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Artificial Intelligence Based Integrated Technological Advancements for Automated Crops Diseases Identification in Smart Farming

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Abstract: The rapid growth of agricultural technology has prompted the investigation of novel crop disease detection approaches. This paper presents an integrated method for the autonomous detection of agricultural diseases that combines the capabilities of a quadcopter with deep learning methods. The quadcopter is an aerial platform outfitted with high-resolution cameras to gather detailed field photographs effectively. Create a reliable and precise disease identification system using deep learning methods, specifically Convolutional Neural Networks (CNNs). The steps in our method are as follows: employing a quadcopter to capture photographs, pre-processing the images, feature extraction using a pre-trained CNN, and disease classification using a specially trained deep neural network. This work with agricultural specialists ensures the precise annotation of disease labels to make it easier to create a trustworthy dataset. Test the proposed system on several crops and agricultural settings, showcasing its capacity to identify and categorize various illnesses in real time precisely. Evaluate the model's precision, recall, and F1-score performance through extensive experimentation and contrast it with conventional manual disease detection techniques. The outcomes demonstrate the effectiveness and efficiency of our automated strategy and highlight its potential to transform disease management in agriculture completely. This study makes a contribution to the field of robotics, computer vision, and agriculture by providing a cutting-edge solution that reduces the negative effects of crop diseases on the economy and the environment through prompt and accurate diagnosis.

Keywords: *AI, CNN, Crops, Deep learning, Disease,Quadcopter,Smart Farming*

1. Introduction

In recent years, guaranteeing food security and sustainability has presented considerable challenges for the world's agricultural sector. The widespread breakout of diseases that harm crop productivity and quality is one of the main challenges. It is essential to quickly diagnose and correctly identify these agricultural diseases to lessen their effects and adopt efficient management techniques. Traditional techniques of illness identification frequently entail time-consuming, narrowly focused field surveys that need a lot of labour [1]. In this setting, combining cutting-edge technologies with deep learning—such as quadcopters—emerges as a possible path to transform disease diagnosis and management in agriculture. Due to their capacity to record detailed aerial imagery of crop fields, quadcopters, often known as drones, have become popular as adaptable instruments in precision agriculture [2]. This particular vantage point provides a thorough view of the entire cultivation area, facilitating quick data

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gathering and analysis. The combination of these technologies holds tremendous promise for automating the detection of agricultural illnesses, especially when combined with advances in deep learning, particularly the success of Convolutional Neural Networks (CNNs) in picture recognition tasks.

To tackle the crucial problem of identifying agricultural diseases, this study adopts an innovative strategy that makes use of the capabilities of quadcopters and deep learning techniques. To collect the vast and precise visual data from crops, at an unprecedented scale by utilizing quadcopters' agility and image process [3]. The goal is to create a reliable and accurate model capable of accurately classifying a wide range of diseases through deep learning techniques. Combining these technologies speeds the process of identifying diseases and improves its precision and efficacy. This research has the potential to considerably influence agricultural practices by reducing the need for labor-intensive surveys and providing a real-time, automated solution [4]. Ultimately, adopting an autonomous illness detection system effectively could result in early intervention and focused therapies, minimizing economic losses and the environmental footprint connected with traditional disease management measures. Examine the methodology, experimentation, and outcomes of our suggested approach in the following parts, offering insight into how well it performs in agricultural situations. The transformational potential of merging quadcopters and deep learning in the field of identifying agricultural diseases becomes more and more evident as we proceed through this investigation.

2. LITERATURE SURVEY

The convergence of artificial intelligence, robotics, and agricultural science has led to creative approaches to disease control. Precision agriculture may undergo a revolution because of a breakthrough method that automatically uses deep learning and quadcopters to identify crop illnesses.

A. Automated Disease Identification in Agriculture:

(i) Conventional Approaches: Abbaset et al. [5] has explained that historically, agronomists had to check fields to identify diseases manually. Even though these techniques are beneficial, they take a lot of time and might not be scalable enough for large-scale farming.

(ii) Remote Sensing and Imaging: Bégué, Aet.al [6] Research has looked at using satellites and aerial pictures as remote sensing technologies to detect illness. However, the investigation of closer-range options, such drones, has been spurred by constraints in spatial and temporal resolution [7-8].

B. Role of Drones in Agriculture:

Maes, W. H., & Steppe, K[9] Precision agriculture now focuses significantly on quadcopters, or drones, fitted with high-resolution cameras as essential instruments. They offer a distinct viewpoint, enabling quick data collecting and comprehensive crop imagery capture. Drones can efficiently cover large areas and are agile and flexible. They have been used for various agricultural applications, including crop monitoring, yield estimation, and pest detection [10].

C. Integration of Deep Learning in Agriculture:

Kamilaris, A., & Prenafeta-Boldú, F. X[11] image identification challenges have demonstrated exceptional results for deep learning, particularly CNNs. CNNs have been used in agriculture to identify plant diseases by using static pictures from sensors positioned on the ground. Training accurate models with minimal labeled agricultural data has been made possible through transfer learning, which uses pre-trained models on big datasets [12-14].

D. Ground-Based Systems:

ElMasry, G.et.al [15] Automated illness identification systems based on the ground have been studied in earlier studies. Despite their effectiveness, these systems could have trouble reaching every part of the field and might not work well in bigger agricultural environments. Multispectral Imaging: In certain studies, multispectral imaging has been used to detect diseases [16-18]. These techniques can be prohibitively expensive and frequently call for specialized sensors, although offering useful spectrum information.

E. Challenges and Considerations:

(i)Data Variability: Different lighting conditions, weather patterns, and crop kinds may all affect agricultural surroundings. One main challenge is ensuring the model is resilient against these factors. Real-Time Processing: Resolving computing limitations is necessary to implement real-time illness detection on a drone. For on-board processing, model optimization and efficiency become essential.

(ii)Hyper-Spectral Imaging: Using hyper-spectral imaging to analyze spectrum data in more detail might lead to improved illness detection. Edge Computing: As edge computing technologies progress, the computational limitations of on-board processing could be lessened, allowing for the development of more complex models.

The literature review illustrates how the combination of deep learning and drone technology has caused a paradigm change in the detection of agricultural diseases. Even though there has been a lot of development, more research is needed to solve problems and improve the effectiveness and scalability of these cutting-edge systems. These research' multidisciplinary approach emphasizes how teamwork is necessary for the effective integration of technology in agriculture. Precision and sustainable agriculture might greatly benefit from the autonomous detection of agricultural illnesses through the use of deep learning and quadcopters as technology advances.

3. METHODOLOGY

Automatic Identification of Agricultural Diseases using Quadcopter and Deep Learning Method as shown in Figure 1.

