PLANTNET: A DEEP LEARNING MODEL FOR EARLY DETECTION OF PLANT DISEASES

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Abstract: Plant leaf disease detection in high-value crops is an important problem for farmers and the agricultural industry, often resulting in significant crop losses and economic losses. This paper presents a deep learning model, PlantNET, for early identification of plant leaf infections based on Convolutional Neural Networks (CNNs) trained on a large collection of leaf images in the PlantVillage database, including both healthy and infected samples from several crops. PlantNET is constructed efficiently to capture the characteristics associated with plant leaf infections and is optimized to provide better accuracy. The PlantNet's performance is computed regarding accuracy, precision, and recall measures. It enables quick diagnosis of infections, allowing for quick intervention solutions to minimize crop loss and the requirement for chemical treatments. The usefulness of PlantNet in agricultural applications emphasizes its potential to improve farming sustainability. The results highlight the need to use modern technology in precision agriculture to protect crop health and boost farmer profitability.

Keywords: Fungal infections, plant pathology, image classification, disease management, agricultural productivity.

I.INTRODUCTION

Agriculture is vital in producing essential resources such as food and fiber. It fosters innovation across various sectors, including biotechnology, environmental management, and automation, while employing millions globally. The necessity for a reliable food supply has driven innovations in sustainable farming techniques, crop protection, soil fertility, and pest control. The primary objective of agriculture remains the provision of sufficient food to meet the demands of the growing global population and evolving dietary preferences.

Agriculture serves multiple functions, with food production being just one of them. The impact extends to environmental systems, rural economies, commerce, and diplomatic relations. The national economies of numerous developing countries rely significantly on agriculture to alleviate poverty, enhance living conditions, and sustain livelihoods. Modern agriculture encompasses horticulture, fisheries, deforestation, and animal husbandry. Technological advancements such as genetically modified crops and precision farming enhance output, enabling farmers to increase yields while reducing inputs and maintaining environmental balance.

The agricultural sector is expected to face numerous challenges in the coming decades. Frequent weather changes, increasing temperatures, and altered precipitation patterns, which are consequences of climate change, pose significant threats to crop yields and food security. The agricultural sector continues to rely heavily on water resources, making water scarcity a significant concern. Environmental degradations such as soil erosion, water contamination, and biodiversity loss result from excessive chemical inputs, including fertilizers and pesticides. Strategies for sustainable agriculture that prioritize both production and environmental stewardship are critical for addressing these challenges.

The detection and analysis of plant leaves to assess plant health, identify diseases, and monitor growth represents a significant area of ongoing research in horticulture, environmental science, and agriculture. This method employs advanced technology to detect specific traits of plant leaves, utilizing machine learning, artificial intelligence, and image processing. It offers numerous practical applications. Enhancing agricultural production and sustainability, particularly in precision farming, necessitates a comprehensive understanding of plant leaf disease detection. Figure 1 presents a pie chart depicting the frequency of several fungal diseases impacting various crops.

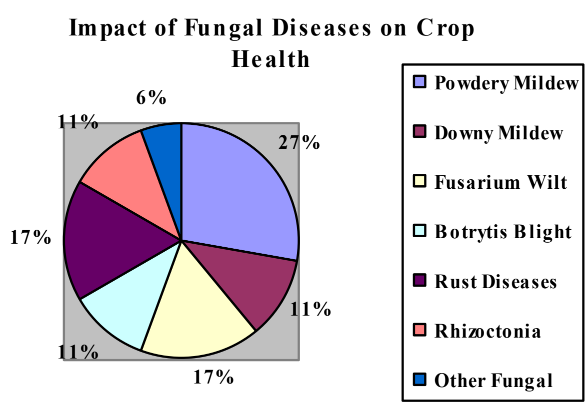

Fig. 1 Prevalence of fungal infections in crops

II. RELATED WORKS

A 10-layer architecture consisting of five Convolutional Layers with differing filter counts is described in [1]. It uses five layers of max-pooling to reduce the dimension of feature maps. Multiple training and testing configurations and diverse dropout parameters are employed for the assessment. The developed system in [2] improves the detection accuracy of Fusarium wilt fungal disease in tomato plant leaves. A large collection of 87,000 images is employed, with 96% of leaves in pristine condition, in contrast to 60% depicting damaged leaves in the open database.

