Comprehensive Studies for Sustainable Agriculture Using Plant Disease Detection.

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Abstract. Agriculture is not just a business sector; it is the backbone of a country's economy and GDP [Gross Domestic Product], both in developing and developed nations. Precision agriculture makes the sector more sustainable and aims towards the achievement of the Sustainable Development Goals [SDGs]. The integration of cutting-edge technology with agriculture is transforming traditional farming into digital agriculture. This revolution enhances agricultural productivity; however, various types of diseases continue to pose challenges due to multiple factors. Several techniques have been developed and proposed for detecting plant disease, including IoT-enabled systems, image processing, machine learning, and AI-based approaches, many of which are non-destructive. This article presents a comparative study of disease detection methods using image processing approaches. Imaging techniques include hyperspectral imaging, thermal imaging, multispectral imaging, and fluorescence imaging. The spectral signatures information related to healthy and ill plants is used in processing imaging techniques. The methodologies of image processing for disease detection are discussed in this article, along with a comprehensive review and discussion of different approaches. Efficient agricultural outcomes largely depend on effective plant health monitoring. Implementing disease detection systems can help to minimize grain loss caused by poor quality and support the growing demand for food. The comparative analysis gives an idea about the strengths and limitations of each technique, thereby guiding future research and enabling practical applications in precision agriculture for sustainable crop production.

Keywords: Sustainable Agriculture, IoT, Image Processing, Data Analysis, ICT Plant Disease Detection, AI.

1 Introduction

Agriculture is the world's largest industry, which plays an important role in food supply. In the Global Hunger Index 2024, India is ranked 105th out of 127 countries [1]. More than a billion people are dependent upon it to make a livelihood, to produce medicines, to produce fibre materials, to help in growing livestock, and to give employment to the rural sectors. To feed a growing global population, which is projected to require a 70% increase in food production by 2050, and to achieve zero hungry men requires attention to focus on large-scale production and less loss [1].

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Sustainable agriculture is a farming practice that supports food production to meet the present needs of the population and secure the future to fulfil their own needs and involves the use of resources by maintaining ecological balance. An image is an important source to collect and process data. AI [Artificial Intelligence], ICT [Information & Communication Technology], and IoT [Internet of Things] are responsible technologies for bringing the world closer and smarter. Image processing plays a wider role in achieving efficiency and accuracy. Integrating different tools and equipment using IoT makes it suitable to achieve faster and growing results [2]. Image processing is the step-by-step procedure to acquire the data and process it to get the information database. Using this data, plant health can be monitored significantly, and relevant actions can be taken accordingly to avoid the crop loss in the field, aiming towards high profit and ensuring food security for all [3].

In today's global warming era, agriculture is more challenging due to inflexibility towards environmental factors like storms, rain, temperature changes, and floods. The sudden changes in these factors affect growth and quality. In today's global warming era, agriculture is more challenging due to inflexibility towards environmental factors like storms, rain, temperature changes, and floods. The sudden changes in these factors affect growth, quality, and outcome from the field, thereby affecting the income of farmers and their living standards. Hence, it is crucial to manage the plant health by monitoring crop details. Image processing is included with the tools and techniques that improve the quality of sample images to study by enhancing the features and reducing the unwanted data in the image. This unwanted data is referred to as 'noise,' which can be reduced using filter algorithms. Processing of the image includes image enhancement, filtering, segmentation, feature extraction, and classification. An automated system can give time-saving and accurate results for the diagnosis of plant disease, thus helping farmers to gain advantages. The use of machine learning, along with image processing, can be proven more beneficial to achieve good results in terms of accuracy and speed. This, in coordination with IoT, can help to transfer the gathered information to and from the farmer's endpoint.

To connect and exchange information from one end to the other through the internet, the network of physical objects is used, which is known as the Internet of Things. Use of IoT gives better efficiency and analysis. Hyperspectral imaging, multispectral imaging, thermal imaging, and fluorescence imaging are widely used image processing methodologies in detecting abnormalities. Hence, the study of these methods is highly beneficial to the areas of agriculture and biomedical science.