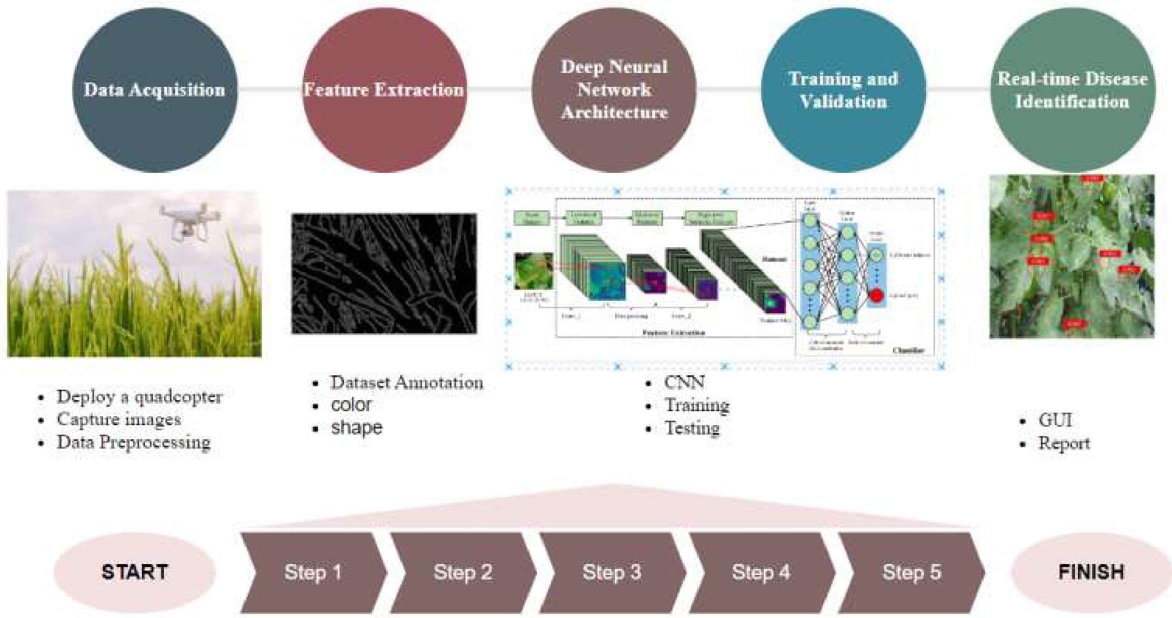


Figure 1. Proposed methodology Automatic Identification of Agricultural Diseases

A. Data Acquisition

Use a quadcopter with high-resolution cameras to fly above crop fields and take pictures.

Figure 2. Quadcopter

A Quadcopter, also known as a quadrotor helicopter or quadrotor, could be a multirotor helicopter that's raised and propelled by four rotors. Quadcopters are classified as rotorcraft, as opposition fixed-wing craft, as a result of their elevate is generated by a collection of rotors (vertically oriented propellers) as shown in Figure 2.

The quadcopter dynamics model can be described as follows

$$\phi = \left(\frac{Jy - Jz}{Jx}\right)\theta\psi + \frac{l}{Jx}U2 \quad (1)$$

$$\theta = \left(\frac{Jz - Jx}{Jy}\right)\phi\psi + \frac{l}{Jy}U3 \quad (2)$$

$$\psi = \left(\frac{Jx - Jy}{Jz}\right)\theta\phi + \frac{l}{Jz}U4 \quad (3)$$

$$x = \frac{1}{m}(\cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi)U1 \quad (4)$$

$$y = \frac{1}{m}(\cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi)U1 \quad (5)$$

$$z = g - \frac{1}{m}(\cos\phi\cos\theta)U1 \quad (6)$$

Where,

φ, θ and ψ – Euler angles roll, pitch and yaw

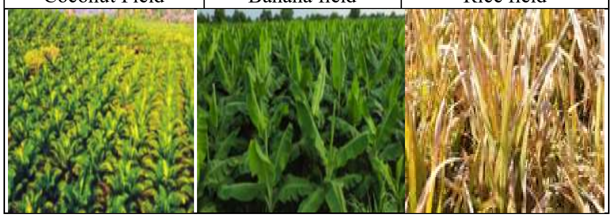
x, y and z – represent the position of the quadcopter

Jx, Jy and Jz – moments of inertia along with x, y and z axes; Ui (i=1, 2, 3, 4) – control inputs

Cover the entire cultivation area methodically, ensuring enough picture overlap for precise reconstruction [19]. To account for eventualities in real life, take pictures in various lighting and weather circumstances as shown in Table 1.

TABLE I. QUADCOPTER AERIAL VIEW IMAGE OF VARIOUS AGRICULTURAL FIELD

Coconut Field	Banana field	Rice field



B. Data Pre-processing

The obtained imagery was geo referenced to establish spatial coordinates for precise mapping. Use image enhancement techniques like histogram equalization and colour correction in equation (7) for enhanced image quality and consistency. Create orthomosaics using picture stitching methods to get a smooth, detailed view of the entire field as shown in Figure 3.

$$P(x, y) = Ih(x, y) + \alpha\big(I(x, y)\big) \qquad (7)$$

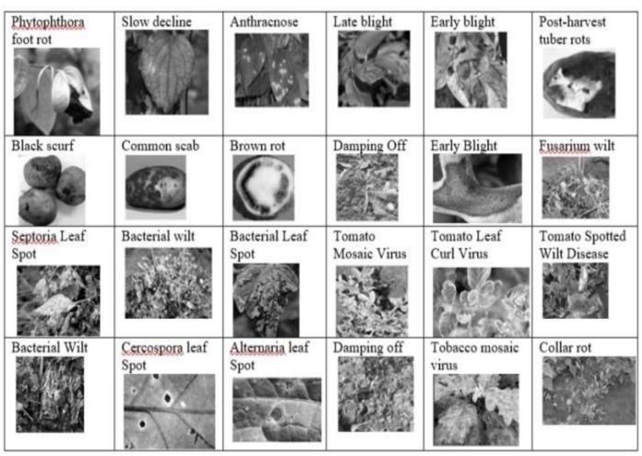


Figure 3. Data Pre-processing output image for agricultural field

C. Dataset Annotation:

Work along with agricultural specialists to spot and label any occurrences of various agricultural illnesses shown in the collected imagery. Add disease labels to the dataset, including classifications for bacterial, fungal, and viral diseases, nutrient deficits, and physical harm, as shown in Figure 4.

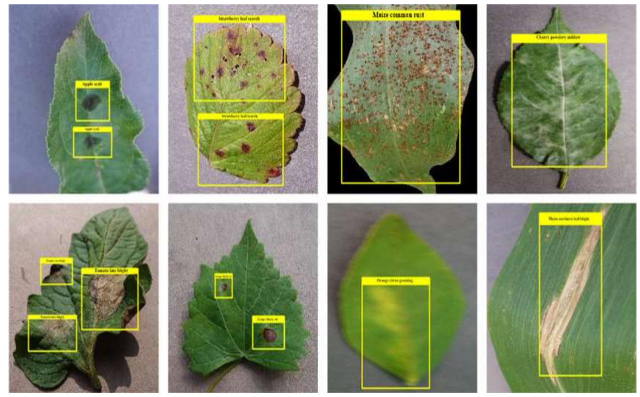


Figure 4. Data Annotation output image for agricultural field

D. Transfer Learning and Feature Extraction

Use a Convolutional Neural Network (CNN) that has already been trained using a sizable image dataset, such as ResNet or VGG.

