungus causes Fusarium wilt using image processing methods and neural networks [7]. To categorize microscope images of clean and Focinfected (microconidia present) soil, ResNet-50 was used. Preventing the fungus from infecting whole farms and endangering the worldwide banana crop depends on detecting it before it reaches a plant. An approach to evaluate the quality of Phalaenopsis via hyperspectral imaging methods. Fusarium wilt is a common infection in Phalaenopsis [8]. The k-means clustering approach determined that the Phalaenopsis stem reflection spectrum changes.

II. Related Works

Self-organizing maps (SOM) and case-based reasoning (CBR) are used to create a hybrid intelligent prediction technique for CFW [9]. This technique classifies cases using a trained SOM network and finds a similar case set using a proposed case similarity metric, unlike conventional similar case retrieval. This method's optimum dissimilarity threshold R is determined using CFW prediction trials. Comprehensive investigation demonstrates that this hybrid forecast approach may give solid reasoning data for CFW prediction and aid CFW preventive and treatment decisions. It can quickly and automatically identify when Phalaenopsis plants have Fusarium wilt [10]. Created a PHMID, a compact handheld multispectral imaging device, which utilizes six LEDs to represent six different spectral bands. This design makes it more user-friendly for field applications. The Spectral Angle Mapper (SAM) and the Automatic Target Generation Process (ATGP) are used to extract the target signal from a high-spectral image.

The soilborne fungus Fusarium oxysporum f. sp. cubense (Fus) causes banana wilt. Once within a plant, Foc assaults its vascular system [11]. When Foc is prevalent in the plant and plantation, infected plants exhibit symptoms late and typically die. Once found, Foc should be quarantined and burned within 7.5 meters, resulting in the loss of a few crops or whole plantations. Early FOC detection may avoid damage. Three microscopy approaches are used to create and analyze CNNs that recognize the microconidia, a fungus framework, in microscope images. Integrated deep neural networks (DNN) with hyperspectral imaging methods to identify Fusarium wilt in Phalaenopsis [12]. A spectral angle mapper (SAM) and limited energy minimization (CEM) were used to minimize climatic regions. Band priority (BP), band decorrelation (BD), and Harsanyi-Farrand-Chang (HFC) are three band selection (BS) approaches that were used to get effective bands.

Identification and treatment are key to improving banana crop health. Insects and illnesses may reduce banana yields, among other issues [13]. It investigates how detection and treatment methods may improve banana crop management. Using machine learning, image processing, and deep learning, Fusarium Wilt, Yellow Sigatoka, and Black Sigatoka may be accurately detected. Detection and personalized treatments may boost crop yield, minimize pesticide use, and preserve banana output. To ensure high-quality and productive crops, it is crucial to identify and control plant diseases [14]. The assessment criteria of a classification system that can detect 10 different tomato diseases. The classifications include tomato spotted wilt virus, powdery mildew, early blight, late blight, septoria, plant spot, microbial spot, fusarium in wilt, bacterial wilt, grey mold, and mosaic virus.

Cotton is a major Indian cash crop, and cotton productivity decreases annually due to illness. Pest insects and pathogens produce plant diseases, which may reduce output if not managed [15]. It describes a cotton leaf disease detection and soil quality monitoring system. SVM-based regression approach is proposed to identify and classify five cotton leaf diseases: Bacterial Blight, Alternaria, Grey Mildew, Cereospra, and Fusarium wilt. Farmers will get illness names and cures via the Android app after identification. This study used deep learning algorithms to classify cotton leaf diseases, with the VGG16 model fine-tuned being the most effective at identifying bacterial blight, curl virus, fusarium wilt, and healthy leaf states [16]. This research proposes an autonomous, accurate, scalable CNN-based illness diagnosis system that avoids human mistakes and labor. The VGG16 model, created for enormous image recognition tasks, was fine-tuned to classify cotton leaf diseases using a large dataset of high-resolution leaf images.