Metric learning utilizing limited samples for classifying cotton leaf spot disease is detailed in [3]. A Support Vector Machine (SVM) and threshold segmentation are evaluated for optimal spot segmentation methodology. A parallel two-way CNN with weight-sharing gathers characteristics from both images, learning a metric space that positions comparable leaf samples in proximity and dissimilar samples at a distance. A decision support system for managing fungal infections in rice cultivation is introduced [4]. This is an important part of ensuring food security on a worldwide scale. As a result of the system's precise diagnoses and management suggestions, farmers can enhance sustainable food production by implementing focused strategies, minimizing losses, and optimizing yields.

A plant leaf disease detection approach utilizing deep learning is described in [5]. Fuzzy c-means clustering initially identifies patches affected by leaf disease. It employs a rapid grey-level co-occurrence matrix alongside a progressive neural architecture search. A deep learning classifier is utilized for the identification and optimization of visual characteristics in optimization processes. The use of infrared and thermal band sensors allows for the early detection of illnesses [6]. The thermal and RGB images are acquired by the unmanned ariel vehicle for the identification of disease progress.

A plant leaf classification system discussed in [7] utilizes SVM and kNN-based CNN architecture. Two deep learning-based architectures have been created for the classification of plant leaves. The initial design consists of a CNN with an SVM, whereas the subsequent one merges a CNN with kNN. An improved ResNeXt deep-learning model for detecting fungal infections in apple crops is discussed in [8]. It is based on the transfer learning method and requires pre-processing, segmentation, and data augmentation to deal with dataset imbalances and extract targeted crop areas.

A compact model utilizing the VGG16 architecture is employed to classify plant leaves [9]. The classification of plant leaves utilizing non-handcrafted features is defined. A modern computer vision system discussed in [10] can swiftly and precisely diagnose ailments, enabling treatment and increased yield. It can recognize plant illnesses from complex images where the leaves are superimposed. A YOLOv8 model diagnoses apple leaf fungal diseases such as cedar rust, scab leaves, and black rot. To enhance the identification of tomato diseases in India's agricultural environment, a tomato plant disease predictor that utilizes CNN and real-time imagery is described in [11].

Plant diseases may cause food production problems, a major setback for countries that rely on agriculture for economic growth [12]. Plant diseases can be identified early by combining image processing with computer vision algorithms. Symptoms of fungal diseases in agricultural and horticultural crops are described and classified using image-processing methods [13]. To better diagnose and control plant diseases in rural agriculture, an Internet of Things (IoT) system that can provide real-time local environmental data is discussed in [14]. A machine learning algorithm and a data-sending gadget work together to predict weather conditions. Agricultural field managers can access data and projections to manage their crops and avoid developing fungal diseases effectively.

Fungal infections may hinder plant development and agricultural output, A low-cost cross-platform smartphone app with machine learning capabilities uses Flutter to collect damaged leaf images and identify the plant, illness, and remedies [15]. It also provides historical weather data based on image locations and lets users access further information. Wheat plant disease is the leading cause of decreased wheat harvest quality and quantity. A pattern recognition-based classifier is used for wheat plant fungal disease detection [16]. The thresholding approach and morphological operators segregate diseased areas and extract texture, color, and shape characteristics. To lower the dimensionality of the feature space, the minimal-redundancy-maximal-relevance criteria are used to find meaningful features.

The prevention of crop damage is made easier with early disease identification by CNN, image processing methods, and artificial intelligence, which all have a role in diagnosing and treating many diseases [17-18]. Improved agricultural productivity directly results from CNN models' ability to correctly identify diseases in fruits and leaves. Strawberry cultivation in Kenya is vulnerable to crop diseases, threatening food security and economic growth. A deep CNN model is designed in [19] for Strawberry plant leaf detection. A recursive minimum cross-entropy method for multilayer crop image thresholding is described in [20] for disease detection.