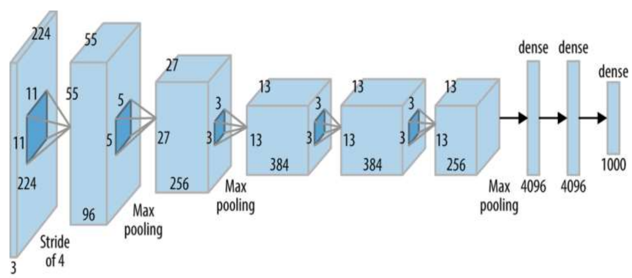


Figure 5. ResNet / VGG Architecture

Use the annotated agricultural illness dataset to fine-tune the pre-trained CNN and adapt it to certain disease recognition tasks. The final fully connected layer of the CNN should be used to extract deep features that will help capture hierarchical representations of the input images, as shown in Figures 6 to 8.

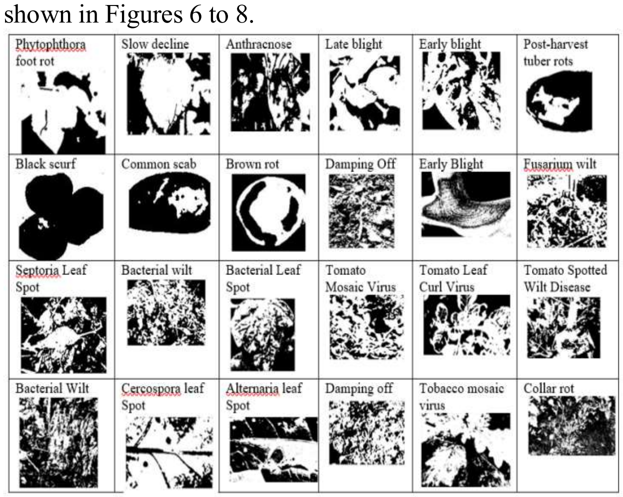


Figure 6. Color feature extraction output image for 24 categories

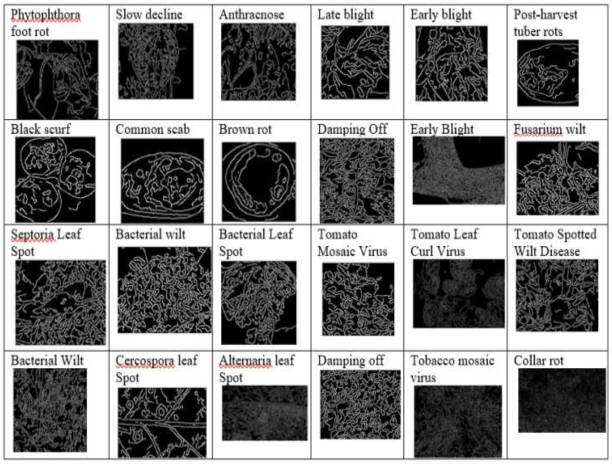


Figure 7. Shape feature extraction output image for 24 categories

E. *Deep Neural Network Architecture:*

Create a unique deep neural network design that uses dropout regularization, softmax activation, and fully associated layers to classify diseases as shown in Figure 9.Kernel convolution and CNNs are crucial components of numerous other computer vision techniques. This technique entails transforming our image using the values of the filter while moving a small number matrix over it [20]. This matrix is referred to as the kernel or filter. The formula below is used to determine the subsequent map values, where the letter h represents our kernel and our input picture is represented by the letter f. The row and column indices of the result matrix are denoted by the letters m and n, respectively.

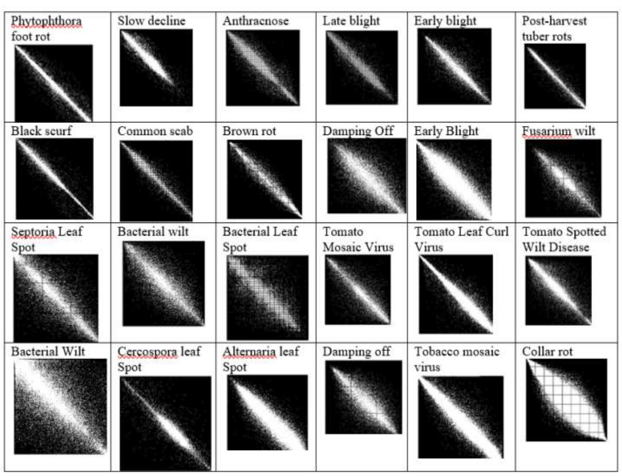


Figure 8. Texture feature extraction output image for 24 categories

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k]f[m-j, n-k] \quad (8)$$

The performance matrix's metrics can be determined using the formula below while considering padding and stride.

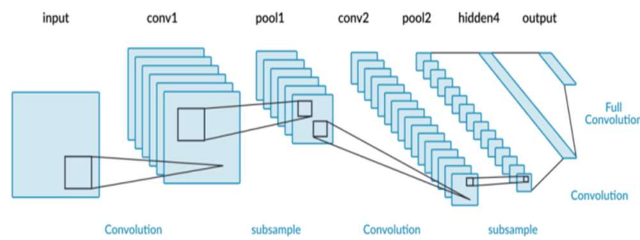


Figure 9. CNN Neural Network Architecture

$$\text{nout} = [\frac{\text{nin}+2\text{p}-\text{f}}{\text{s}} + 1] \quad (9)$$

The resulting tensor's dimensions, also known as our 3D matrix, satisfy the equation where: n is the size of the picture; f is the size of the filter; nc is the number of channels in the image; p is the amount of padding utilised; s is the employed step; and nf is the number of filters used.

$$[\text{n},\text{n},\text{nc}] * [\text{f},\text{f},\text{nc}] = [\left[\frac{\text{nin}+2\text{p}-\text{f}}{\text{s}} + 1\right], \left[\frac{\text{nin}+2\text{p}-\text{f}}{\text{s}} + 1\right], \text{nf}] \quad (10)$$

In contrast to the method utilized for strongly connected neural networks, will use convolution this time around rather than just a straightforward matrix multiplication. Forward propagation happens in two steps. Apply bias b first, then use a W tensor, which consists of filters, to convert the input data from the previous layer to ascertain the intermediate value Z. Our activation is denoted by the symbol g in the second, which stands for a non-linear activation function applied to our intermediate value. These formulas are suitable for matrix equation fans.

$$z^{[l]} = W^{[l]}.A^{[l-1]} + b^{[l]} \quad (11)$$
$$A^{[l]} = g^{[l]}(z^{[l]}) \quad (12)$$

Use the pre-trained CNN's extracted features to include both low-level and high-level visual information into the design.

F. *Model Training and Validation*

Divide the annotated dataset into training, validation, and test sets to achieve accurate model evaluation. To make training samples more diverse, use data augmentation techniques including rotation, scaling, and flipping. Utilize the relevant optimization algorithms (such as Adam) and loss functions (such as categorical cross-entropy) to train the customized deep neural network [21].

To avoid overfitting, keep an eye on the model's performance on the validation set and use early stopping as shown in Figure 10.