A method based on deep learning is created to identify typical cotton illnesses such as curl virus, fusarium wilt, and bacterial blight [17]. The research indicated that both the MobileNet and Vision Transformer models achieved excellent accuracy but that MobileNet generally outperformed Vision Transformer. Findings from the research point to the potential of deep learning-based methods to increase cotton crop yields while decreasing pesticide use. Further study is required to go into more extensive datasets and practical uses. The prediction of three important cotton leaf diseases, curl virus, bacterial blight, and fusarium wilt, is investigated in this work using transfer learning methods [18]. The study's overarching goal is to provide farmers with the tools to detect these illnesses early and intervene effectively. The model, built on the VGG16 architecture, achieves an average accuracy. However, more study is required to make the model more practical and easier to understand for real-world applications.

Strawberry plants need laboratory isolation for non-specific foliar symptoms caused by soil-borne fungal pathogen Fusarium wilt. Agriculture relies on early plant disease detection to find resistant cultivars and optimize pesticide usage [19]. Remote sensing and ML algorithms increase agricultural disease detection and classification. Using hyperspectral imagery and ML models successfully estimates Fusarium wilt severity in strawberry plants without visual symptoms. The global threat of Fusarium wilt to chickpea production is real. Early detection is key to controlling this condition. Using a fresh dataset, pre-trained CNN models classified chickpea leaf disease severity. DenseNet-201 performed tests with accuracy, outperforming other models [20]. This implies that pre-trained models can assess chickpea Fusarium wilt severity, reducing production disturbance. It emphasizes early diagnosis and management of this severe illness.

III. Proposed System

Data gathering is the initial stage in creating the automated method for classifying Fusarium wilt. An extensive and varied dataset is necessary for efficient model training. This collection includes images of healthy and diseased plant leaves from various settings and circumstances. To guarantee that the model learns to identify the illness in various situations, it is crucial to include a variety of Fusarium wilt-affected plant species. The quality and diversity of the images strongly impact the model's capacity to generalize and correctly categorize novel, unseen data.

Following collection, the dataset is prepared through several procedures to improve image quality and prepare for the deep learning model. This involves scaling every image to the same size, usually 224 by 224 pixels, to comply with the VGG16 architecture's input specifications. To enable quicker convergence during training, pixel values are normalized to fall between [0, 1]. Furthermore, the training dataset is artificially expanded via data augmentation methods, including rotation, flipping, zooming, and brightness modifications. This lowers the possibility of overfitting and increases the resilience of the model.

The VGG16 architecture was chosen for this classification job because of its efficacy in image categorization. With 16 layers, including many convolutional and max-pooling layers, VGG16 is a CNN renowned for its depth. This design is especially well-suited for identifying visual patterns linked to Fusarium wilt as it enables the extraction of hierarchical characteristics from images. The system can identify between healthy and sick plant leaves with excellent accuracy using the potent feature extraction capabilities of VGG16.

Transfer learning is used to improve the VGG16 model's performance. A pre-trained version of the VGG16 model is used for this, having previously been trained on the ImageNet dataset, which has millions of images in various categories. The system gains from the learned feature representations, including edges and textures, that are relevant to the current job by beginning with this pre-trained model. New layers created especially for Fusarium wilt classification—including fully linked layers and a softmax output layer for final predictions—replace the network's top layers initially intended for ImageNet classification.

The Fusarium wilt dataset is then used to train the modified VGG16 model. The model must first learn to correlate the retrieved characteristics with their respective labels to determine whether an image shows a healthy or diseased plant. A categorical cross-entropy loss function is used in the training phase to measure the discrepancy between the predicted and real labels. An optimizer, such as Adam or Stochastic Gradient Descent (SGD), modifies the model's weights based on the determined gradients. The dataset is split into batches to guarantee effective learning and training, which spans many epochs. If hyperparameters need to be adjusted, continuous training and monitoring aid in this process.