III. PROPOSED SYSTEM

The proposed system, which uses CNNs, aims to detect early leaf diseases in crops. It improves crop management, decreases economic losses, and supports sustainable agricultural practices by allowing farmers to make educated decisions and early interventions based on precisely classified images of healthy or diseased leaves. The proposed method for the early identification of fungal infections in high-value crops uses CNN functions via a structured workflow encompassing data collecting, model training, and real-time monitoring. The approach starts with aggregating an extensive dataset of high-resolution images from the PlantVillage database. This dataset comprises a broad collection of samples covering healthy leaves and those impacted by different diseases. Figure 2 presents a block diagram that outlines the flow of the PlantNET system, highlighting the essential components and interconnections.

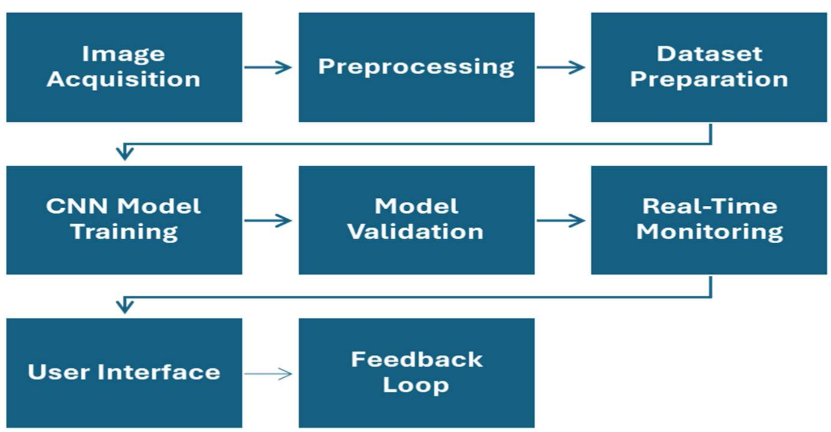

Fig. 2 Overall flow for early detection of plant leaf diseases

The images are obtained from the PlantVillage dataset. The images are preprocessed, which includes image resizing, normalization, and augmentation. Augmentation methods such as rotation, flipping, and brightness manipulation artificially enhance the dataset's size and variety, facilitating the model's acquisition of more robust features. The pre-processed images are then divided into training (60%), validation (20%), and test sets (20%) to enhance model training and assessment. The fundamental component of the proposed system is the CNN model, designed to learn and extract features from input images autonomously. The design often comprises many convolutional layers, each succeeded by activation functions and pooling layers. These layers collaboratively diminish the input images' spatial dimensions while augmenting the feature maps' depth. A fully connected layer generates classification outputs after flattening, identifying between healthy and infected crops, facilitating early identification of fungal infections in high-value crops. Figure 3 shows the proposed PlantNET architecture.

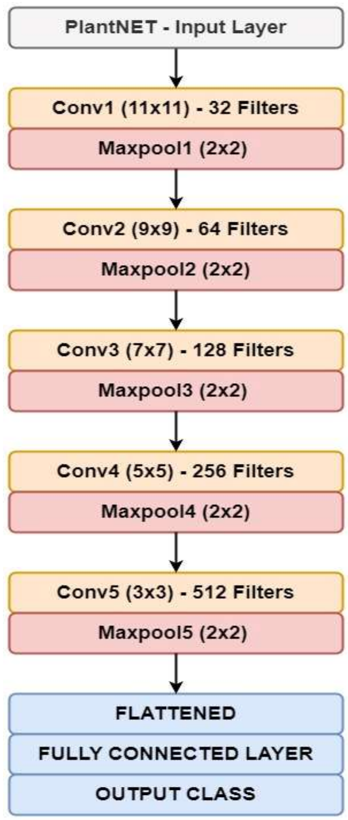

Fig. 3 PlantNET architecture

The convolutional layers discern spatial hierarchies among the data, recognizing patterns such as color changes, textures, and forms that signify fungal infections. After several convolutional and pooling processes, the output is flattened and input into one or more fully connected layers, finally providing the final classification result. Several hyperparameters, such as learning rate, batch size, and number of epochs, are meticulously adjusted using a systematic methodology to optimize the model's performance. This entails assessing the model's efficacy on the validation set and modifying parameters to prevent overfitting. The loss function, often categorical binary cross-entropy (BCE) and Hinge Loss (HE), is minimized by optimization techniques such as Adam or Stochastic Gradient Descent (SGD).