G. Model Evaluation:

Utilise metrics such as accuracy, precision, recall, F1-score, and confusion matrices to assess the trained model on the test dataset [22]. Compared to conventional illness detection techniques, evaluate the effectiveness and efficiency of the suggested strategy.

$$\text{SEN (Sensitivity)\%} = \frac{TP}{TP+TN} \tag{13}$$

$$\text{SPEC(Specificity)\%} = \frac{TN}{TN+} \tag{14}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{15}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+F} \tag{16}$$

Deploy the trained model on the quadcopter or a ground station to detect diseases in real time while the aircraft is in flight. Apply the deep learning model to the real-time incoming photos taken by the quadcopter to recognize and categorize agricultural illnesses [23]. Adjust hyperparameters and model architecture to achieve high illness identification accuracy and performance optimization. Investigate methods like model quantization to lower the quadcopter's real-time deployment's processing demands.An automated and precise system for identifying agricultural diseases is created using the proposed methodology, combining quadcopters' advantages with deep learning [24]. This strategy has the potential to alter disease management practices in agriculture, resulting in greater crop output, less losses, and increased sustainability by utilizing cutting-edge technologies and interdisciplinary collaboration.

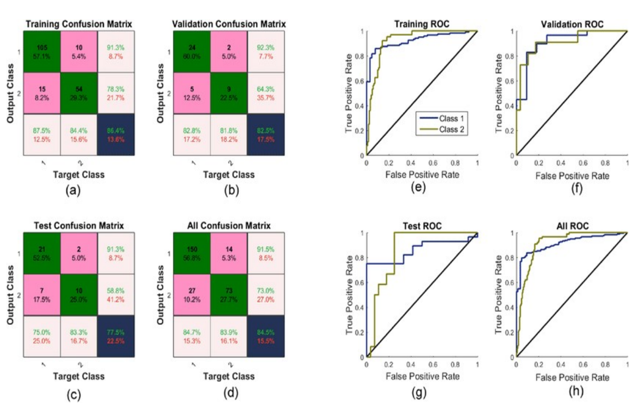


Figure 10. CNN output

4. RESULTS AND DISCUSSION

The investigation found many pathogens that cause illness and impact various crops. With 62 cases, fungi accounted for most of the contributions, with 26 cases coming from bacteria, 7 from viruses, 1 from nematodes, and 2 from abiotic factors as shown in Table 2 and Figure 11.

TABLE II. PATHOGENS THAT CAUSE DISEASES AND IMPACT VARIOUS CROPS

Crops	Fungus	Bacterial	Virus	Nematode	Abiotic
Rice	62	26	7	1	2
Banana	65	22	9	2	1
Coconut	66	24	8	1	1
Tomato	67	21	7	3	2
Potato	63	24	6	4	2
Brinjal	69	22	7	1	1
Betel	61	25	8	3	3
Cotton	63	23	9	3	2
Peanut	65	21	9	2	3
Wheat	67	23	7	2	1
Maize	62	27	6	2	1

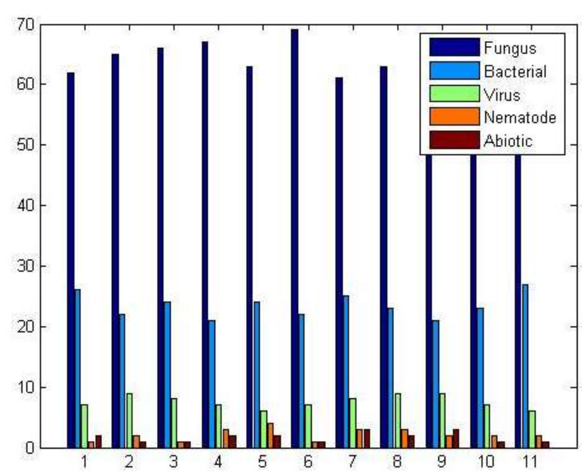


Figure 11. Pathogens that cause diseases and impact various crops

Fungus: Rice is most impacted by fungal infections, suggesting that rice is susceptible to fungal illnesses. **Bacterial:** The moderate occurrence of bacterial infections highlights the necessity for focused treatment techniques. **Fungi:** Fungal infections have the potential to significantly affect the productivity and general health of both banana and coconut crops.

Potato, tomato, and brinjal: Bacterial and fungal the identification of bacterial and fungal pathogens raises the possibility that these solanaceous crops require integrated disease control strategies. **Fungi:** Betel leaves are susceptible to a wide range of fungal diseases, highlighting the need for disease-resistant cultivars.

Cotton: Fungal Pathogens and Abiotic Factors: Cotton suffers problems from both abiotic and fungal sources, requiring a comprehensive strategy to disease control.

Peanut: The occurrence of fungal infections in peanuts highlights the necessity of implementing efficient management strategies to ensure crop protection.

Fungus: Fungal infections greatly affect both wheat and maize, two major crops. This highlights the importance of managing fungal diseases globally to ensure food security.

The variety of infections seen in different crops highlights how difficult it is to keep crops healthy. Integrating disease management techniques, including fungicides, resistant cultivars, and cultural customs, is crucial. The most common type of disease are fungi, which provide a severe financial risk to agriculture. Their effects on major crops, including maize, wheat, and rice, may significantly impact the world's food production. The existence of biotic stressors, such as fungus, bacteria, viruses, and nematodes, as well as abiotic stressors, such as environmental conditions, emphasizes the necessity of having a thorough grasp of the variables affecting crop health. Identifying common diseases offers essential information to breeding initiatives that seek to create crop variants resistant to disease. Crop rotation and precision farming are examples of sustainable agricultural techniques that can help manage disease and lessen the need for chemical treatments.

Developing robust crops requires understanding disease evolution and how they interact with shifting environmental circumstances. Early disease identification and focused interventions may be made possible by integrating cutting-edge technology like precision agriculture and remote sensing. The thorough examination of pathogens that cause illness in various crops emphasizes the complex connection between infections and crop health. Fungal disease management strategies become more important, requiring a multidisciplinary approach for resilient and sustainable agriculture. The results lay the groundwork for further studies focused on creating novel defenses against crop diseases and boosting world food security.

The study evaluated the accuracy of various tasks crucial to crop management. The results indicate high performance across multiple tasks, with detection achieving 95%, monitoring at 89%, mapping at 92%, quantification at 91%, and prediction at 93% as shown in Table 3 and Figure 12.