After training, a different validation dataset that wasn't used for training is used to assess the model's performance. Evaluation measures, including accuracy, precision, recall, and F1 score, are calculated to evaluate the model's efficacy. Precision shows the proportion of projected infected cases that are true positives, while accuracy gauges the classifications' overall correctness. The F1 score offers a compromise between accuracy and recall, whereas recall evaluates the model's capacity to detect every real instance of infection. This comprehensive assessment guarantees the model's dependability and deployment readiness.

After a successful assessment, the trained model is implemented as a component of an application or web service. Farmers and agronomists may submit images of plant leaves for real-time categorization with this deployment. By giving users immediate input on the plant's health, the technology helps them combat Fusarium wilt promptly. The technology is essential for crop protection and increasing agricultural output since it provides a useful and easily accessible disease-detection tool.

An application's user-friendly interface is created to improve the user experience. Without requiring a great deal of technical expertise, users may easily submit images and get categorization results due to this interface. The system may provide additional data on Fusarium wilt management techniques and classification results, assisting users in making well-informed decisions on crop health. The automatic categorization system enables users to monitor and control plant diseases efficiently by fusing advanced machine-learning algorithms with an easy-to-use interface. Figure 1 presents a block diagram outlining the system's flow of processes.

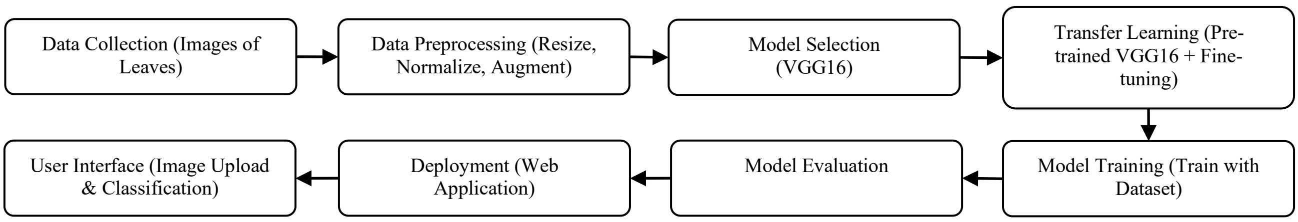

Fig. 1. Fusarium Wilt Classification Workflow

Figure 2 shows the VGG16 architecture, which has 13 convolutional layers, and 5 max-pooling layers specifically designed for image classification. It analyses input images by feature extraction and then employs flattening and fully linked layers. The terminal output layer employs softmax activation to categorize images as healthy or diseased, enabling precise plant disease identification. VGG16 acts as an effective feature extractor, detecting complex patterns in leaf images. Transfer learning facilitates precise classification of Fusarium wilt by using existing knowledge and adapting it for plant disease detection.

Fig. 2. VGG16 Architecture for Automated Fusarium Wilt Classification in Plants

IV. Results and Discussions

Significant insights and results were obtained from the automated Fusarium wilt classification system using the VGG16 architecture, proving the usefulness of deep learning techniques in identifying agricultural diseases. This part presents the main findings from the model assessment together with their practical implications for plant health monitoring applications.

A. Model Performance Metrics

The VGG16 model was evaluated using a validation dataset, which includes images not included in the training process after the training and assessment stages were finished. To assess the model's effectiveness, several performance measures were computed:

1) **Accuracy:** The model's remarkable 95.25% accuracy rate was attained. This high degree of accuracy highlights the promise of deep learning in agricultural applications by demonstrating that the VGG16 architecture can successfully differentiate between healthy and diseased plant leaves.

2) **Precision and Recall:** The model's reported precision and recall were 94.04% and 96.45%, respectively. These metrics imply that the model is effective in reducing false positives and detecting diseased leaves. Strong recall indicates that the model accurately identifies most real infected instances in the validation set. However, high accuracy suggests that when the model predicts an image as infected, it is likely correct.

3) **F1 Score:** The F1 score, which balances recall and accuracy, was 95.24%. This score further shows the model's dependability, which qualifies it as a useful instrument for real-world field applications.