After training and validation, the model is implemented into a real-time monitoring system. This method may be used in agricultural environments, enabling farmers to acquire images of crop foliage using mobile phones or drones fitted with high-resolution cameras. The acquired images are then analyzed in real-time using the trained CNN model, which categorizes each image as healthy or diseased. The system delivers prompt feedback to farmers, notifying them of fungal diseases and suggesting early solutions. The system facilitates detection for a user interface that enables farmers to visualize data, monitor infection trends over time, and get treatment assistance.

This interface may be designed as a mobile application or a web-based platform, ensuring accessibility and user-friendliness. Furthermore, the system may be improved by including meteorological data and other environmental variables, offering farmers detailed insights about conditions that may lead to fungal epidemics. To enhance the validation of the system's efficacy, further study should concentrate on optimizing the model using supplementary data gathered from diverse cultivation environments and geographical locations. Users with agricultural specialists and pathologists may provide critical insights into fungal species, improving the model's precision in recognizing and distinguishing various forms of infections.

III. RESULTS AND DISCUSSIONS

The proposed PlantNET for disease detection is evaluated using the PlantVillage dataset [21]. PlantVillage is a dataset that has become widely recognized in agricultural research and the classification of plant diseases. This collection includes images of plant leaves impacted by various diseases and ailments. The dataset is available at no cost and is utilized to evaluate the proposed PlantNET system. The dataset comprises 54,303 leaf images from 38 distinct plant species, categorized into 15,084 healthy images and 39,221 diseased images. Figure 4 presents the samples from the PlantVillage dataset.

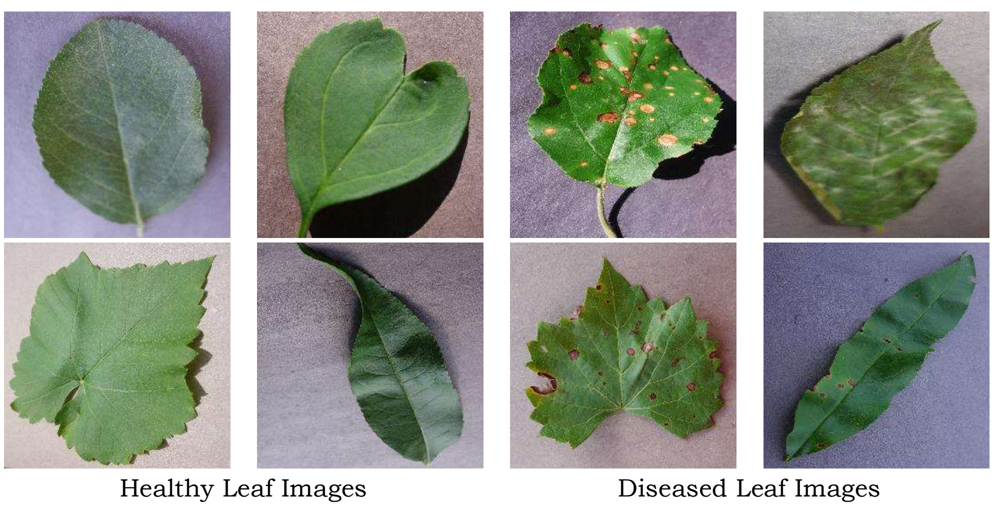

Fig. 4 Samples in PlantVillage database

Table 1 presents the performance measures employed to evaluate the PlantNET system. It employs the following symbols: True Positive (diseased leaves accurately identified as diseased), False Positive (healthy leaves erroneously identified as diseased), False Negative (diseased leaves mistakenly identified as healthy), and True Negative (healthy leaves correctly identified as healthy).

TABLE. 1 Performance measures used by the PlantNET system

Performance metrics	**Formula**
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1 Score	$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

A crucial stage in developing and evaluating the PlantNET system is partitioning the dataset into training, validation, and testing instances. The proposed approach incorporates a random partitioning of the data into three groups. One group comprises 60% of samples for model training and 20% of samples for validating the model, while the last group, consisting of 20% of the remaining images, is employed for performance evaluation of the model. The suggested approach is evaluated for the detection of three distinct plants: strawberry, Peach, and cherry. Figure 5 shows the number of training, validation, and testing images the system utilizes for evaluation purposes. The number of images is increased to 10000 samples by the augmentation process.