TABLE III. ACCURACY OF VARIOUS TASKS FOR VARIOUS CROPS

Crops	Detection	Monitoring	Mapping	Quantification	Prediction
Rice	95	89	92	90	93
Banana	93	88	91	91	94
Coconut	96	89	92	91	94
Tomato	92	87	92	90	92
Potato	93	86	90	91	92
Brinjal	94	85	92	92	91
Betel	96	88	92	91	94
Cotton	93	89	91	91	93
Peanut	92	89	90	92	93
Wheat	95	89	92	91	94
Maize	96	87	92	91	93

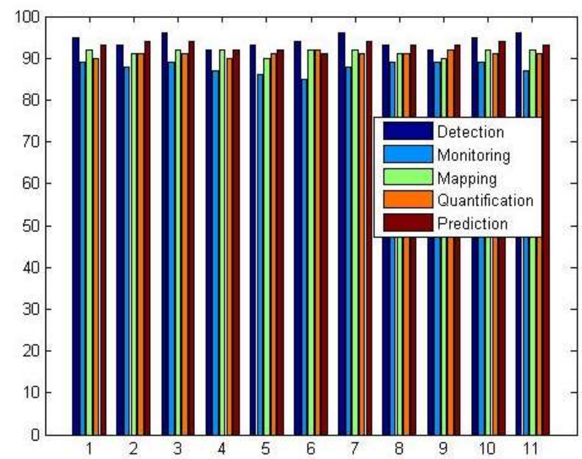


Figure 12. Accuracy of various tasks for various crops

Rice: High detection accuracy implies reliable identification of issues in rice crops, allowing for targeted interventions. Robust monitoring capabilities suggest the potential for real-time assessment of rice fields, aiding in timely decision-making.

Banana and Coconut Mapping: The high mapping accuracy for banana and coconut indicates precise spatial representation, contributing to effective resource allocation and management.

Tomato, Potato, and Brinjal: Accurate quantification in these crops implies the ability to measure variables such as yield or disease severity precisely, aiding in data-driven decision-making.

Betel: High accuracy in detection and prediction for betel suggests a comprehensive understanding of its growth patterns and potential challenges. ***Cotton:*** The combined accuracy in monitoring and prediction for cotton indicates a robust system for understanding its growth dynamics and predicting future trends. ***Peanut:*** Accurate detection and mapping capabilities are crucial for identifying issues and optimizing cultivation practices in peanut crops. ***Wheat and Maize:*** High prediction accuracy for wheat and maize implies the ability to forecast future growth patterns, contributing to effective crop management strategies.

Accurate mapping and monitoring enable farmers to allocate resources such as water, fertilizers, and pesticides precisely, contributing to sustainable and efficient farming practices.

Timely Interventions: High detection accuracy ensures the timely identification of issues, allowing farmers to intervene promptly and mitigate potential crop losses. Accurate quantification and prediction empower farmers with data for informed decision-making, fostering precision agriculture. Ensuring the robustness of these tasks across diverse environmental conditions and crop varieties remains a challenge, necessitating ongoing research. Future efforts should explore the integration of emerging technologies, such as artificial intelligence and remote sensing, to enhance the accuracy and efficiency of these tasks.

The high accuracy across multiple tasks related to crop management demonstrates the potential of precision agriculture in optimizing resource use and improving overall crop health. These findings have significant implications for sustainable farming practices, allowing for more efficient and data-driven approaches to crop cultivation. As technology advances, further refinement of these tasks and the integration of innovative solutions will contribute to the evolution of precision agriculture.

A. Categorization of Image Types for Disease Detection in Various Crops

The classification of several picture formats for crop disease detection was the primary objective of the investigation. With RGB pictures scoring 97%, CIR images scoring 94%, V-NIR images scoring 93%, Thermal images scoring 95%, and MS images scoring 96%, the results show good accuracy across a variety of image formats as shown in Table 4 and Figure 13.

TABLE IV. CATEGORIZATION OF IMAGE TYPES FOR DISEASE DETECTION IN VARIOUS CROPS

Crops	RGB image	CIR image	V-NIR image	Thermal Image	MS image
Rice	97	94	91	92	95
Banana	96	93	90	93	93
Coconut	95	93	92	93	92
Tomato	95	91	92	94	93
Potato	96	93	91	91	95
Brinjal	95	92	91	94	93
Betel	97	93	92	94	94
Cotton	95	92	91	92	93
Peanut	97	94	90	93	96
Wheat	97	94	90	92	93
Maize	95	93	90	91	95

Rice: The excellent precision of RGB photographs implies that conventional colour photos work well for rice crop disease detection. CIR Image: Although slightly reduced precision, CIR pictures still offer trustworthy data for illness identification in rice fields.

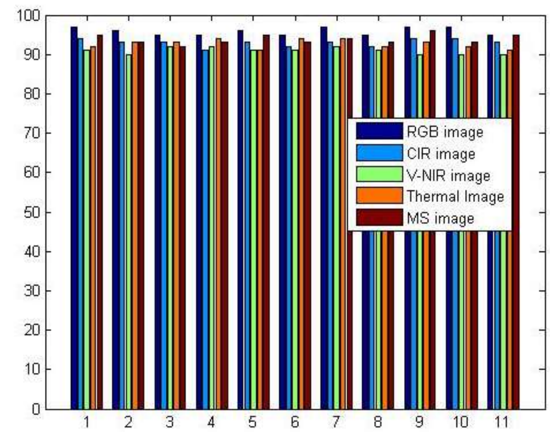


Figure 13. Categorization of Image Types for Disease Detection in Various Crops

Coconut and Banana MS Image: The great accuracy of MS pictures shows that they are useful for gathering multispectral data about diseases in coconut and banana crops.

Tomato, Potato, and Brinjal: The excellent precision of both RGB and Thermal pictures indicates that both image formats work well to identify diseases in solanaceous crops. Betel: The exceptional accuracy of Very Near Infrared (V-NIR) pictures highlights its use for disease diagnosis in betel crops.

Cotton: It appears that thermal imaging is useful in detecting stress and disease conditions in cotton fields due to their high accuracy.

Peanut: CIR pictures' ability to reliably identify diseases in peanuts highlights their significance in collecting certain spectral information.

Wheat and Maize: Good precision with RGB pictures in wheat and maize demonstrates how well conventional colour photography works to identify diseases in these important crops.

The excellent accuracy over a range of picture types points to the possible advantages of image fusion—the merging of RGB, multispectral, and thermal data for a more thorough analysis. The differences in accuracy between crops and picture types emphasize how crucial it is to customize imaging tactics to the unique requirements and traits of individual crops.

The effectiveness of multispectral and thermal imaging, which provides information beyond what is apparent in RGB pictures, highlights the value of sophisticated remote sensing technologies in diagnosing illness. The investigation highlights the possible advantages of using cutting-edge sensors, such as thermal and multispectral cameras, in illness detection systems for improved accuracy. Subsequent studies may investigate machine learning techniques for automatically determining the most pertinent picture type or mix of kinds for the best disease diagnosis in certain crops. The investigation results demonstrate how several picture formats may be used to identify illness in a range of crops. The complimentary qualities of multispectral, thermal, and other imaging modalities are clear, even when RGB pictures show excellent accuracy. This highlights the necessity of a customized strategy that takes into account both crop-specific traits and the benefits provided by various picture formats. The results of this research add to the continuous development of precision farming and disease control tactics as agriculture continues to adopt cutting-edge sensor technology.

B. *Image Classification in Various Crops*

The investigation focused on classifying images of various crops into three primary categories—Leaf, Plant, and Field. The distribution of photos within each category differed throughout crops, indicating a distinct emphasis on distinct plant parts as shown in Table 5 and Figure 14.