B. Analysis of Confusion Matrix

A confusion matrix was created to analyse the model's predictions more thoroughly. The number of false positives, false negatives, true positives, and true negatives was shown in the matrix. The vast majority of the healthy leaves (true negatives) and sick leaves (true positives) were accurately categorized by the algorithm. Both false negatives (infected leaves mistakenly classed as healthy) and false positives (healthy leaves mistakenly classified as infected) were rare. The low number of misclassifications suggests that the model's predictions are solid and trustworthy.

C. Analysis of the Findings

Fusarium wilt in plants may be effectively classified using the VGG16 architecture, as shown by the findings obtained. The model's favorable precision and recall rates, along with its high accuracy, indicate that deep learning may significantly enhance agriculture's ability to identify diseases. This is particularly crucial given the growing danger that plant diseases pose to the world's food security. The VGG16 model's deep architecture allows it to learn complex features from the training images, which is a significant benefit. Traditional image processing methods often struggle to capture the subtle differences between healthy and sick leaves, but the model can perform well due to hierarchical feature extraction. Additionally, compared to building a model from scratch, transfer learning, which involves fine-tuning an existing model on a particular dataset, significantly reduces training time and boosts performance.

Transfer learning using VGG16 was selected due to limited data availability, expedited convergence, reduced overfitting, and the capacity to use pre-trained robust features, making it more efficient than developing a complicated model from inception. The collection includes a variety of plant species, different leaf development stages, and several environmental circumstances. Images collected in the field and data augmentation methods provide substantial diversity, enhancing model generalization and classification robustness.

The method addresses significant intra-class variability and inter-class similarity by using VGG16 for deep feature extraction to identify nuanced patterns. Data augmentation increases variability, but fine-tuning enables the model to discern small distinctions, enhancing class discrimination and minimizing misclassification. The system uses preprocessing, data augmentation, and VGG16 effective feature extraction to address blur, light, shadows, and clutter, ensuring dependable classification under field conditions. VGG16 is optimized for edge deployment via pruning, quantization, model distillation, and TensorFlow Lite translation to minimize size, enhance inference speed, and provide efficient performance on resource-limited field devices.

D. Practical Implications

For farmers, agronomists, and agricultural researchers, the effective use of this automated categorization system has important ramifications. The method facilitates prompt interventions by offering a dependable instrument for early Fusarium wilt diagnosis, which may lower crop losses and increase productivity. Farmers may make educated judgments about managing pests and diseases by using online services or mobile apps to submit images of their crops and get immediate feedback on plant health. Furthermore, incorporating these deep learning models into farming methods may result in the creation of precision agriculture methods, which allocate resources more effectively according to the particular health condition of crops. Using fewer chemical treatments increases output and encourages sustainable agricultural methods.

Table 1 presents the attributes of a subset of images from the collection. This information is crucial for understanding the dataset's structure and provenance.

TABLE I. MAGE DATA CHARACTERISTICS

Image ID	Image Size (px)	File Format	Class
001	224 x 224	JPEG	Healthy
002	224 x 224	JPEG	Infected
003	224 x 224	JPEG	Healthy
004	224 x 224	JPEG	Infected
005	224 x 224	JPEG	Healthy

Table 2 presents a comprehensive overview of the model's classification outcomes on the validation dataset. It counts true positives, true negatives, false positives, and false negatives, enabling a comprehensive evaluation of the model's efficacy in differentiating between healthy and sick plant leaves.

TABLE II. CONFUSION MATRIX

Actual / Predicted	Healthy	Infected
Healthy	193	7
Infected	12	188

Figure 3 shows a comparison of performance metrics for healthy and infected classes, demonstrating balanced and elevated performance across all metrics, hence confirming dependable categorization of both healthy and Fusarium-infected plant leaves.