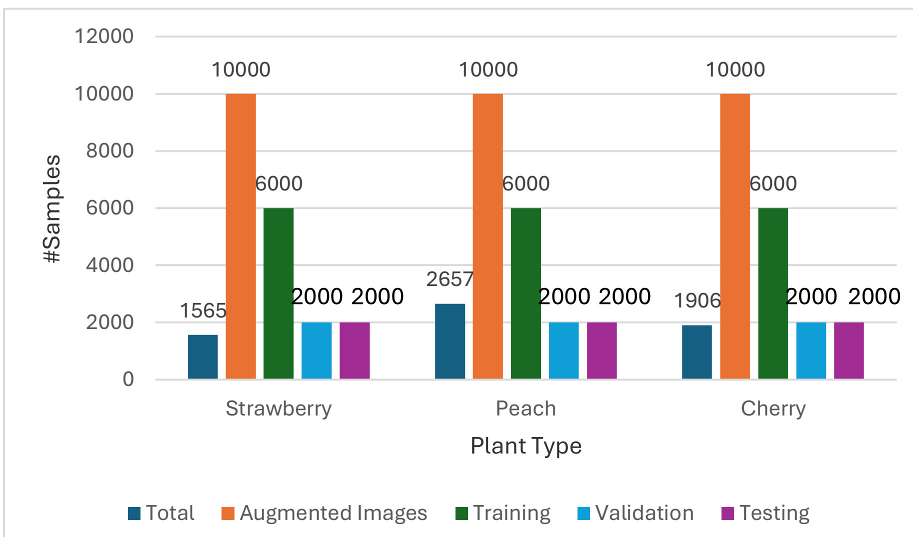

Fig. 5 Number of training, augmented, validation, and testing samples of the PlantNET system

Tables 2 to 4 show the proposed PlantNET system's performance in terms of precision, recall, and F1 Score, respectively.

TABLE. 2 Precision of the PlantNET system for plant leaf disease detection

Model	Loss Function	Optimization	Precision (%)		
			Strawberry	Peach	Cherry
PlantNET	BCE	SGD	95.96	96.52	96.21
		Adam	98.08	98.54	98.23
	HL	SGD	97.37	98.68	98.03
		Adam	99.45	99.55	99.50

TABLE. 3 Recall of the PlantNET system for plant leaf disease detection

Model	Loss Function	Optimization	Recall (%)		
			Strawberry	Peach	Cherry
PlantNET	BCE	SGD	95.00	95.60	95.30
		Adam	97.25	97.55	97.40
	HL	SGD	96.25	97.50	96.90
		Adam	99.25	99.10	99.20

TABLE. 4 F1-Score of the PlantNET system for plant leaf disease detection

Model	Loss Function	Optimization	F1-Score (%)		
			Strawberry	Peach	Cherry
PlantNET	BCE	SGD	95.48	96.06	95.75
		Adam	97.67	98.04	97.82
	HL	SGD	96.81	98.09	97.46
		Adam	99.35	99.32	99.35

It can be seen from Tables 2 to 4 that for all three metrics, the system performs better when using the HL loss function compared to BCE. Furthermore, the Adam optimizer consistently outperforms the SGD optimizer across all loss functions and metrics. Specifically, the combination of HL with Adam achieves the highest precision, recall, and F1-score for all three plant types—Strawberry, Peach, and Cherry—indicating superior performance in accurately detecting diseases. Notably, the highest precision (99.55%), recall (99.25%), and F1-score (99.35%) are achieved for Peach using HL and SGD, reflecting the system's robustness and generalizability. These results highlight the importance of selecting appropriate loss functions and optimization strategies to maximize the model's accuracy in disease detection.