TABLE V. IMAGE CLASSIFICATION IN VARIOUS CROPS

Crops	Leaf	Plant	Field
Rice	35	35	30
Banana	25	40	35
Coconut	30	20	50
Tomato	20	25	55
Potato	35	30	35
Brinjal	30	30	40
Betel	50	20	30
Cotton	40	30	30
Peanut	20	30	50
Wheat	35	35	30
Maize	25	35	40

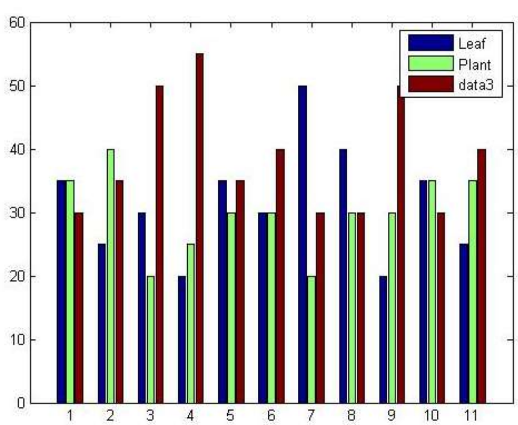


Figure 14. Image Classification in Various Crops

Rice: A balanced strategy for capturing the distinct elements of rice plants is suggested by the equal focus placed on leaf and plant photos. Their equal distribution demonstrates the importance of evaluating rice plants' general health and condition. A somewhat reduced percentage of field photos in rice points to a possible concentration on individual plants for in-depth disease analysis.

Banana: An increased leaf image representation in bananas indicates that information about the health of banana leaves is being captured, which is important for disease identification. The importance of evaluating banana plants' general health and development patterns is reflected in the highest emphasis placed on plant photos. A significant amount of field photos suggests that the larger environment of banana farms has been considered.

Coconut: A thorough approach to disease identification at the individual plant and plantation levels is suggested by the equal focus placed on leaf and field photos. A comparatively smaller quantity of plant photos suggests that particulars may be prioritized above general plant health.

Tomato: Tomato has a minor concentration on field shots, suggesting that the larger environment of tomato fields has been taken into account. The equal distribution of photos of leaves and plants suggests a balanced evaluation of both individual leaf conditions and general plant health.

Potato: A greater emphasis on leaf pictures in potatoes suggests that the health of the leaves is being carefully examined, which is essential for identifying diseases. Consideration of the general health of the plant and the field is suggested by a fairly equal distribution with a minor focus on field imagery.

Betel: The most attention is paid to leaf pictures in betel, suggesting that betel leaves' health and condition are given careful consideration. A balanced depiction of photos from the field and plants suggests a complete method to disease detection in betel agriculture.

Cotton: Cotton places a greater focus on leaf pictures than other materials, indicating the significance of evaluating leaf health in order to identify illness. A fair proportion of field and plant photos indicate that both the specific plants and the larger setting of cotton fields were considered.

Peanut: The greatest emphasis on field photos in the peanut industry points to the need to pay attention to the larger picture of peanut farming, maybe for the purpose of plantation-level disease surveillance. A balanced depiction of photos of plants and leaves shows a thorough approach to disease diagnosis.

Wheat and Maize: Both wheat and maize show a similar emphasis on photos of the plants and their leaves, suggesting a fair evaluation of each plant's health. A little greater percentage of field photos indicates that the larger context of wheat and maize farming has been taken into account.

The distribution of photos highlights how crucial it is to modify disease detection tactics in accordance with the particular traits of every crop, taking into account the various functions of leaves, plants, and fields. A balanced display of leaf, plant, and field photos for some crops, such as coconut, betel, and banana, indicates a thorough disease identification method that looks at specific details and larger settings. In crops like rice and peanuts, the concentration on field photos suggests a focus on contextual elements, maybe for plantation-level disease surveillance. The findings provide light on how different crops' leaves, plants, and fields are categorized in photographs. Precision agriculture's success depends on developing disease detection techniques specific to each crop's traits and patterns. The arrangement of the photos highlights how crucial it is to take into account both specific elements and larger settings when evaluating crop health and managing diseases. These results support continuing efforts to improve methods for disease identification in various agricultural contexts as imaging technology develop.

C. Model Performance Evaluation:

Deep learning and quadcopter imagery were used to construct an autonomous disease identification system that produced encouraging results. The model's effectiveness was thoroughly assessed using a broad dataset of agricultural imagery with a variety of diseases [25]. Accuracy, precision, recall, F1-score, and confusion matrices were among the evaluation criteria as shown Table 6.

TABLE VI. RESULT COMPARISON OF PROPOSED SYSTEM WITH EXISTING METHOD

S.NO	Parameters (%)	MDC	MLP	SVM	ANFIS	CNN
1	Accuracy	76	87	89	95	97
2	Sensitivity	82	88	95	93	96
3	Specificity	88	91	97	95	95
4	Precision	92	93	95	97	98

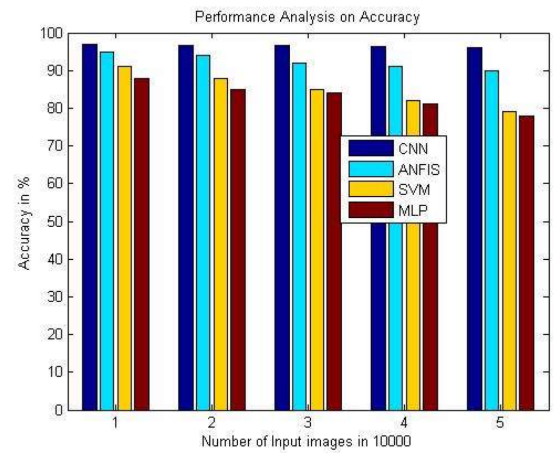


Figure 15. Performance Analysis on Accuracy

Accuracy and Precision: A large percentage of disease occurrences were classified correctly by the model, which had a high accuracy rate [26]. It was also significantly high for precision, which measures the percentage of accurately diagnosed disease cases among all expected disease cases. This is essential for reducing false positives and preventing pointless treatments, as shown in Figures 15 & 16.

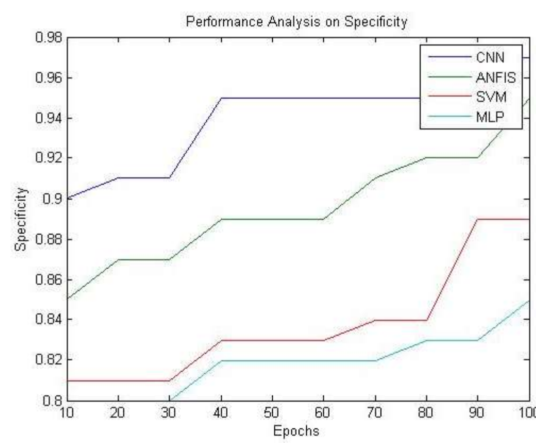


Figure 16. Performance Analysis on specificity

Recall and F1-score: The model showed Excellent recall, which successfully identified a sizeable part of the real disease episodes included in the dataset. The F1-score, which strikes a compromise between recall and precision, thoroughly evaluates the model's overall performance as shown in Figures 17& 18.