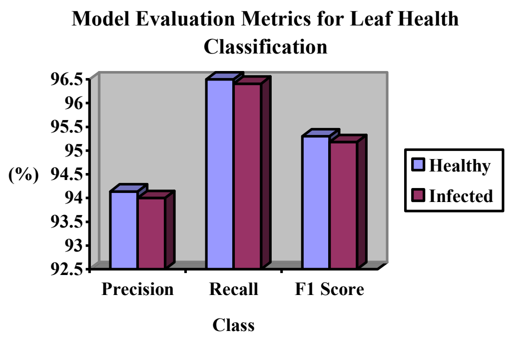

Fig. 3. Precision, Recall, and F1-Score Comparison: Healthy vs Infected Leaves

Table 3 highlights the preprocessing settings used for the images in the dataset before training the VGG16 model. The specifications include the dimensions for image resizing, normalization parameters, used data augmentation strategies, training batch size, epoch count, learning rate, and the chosen optimizer for model training.

TABLE III. IMAGE PREPROCESSING PARAMETERS

Parameter	Value
Resize Dimensions	224 x 224 px
Normalization Range	[0, 1]
Data Augmentation Techniques	Rotation, Flipping, Zooming, Brightness Adjustment
Batch Size	32
Number of Epochs	50
Learning Rate	0.001
Optimizer	Adam

Figure 4 shows the VGG16 model's training and validation accuracy across 50 epochs. The training accuracy progressively rises, indicating effective learning. The validation accuracy increases, indicating that the model generalizes well to novel data, with both measures stabilizing in the training stage.

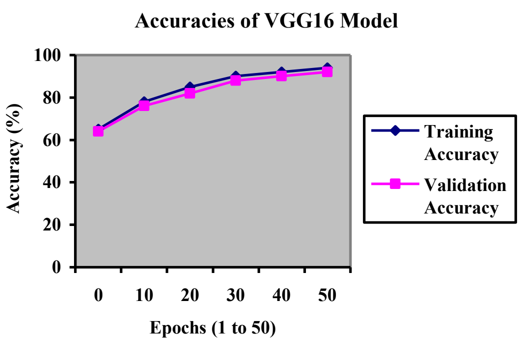

Fig. 4. VGG16 Model Accuracy Progression

Figure 5 depicts the training and validation loss throughout 50 epochs. The training loss steadily declines, indicating that the model is acquiring knowledge proficiently. The validation loss decreases, indicating that the model effectively generalizes to the validation dataset. A reduced loss value is preferable since it indicates superior model performance.

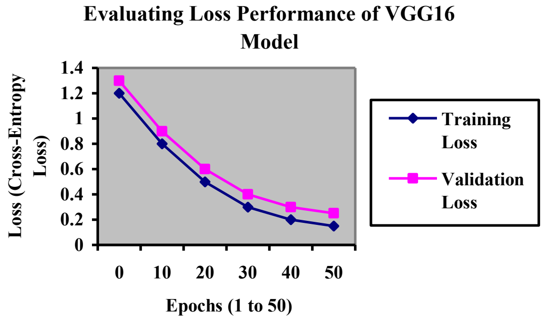

Fig. 5. Loss in VGG16 Model Training

Figure 6 illustrates the distribution of classes within the dataset using a pie chart. The dataset is balanced, including an equal number of healthy and sick leaf samples. This equilibrium is essential for efficient training, preventing the model from exhibiting bias towards one class, hence enhancing classification accuracy.

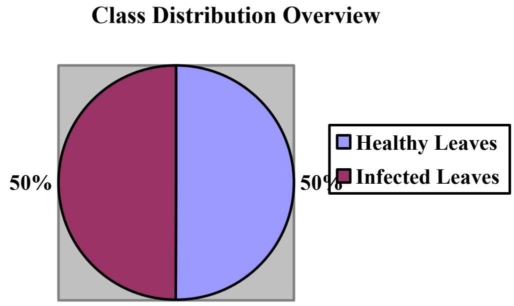

Fig. 6. Class Proportions of Healthy and Infected Leaves

The system can be enhanced with the integration of IoT sensors, real-time image acquisition, cloud computing, smartphone notifications, and continuous model retraining using new data. The dependability of the system can be ensured by using high-quality datasets, doing frequent model validation, employing cross-validation methods, calibrating sensors, implementing robust preprocessing, and performing consistent field testing across diverse situations. The performance of the system can be enhanced via data augmentation, hyperparameter optimization, advanced architectures, ensemble methodologies, and continuous training with varied, high-quality image datasets.