Figure 6 shows the overall accuracy of the proposed PlantNET system. It presents the accuracy of the PlantNET system under different configurations of loss functions (BCE, HL) and optimizers (SGD, Adam) for detecting diseases in Strawberry, Peach, and Cherry plants. HL with Adam achieves the highest accuracy across all three crops (Strawberry: 99.35%, Peach: 99.32%, Cherry: 99.35%), showcasing the effectiveness of this combination for disease detection. It is also noted that HL consistently outperforms BCE in all settings, emphasizing its suitability for the task. Adam generally results in higher accuracy than SGD when paired with the same loss function, highlighting its optimization advantage. These results reinforce the importance of pairing the right loss function and optimizer to maximize model performance.

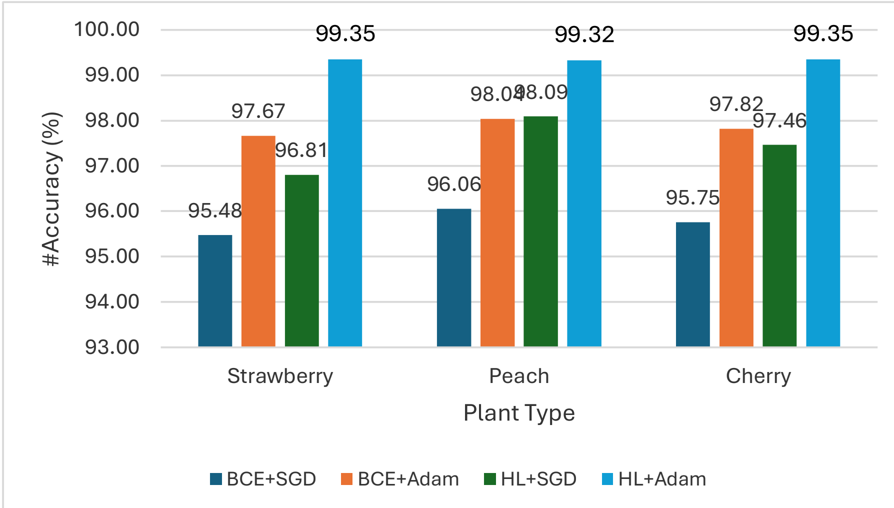

Fig. 6 Overall accuracy of the proposed PlantNET system

IV. CONCLUSIONS

The proposed PlantNET for the early identification of plant leaf disease detection in strawberry, Peach, and cherry crops using CNNs has considerable promise in agricultural health monitoring. Deep learning methodologies facilitate efficient and precise categorization of plant health, allowing prompt intervention and minimizing crop losses. The CNN model proficiently differentiates between healthy and infected plants, attaining high accuracy and strong performance across many dataset divisions. The training, validation, and testing steps demonstrate that the model generalizes well, reducing overfitting while preserving excellent sensitivity and specificity. Image augmentation and preprocessing approaches improve the model's ability to identify fungal signs across different situations. This study advances precision agriculture and underscores the significance of using artificial intelligence in agricultural techniques. Future research may investigate integrating other data sources, including environmental variables, to enhance detection efficacy. This approach signifies a substantial advancement in sustainable crop management, enhancing yields and resource efficiency in agricultural practices.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

REFERENCES

[1]. M. Sadhasivam, M. K. Geetha and G. Britto, “Efficient deep learning architecture for the classification of diseased plant leaves,” Indonesian

Journal of Electrical Engineering and Computer Science," vol. 33, no. 1, pp. 2024,198-206.

[2]. D. Suresh and T. S. Kala, "Detection Of Fungal Infection On Tomatoes using Image Processing With Machine Learning Algorithms," International Conference on New Frontiers in Communication, Automation, Management, and Security, pp. 1-6, 2023.

[3]. R. Sharma and Aarti, "Revolutionizing Rice Agriculture: A Machine Learning Approach to Fungal Disease Management for Economic Sustainability," International Conference on Communication, Computer Sciences and Engineering, 2024, pp. 798-805, X. Liang, "Few-shot cotton leaf spots disease classification based on metric learning," Plant Methods, vol. 17, 2021, pp. 1-11.

[4]. R. Sharma and Aarti, "Revolutionizing Rice Agriculture: A Machine Learning Approach to Fungal Disease Management for Economic Sustainability," International Conference on Communication, Computer Sciences and Engineering, 2024, pp. 798-805.