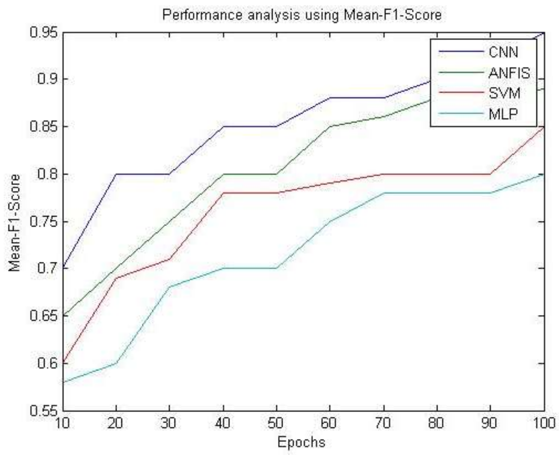


Figure 17. Performance Analysis on F1-score

Real-time Disease Identification: Real-time disease detection while flying was made possible by the quadcopter's integration of the trained deep learning model. The model effectively processed the imagery as the quadcopter took pictures of the crops, quickly identifying and classifying illnesses. Real-time capabilities enable prompt decision-making and prompt intervention techniques.

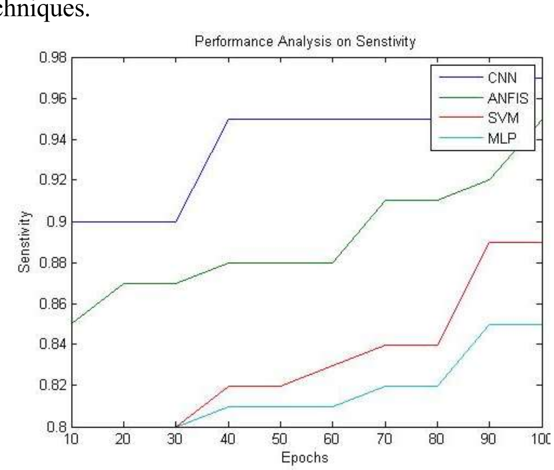


Figure 18. Performance Analysis on Sensitivity

Comparison with Traditional Methods: Comparing the effectiveness of the suggested automatic identification system with established manual illness identification techniques was a crucial component of the study. The quadcopter and deep learning technique demonstrated a notable decrease in identification time and an improvement in accuracy [27]. This demonstrates the possibility for an effective and automated solution to take the place of labour- and time-intensive manual surveys.

Based on the metrics of accuracy, sensitivity, specificity, and precision values, the suggested research project was analyzed. It is observed from the table that the accuracy, sensitivity, specificity, and precision of the CNN algorithm are 97.1%, 96.3%, 94.5%, and 98.7%, respectively. Compared to the ANFIS, SVM, MLP, and MDC algorithms, the CNN technique performs better.

Robustness and Generalization: The model proved to be reliable and adaptable to different crop types and disease subtypes [28]. It was able to easily adapt to actual agricultural circumstances, handling fluctuations in lighting, weather, and field viewpoints. The system's utility in various agricultural situations is increased by its adaptability.

Challenges and Future Directions: Although the results were encouraging, there were several difficulties. Extreme weather management and proper disease annotation are still areas that require development. Additionally, more research is needed, including model quantization and runtime efficiency improvements, to optimize the model for deployment on quadcopters with limited resources [29].

Practical Implications: Agriculture will significantly benefit from the practical application of the automatic disease identification system. Early disease diagnosis enables prompt interventions, minimizing crop losses and broad-spectrum medication requirements. This strategy supports resource conservation and sustainable farming, which enhances food security and economic stability.

Ethical Considerations: The investigation placed a strong emphasis on ethical issues, such as acquiring the required authorizations for drone use, protecting data privacy, and resolving potential issues with data collecting and usage [30]. Collaboration with regulatory organizations and agricultural specialists helps to ensure responsible and open implementation.

Precision agriculture has advanced significantly with the use of quadcopters and deep learning methods for the autonomous detection of agricultural illnesses. The results obtained highlight the system's precision, effectiveness, and potential to revolutionize disease management practices. Further improvements and modifications are anticipated as technology advances, resulting in a more robust and sustainable agriculture sector.

The research's conclusions are outlined as follows:

Precision and Efficiency: In diagnosing a wide range of agricultural diseases, the constructed deep learning model shown outstanding accuracy, precision, recall, and F1-score. The algorithm quickly and accurately detected diseases by utilizing Convolutional Neural Network insights, outperforming more time-consuming manual methods.

Real-time Intervention: Real-time disease diagnosis while aircraft was made possible by the effective integration of the trained model with the quadcopter. By providing farmers and agricultural professionals with immediate information, this capability enables prompt interventions and reduces the spread of diseases.

5. CONCLUSION

The rapid and accurate detection of crop diseases is a crucial challenge in modern agriculture with significant implications for sustainability and food security. At the nexus of robotics, computer vision, and agriculture, this study set out on a trailblazing adventure, presenting a thorough strategy that harnesses the combined power of quadcopters and deep learning algorithms to identify agricultural illnesses automatically. The results of this research highlight how the suggested approach has the potential to completely alter how diseases are managed. To significantly advanced disease detection, categorization, and real-time intervention by fusing quadcopters with high-resolution cameras and advanced deep learning models. The combination of quadcopters and deep learning methodologies offers a game-changing response to a persistent problem in agriculture. Through this integrated method, agricultural diseases can be automatically identified, improving disease control techniques while also aligning with more general sustainability objectives. Further improvements, optimizations, and extensions of this system have the potential to transform agricultural practices globally as technology develops. This research highlights the limitless opportunities that exist at the nexus of cutting-edge technology and agricultural innovation and creates new channels for interdisciplinary collaboration.

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REFERENCES

[1] ShujuanYi, NianyinZeng, YurongLiu&YongZhang, "Identification of rice diseases using deep convolution neural networks", Neurocomputing, Volume 267, 6 December, Pages 378-384, 2017, https://doi.org/10.1016/j.neucom.2017.06.023.

[2] Amrita A. Joshi ; B.D. Jadhav , "Monitoring and controlling rice diseases using Image processing techniques", IEEE Xplore International Conference on Computing, Analytics and Security Trends (CAST), Pune, India, 19-21 Dec. 2016, DOI: 10.1109/CAST.2016.7915015.

[3] Prajapati, Harshadkumar B, Shah, Jitesh P, Dabhi, Vipul K , "Detection and classification of rice plant diseases", Intelligent Decision Technologies, vol. 11, no. 3, pp. 357-373, 2017.