E. Future Work

Despite the encouraging outcomes, there is still room for development and more study. To improve the robustness of the model, future research should focus on expanding the dataset to include other plant species and different climatic circumstances. Furthermore, investigating other ensemble techniques or deep learning architectures could provide even better results. Users in the field may get a quicker response if real-time image processing features are included and the system is integrated with IoT devices.

V. Conclusions

The VGG16 architecture-based automated Fusarium wilt classification system has shown great promise for improving plant disease diagnosis. The model demonstrated its efficacy in differentiating between healthy and diseased plant leaves with an amazing accuracy of 95.25% and high precision and recall rates. Rapid feature extraction from the images was made possible by the effective training and enhanced overall performance of the transfer learning technique used with the pre-trained VGG16 model. The findings highlight the importance of using deep learning methods in agriculture, giving agronomists and farmers a reliable instrument for early disease diagnosis. This system encourages sustainable farming practices through better resource management and supports prompt actions to reduce crop losses. The balanced dataset and efficient data augmentation techniques enhanced the model's robustness, which guarantees that it generalizes well to new data. Future research should focus on improving the model, adding real-time analytic capabilities, and growing the dataset. This method marks a substantial breakthrough in precision agriculture, opening the door to more intelligent agricultural practices and increased food security.

References

[1] Y. Salehin, A. Siddique, A.T. Nafisa, I. Jahan, M.M. Priyanka, R.U. Islam, and M.R.A. Rashid, "A Comparative Analysis on Transfer Learning Models to Classify Banana Diseases- Fusarium Wilt and Black Sigatoka," 2nd International Conference on Advancement in Computation & Computer Technologies, pp. 208-213, 2024.

[2] S. -T. Chen, Y. -C. Ouyang, M. -S. Shih, T. -S. Liu and C. -I. Chang, "Fusarium Wilt Detection in Phalaenopsis Through Integrated Hyperspectral Imaging and Deep Learning Techniques," International Geoscience and Remote Sensing Symposium, Athens, Greece, 2024, pp. 9446-9449, 2024.

[3] Sivaganesh, C. H, M. K. C. V. S. S., M. Kaushik, R. G. Sharathchandra and R. Rao Nidamanuri, "Hyperspectral Detection of Fusarium Wilt in Tomato Plants Using Machine Learning-Based Approaches," IEEE International Geoscience and Remote Sensing Symposium, pp. 7583-7585, 2024.

[4] A. Kaur, V. Kukreja, M. Aeri, S. Tanwar, and N. Mohd, "Nature's Secrets Revealed: Unraveling Fusarium Wilt Diseases through CNN and SVM," 4th IEEE Global Conference for Advancement in Technology, pp. 1-7, 2023.

[5] J. Lenin, S. Muthumarilakshmi, and V. S. Prabhu, "Plantnet: A deep learning model for early detection of plant diseases", International Journal of Advances in Signal and Image Sciences, vol. 10, no. 2, pp. 37–47, 2024.

[6] A. Jiménez-Hernández, R. G. Guevara-González, E. Rico-García, and I. Torres-Pacheco, "Evaluation of chemical and biological fungicides for the management of Fusarium Oxysporum," XVII International Engineering Congress, pp. 1-6, 2021.

[7] E. G. T. Abigan, L. G. A. Cajucom, J. D. L. Ong, P. A. R. Abu, and M. R. J. E. Estuar, "Detection of Microconidia in Microscopy Images of Fusarium oxysporum f. sp. cubense Using Image Processing Techniques and Neural Networks," IEEE 4th International Conference on Image Processing, Applications, and Systems, pp. 40-45, 2020.