[5]. U. Arasakumaran, S. D. Johnson, D. Sara and R. Kothandaraman, "An Enhanced Identification and Classification Algorithm for Plant Leaf Diseases Based on Deep Learning," Traitement du Signal, vol. 39, no. 3, 2022, pp. 1013-1018.

[6]. R.A.F. Ishaq, S.R.A. Shah and Y. Shabbir, "UAV Assessment of Crop Evapo-transpiration Dynamics in Winter Wheat and Barley under Varying Pressures of Fungal Diseases," Seventh International Conference on Aerospace Science and Engineering, 2021, pp. 1-8.

[7]. S. Ghosh, A. Singh, N. Z. Jhanjhi, M. Masud and S. Aljahdali, "SVM and KNN Based CNN Architectures for Plant Classification," Computers, Materials & Continua, vol. 71, no. 3, 2022, pp. 1-18.

[8]. N. Upadhyay and N. Gupta, "Diagnosis of fungi affected apple crop disease using improved ResNeXt deep learning model," Multimedia Tools and Applications, 2024, pp. 1-20.

[9]. K. Abinaya, K. Iswarya, S. Saraswati, and P. Kasinathan, "Plant Leaf Classification Using a Compact Deep Learning Model Use of VGG-16", Journal of Advanced Research In Technology And Management Sciences, vol. 6, no. 1, 2024, pp. 1-5.

[10]. S. BalaChandralekha and J. Thangakumar, "Deep Learning-Based Detection of Fungal Diseases in Apple Plants Using YOLOv8 Algorithm," International Conference on Advances in Data Engineering and Intelligent Computing Systems, 2024, pp. 1-6.

[11]. M. Manchanda, K. Jadli, P. Butola, V. Sharma, D. Bisht, and K. Purohit, "A Real Time Tomato Crop Disease Prediction using Deep Learning," International Conference on Inventive Computation Technologies, 2024, pp. 649-656.

[12]. K. Chelladurai, N. Sujatha and L. N. Valli, "Fungal infection in plant leaves-A Review," In E3S Web of Conferences, vol. 399, 2023, pp. 1-12.

[13]. J. D. Pujari, R. Yakkundimath and A. S. Byadgi, "Identification and classification of fungal disease affected on agriculture/horticulture crops using image processing techniques," IEEE International Conference on Computational Intelligence and Computing Research, 2014, pp. 1-4.

[14]. T. Truong, A. Dinh and K. Wahid, "An IoT environmental data collection system for fungal detection in crop fields," IEEE 30th Canadian Conference on Electrical and Computer Engineering, 2017, pp. 1-4.

[15]. R. K. Moloo and K. Caleechurn, "An App for Fungal Disease Detection on Plants," International Conference for Advancement in Technology, pp. 1-5, 2022.

[16]. Z. Sarayloo and D. Asemani, “Designing a classifier for automatic detection of fungal diseases in wheat plant: By pattern recognition techniques,” 23rd Iranian Conference on Electrical Engineering, 2015, pp. 1193-1197.
[17]. S. Muthuselvan, V. Rajasekhar, B. Shankar, P. Mohana, N. Doddabasappa and B. Suresh, “Classification of Automatic Detection of Plant Disease in Leaves and Fruits using Image Processing with Convolutional Neural Network,” 4th International Conference on Smart Electronics and Communication, 2023, pp. 1408-1414.
[18]. U.M.M.P.K. Nawarathne and H.M.N.S. Kumari, “Classification of Fungi Images Using Different Convolutional Neural Networks,” 8th International Conference on Information Technology Research, 2023, pp. 1-6.
[19]. D. Kerre and H. Muchiri, “Detecting the simultaneous occurrence of strawberry fungal leaf diseases with a deep normalized CNN,” In Proceedings of the 7th International Conference on Machine Learning Technologies, 2022, pp. 147-154.
[20]. A. Kumar, A. Kumar, and A. K. Vishwakarma, “Improvement of Complex Background Crop Image Segmentation using Sparse PSO,” IEEE 7th Conference on Information and Communication Technology, 2023, pp. 1-6.
[21]. S.P. Mohanty, D.P. Hughes and M. Salathé, “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, 2016, pp. 1-10.