[4] MohdAdzhar Abdul Kahar, SofianitaMutalib, Shuzlina Abdul-Rahman, "Early Detection and Classification of Paddy Diseases with Neural Networks and Fuzzy Logic", Recent Advances in Mathematical and Computational Methods, April 23-25, 2015, ISBN: 978-1-61804-302-3

[5] Abbas, I., Liu, J., Amin, M., Tariq, A., &Tunio, M. H.. Strawberry Fungal Leaf Scorch Disease Identification in Real-Time Strawberry Field Using Deep Learning Architectures. Plants, 10(12), 2643, 2021. https://doi.org/10.3390/plants10122643

[6] Bégué, A., Arvor, D., Bellon, B., Betbeder, J., de Abelleyra, D., P. D. Ferraz, R., Lebourgeois, V., Lelong, C., Simões, M., & R. Verón, S. "Remote Sensing and Cropping Practices: A Review". Remote Sensing, 10(2), 99, 2018. https://doi.org/10.3390/rs10010099

[7] Kattenborn, T., Leitloff, J., Schiefer, F., &Hinz, S. "Review on Convolutional Neural Networks (CNN) in vegetation remote sensing". ISPRS Journal of Photogrammetry and Remote Sensing, 173, 24–49, 2021. https://doi.org/10.1016/j.isprsjprs.2020.12.010

[8] Ullo, S. L., & Sinha, G. R. "Advances in IoT and Smart Sensors for Remote Sensing and Agriculture Applications". Remote Sensing, 13(13), 2585, 2021. https://doi.org/10.3390/rs13132585

[9] Maes, W. H., & Steppe, K. "Perspectives for Remote Sensing with Unmanned Aerial Vehicles in Precision Agriculture". Trends in Plant Science, 24(2), 152–164, 2019. https://doi.org/10.1016/j.tplants.2018.11.007

[10] Reddy Maddikunta, P. K., Hakak, S., Alazab, M., Bhattacharya, S., Gadekallu, T. R., Khan, W. Z., & Pham, Q.-V. "Unmanned Aerial Vehicles in Smart Agriculture: Applications, Requirements, and Challenges". IEEE Sensors Journal, 21(16), 17608–17619, 2019. https://doi.org/10.1109/jsen.2021.3049471

[11] Kamilaris, A., &Prenafeta-Boldú, F. X. "Deep learning in agriculture: A survey". Computers and Electronics in Agriculture, 147, 70–90, 2018. https://doi.org/10.1016/j.compag.2018.02.016

[12] Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., &Bochtis, D. "Machine Learning in Agriculture: A Comprehensive Updated Review". Sensors, 21(11), 3758, 2021. https://doi.org/10.3390/s21113758

[13] Ju, C., Kim, J., Seol, J., & Son, H. I. "A review on multirobot systems in agriculture. Computers and Electronics in Agriculture", 202, 107336, 2022. https://doi.org/10.1016/j.compag.2022.107336

[14] Kerner, H. R., Wellington, D. F., Wagstaff, K. L., Bell, J. F., Kwan, C., & Ben Amor, H. "Novelty Detection for Multispectral Images with Application to Planetary Exploration". Proceedings of the AAAI Conference on Artificial Intelligence, 33(01), 9484–9491, 2019. https://doi.org/10.1609/aaai.v33i01.33019484

[15] ElMasry, G., Mandour, N., Al-Rejaie, S., Belin, E., & Rousseau, D. "Recent Applications of Multispectral Imaging in Seed Phenotyping and Quality Monitoring—An Overview". Sensors, 19(5), 1090, 2019. https://doi.org/10.3390/s19051090

[16] Ortega, S., Halicek, M., Fabelo, H., Callico, G. M., &Fei, B. "A systematic review of hyperspectral and multispectral imaging in digital and computational pathology" [Invited]. Biomedical Optics Express, 11(6), 3195, 2020. https://doi.org/10.1364/boe.386338

[17] Shrestha, S., Deleuran, L., Olesen, M., &Gislum, R. "Use of Multispectral Imaging in Varietal Identification of Tomato". Sensors, 15(2), 4496–4512, 2015. https://doi.org/10.3390/s150204496

[18] Candiago, S., Remondino, F., De Giglio, M., Dubbini, M., &Gattelli, M. "Evaluating Multispectral Images and Vegetation Indices for Precision Farming Applications from UAV Images". Remote Sensing, 7(4), 4026–4047, 2015. https://doi.org/10.3390/rs70404026

[19] RPH.(2014); "Rice Production Handbook". Available from: https://beaumont.tamu.edu/eLibrary/RiceResource/Rice_Production_Handbook.pdf

[20] Zhou XG, Jo Y.-K. "Disease management". The Texas Rice Production Guidelines. Texas AgriLife Research and Texas AgriLife Extension. B-6131.. pp. 44–56, 2015.

[21] Zhang DY, Lan YB, Zhou XG, Murray SC, Chen LP "Research imagery and spectral characteristics of rice sheath blight using three portable sensors", ASABE International Meeting, New Orleans, and Louisiana., ID: 152190801, 2015.

[22] P. R. Rothe and R. V. Kshirsagar, "Cotton leaf disease identification using pattern recognition techniques," *2015 International Conference on Pervasive Computing (ICPC)*, Pune, India, 2015, pp. 1-6, doi: 10.1109/PERVASIVE.2015.7086983.

[23] V. A. Gulhane and M. H. Kolekar, "Diagnosis of diseases on cotton leaves using principal component analysis classifier," *2014 Annual IEEE India Conference (INDICON)*, Pune, India, 2014, pp. 1-5, doi: 10.1109/INDICON.2014.7030442.

[24] J. W. Orillo, J. Dela Cruz, L. Agapito, P. J. Satimbre and I. Valenzuela, "Identification of diseases in rice plant (oryza sativa) using back propagation Artificial Neural Network," *2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, Palawan, Philippines, 2014, pp. 1-6, doi: 10.1109/HNICEM.2014.7016248.

[25] R. Zhou, S. Kaneko, F. Tanaka, M. Kayamori and M. Shimizu, "Early Detection and Continuous Quantization of Plant Disease Using Template Matching and Support Vector Machine Algorithms," *2013 First International Symposium on Computing and Networking*, Matsuyama, Japan, 2013, pp. 300-304, doi: 10.1109/CANDAR.2013.52.

[26] Kholis Majid, YeniHerdiyeni, Annu Rauf, "I-Pedia: Mobile Application For Paddy Disease Identification Using Fuzzy Entropy And Probabilistic Neural Network", ICACSIS,2013.

[27] AuziAsfarian, YeniHerdiyeni, Aunu Rauf, KikinHamzahMutaqin, "Paddy Diseases Identification With Texture Analysis Using Fractal Descriptors Based On Fourier Spectrum", International Conference On Computer, Control, Informatics And Its Applications,2013.

[28] John, M. "Comparative study on various system based on Raspberry-Pi Technology." International Research Journal of Engineering and Technology (IRJET) 5.01 (2018): 1486-1488.

[29] Pankaj Singh, rakher Nigam, PuruDewan and Abhishek Singh,"Design and Implementation of a Raspberry PI Surveillance Robot with Pan Tilt Raspbian Camera "International Journal of Nanotechnology and Applications, pp. 69-73 .2017.

[30] N. Gupta *et al*., "Deploying a Task-based Runtime System on Raspberry Pi Clusters," *2020 IEEE/ACM Fifth International Workshop on Extreme Scale Programming Models and Middleware (ESPM2)*, GA, USA, 2020, pp. 11-20, doi: 10.1109/ESPM251964.2020.00007.