[8] B.H. Chen, Y.C. Ouyang, M. Ou-Yang, H.Y. Guo, T.S. Liu, H.M. Chen, and M.S. Shih, "Fusarium Wilt Inspection for Phalaenopsis Using Uniform Interval Hyperspectral Band Selection Techniques," IEEE International Geoscience and Remote Sensing Symposium, pp. 2831-2834, 2020.

[9] A.A.M.A. Riazulhameed, C.S. Ranganathan, P. Pandey, B. Sakthisaravanan, K. Sasikala, and S. Murugan, "Smart Composting Solutions for Organic Waste Management and Soil Enrichment in Agriculture with IoT and Gradient Boosting," 4th International Conference on Sustainable Expert Systems, pp. 339-345, 2024.

[10] K.C.Chang, S.A. Chou, M.S. Shih, T.S. Liu, Y.C. Ouyang, C.I. Chang, and S.T. Chen, "Detection and Analysis of Phalaenopsis Fusarium Wilt Using Machine Learning," IEEE International Geoscience and Remote Sensing Symposium, pp. 5305-5308, 2023.

[11] E. G. T. Abigan, L. G. A. Cajucom, J. D. L. Ong, P. A. R. Abu, and M. R. J. E. Estuar, "Analysis of the Effects of Microscopy Techniques on the Performances of Convolutional Neural Network Architectures in Microscopic Fusarium Microconidia Detection," International Conference on Electrical, Computer, Communications and Mechatronics Engineering, pp. 1-6, 2021.

[12] Y. Hsu, Y.C. Ouyang, J.Y. Lu, M. Ou-Yang, H.Y. Guo, T.S. Liu, C.I. Chang, "Using Hyperspectral Imaging and Deep Neural Network to Detect Fusarium Wilton Phalaenopsis," IEEE International Geoscience and Remote Sensing Symposium, IGARSS, Brussels, Belgium, pp. 4416-4419, 2021.

[13] V. Thirumeninathan, S. Vijayalakshmi and S. T. Palathara, "Enhancing Banana Cultivation: Disease Identification through CNN and SVM Analysis for Optimal Plant Health," International Conference on Trends in Quantum Computing and Emerging Business Technologies, pp. 1-6, 2024.

[14] S. N. Sheela Evangelin Prasad, N. Rakesh, E. V. G, N. Mohankumar, R. Vinodha, and S. Murugan, "VGG16-Based Deep Learning Approach for Accurate Detection of Fruit Diseases in Precision Agriculture," 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things, pp. 1935-1940, 2025.

[15] A. A. Sarangdhar, and V. R. Pawar, "Machine learning regression technique for cotton leaf disease detection and controlling using IoT," International Conference of Electronics, Communication and Aerospace Technology, pp. 449-454, 2017.

[16] A. Kaur, V. Kukreja, M. Kumar, A. Choudhary, and R. Sharma, "A Fine-tuned Deep Learning-based VGG16 Model for Cotton Leaf Disease Classification," 5th International Conference for Emerging Technology, pp. 1-4, 2024.

[17] Y. S. K. Gudela, E. Jangam, and S. Mogili, "Cotton Crop Disease Detection using MobileNet Snapshot Ensemble Technique and Vision Transformers," 8th International Conference on Communication and Electronics Systems, pp. 1601-1608, 2023.

[18] A. K. Uttam, "Cotton Leaves Diseases Classification Using VGG16 Based Transfer Learning," Third International Conference on Ubiquitous Computing and Intelligent Information Systems, pp. 296-300, 2023.

[19] S. Srinivasan, S. LK, T. Alavanthar, C. Srinivasan, S. Murugan and S. Sujatha, "IoT-Enabled Horticultural Lighting for Optimizing Plant Growth and Agriculture Operations," 2nd International Conference on Networking and Communications, pp. 1-7, 2024.

[20] T. Hayit, A. Endes, and F. Hayit, "The severity level classification of Fusarium wilt of chickpea by pre-trained deep learning models. Journal of Plant Pathology, vol. 106, no. 1, pp. 93-105, 2024.