Digital Image Processing:

This involves processing the image. It is a step-by-step process for achieving a better quality of an image according to the applications. It involves algorithms for the processing of an image. The image is captured and stored as two-dimensional information as a matrix and stored in the memory; it is then pre-processed to achieve the required results including the reduction of noise in an image. This noise reduction is done effectively in the process of Image enhancement and image filtering. The image enhancement includes sharpening, brightening, and color correction. Restoration to correct the blurriness in the image is followed by segmentation. Segmentation divides an image into different parts to process it in regions. Then, from the segmented regions, features like edges, shapes, and textures are extracted. This step is feature extraction. To reduce the size of an image and manage memory space, image compression is performed. Then, dilation and erosion are performed on the image data under the morphological processing step. Outputs are obtained from the extracted features, and information is achieved; this is known as object recognition.

A digital image is represented as pixels. Pixels are the picture elements a two-dimensional form with a finite set of digital values. Digital image processing focuses mainly on the improvement of pictorial information for human interpretation[4].

2 Literature Review

Among various techniques used to detect disease in plants and crops, image processing techniques are very popular and effective. N. Xu et al. described the trends of image processing in the agricultural sector [5]. This paper describes the application of image processing in the agricultural field, along with the implementation. The results of different technologies are compared, and the analysis shows that image processing is better for the detection of different crop diseases. This research introduces image processing technologies, namely image denoising, image correction, image segmentation, and image feature extraction [5]. In the study they got spectral results for image processing technology implementation for various factors, including crop growth monitoring, diseases, weeds, insect diagnosis, nutritional status monitoring, and identification of crop color. The overall result of the comparison shows that image processing is superior to traditional machine learning technologies by 64%. The result was obtained for different diseases and pests. The review article on smart farming for improving agricultural management. Authors have worked on data gathering, transmission, storage, analysis, and also suitable solutions [2]. They briefly discussed different challenges in the agriculture field and introduced the smart farming cycle, which includes cloud-based events and data management. The use of information and communication technology in smart farming is a part of the fourth agricultural revolution. Smart sensing, monitoring, smart control, smart analysis, and planning are included in smart farming. Smart agriculture gives benefits including increasing the amount of real time data, remote monitoring and controlling water and other natural resources. This also improves livestock management, accurate evaluation of soil and the crops, thus improving overall agricultural production [2]. Implementation of sensors with IoT helps to monitor soil parameters such as temperature, humidity, pH, and water level, thereby helping farmers to make better decisions for preventing the loss. It also helps in monitoring the livestock to earn more profit for the farmer. Agriculture is closely related to livestock management, which gives farmers additional income. A smart decision support system is discussed, which mainly assists in controlling the input factors like fertilizers and water management. Thus, making agriculture a more productive resource to fulfil food demand.

In the paper Image-crop disease detection using machine learning by Aria et.al authors have discussed thermal sensing to identify plants carrying insects [6]. As thermal sensors can sense the temperature differences in the surroundings, the presence of insects is easily located, which helps to identify healthy and unhealthy plants. Using thermal sensors early temperature differences calculations are more feasible which leads to early disease detection. Further image-based crop disease detection under climate changes is discussed. Due to variation in climatic changes, rainfall patterns are affected which affects pH levels in soil, also the life cycle of pests and insects is affected, and more pathogens are incubated during the continuous changing environmental factors. Different methods are tabulated to detect disease in various crops. The emerging use of deep learning and machine learning is elaborated to sustain the climatic changes [6].

Smart agriculture was defined from the author viewpoint in the paper “A Real and Novel Smart Agriculture Implementation with IoT Technology” [3]. The importance of a standardized planting method is pointed out for stable and good-quality crops. The TIAGA system is proposed. This system includes a micro weather station, an automated control system, cloud management, production and marketing traceability. The cloud management system organises data collected and is analysed by IOT crop expert system, and crop growth is analysed. Using this system the use of pesticides is significantly reduced, making it more environmentally friendly. They implemented a system that gives instant massaging using the LINE app. GASP-based system helps in tracing products from the farmer to the customers.

PiTLiD and Inception-V3-based transfer learning methods are proposed for disease classification on apple trees and grape trees by Kangchen Liu and Xiujun Zhang. The comparative study of proposed methods with others shows that PiTLiD is superior in terms of accuracy, precision [7]. Considering the losses caused due to unidentified diseases and the requirement to minimize the pesticides and fertilisers they aim to improve the quality as well as yield of the crop. PiTLiD gives good accuracy of 99.45 ± 0.17%. This approach helps to increase the scope of phenomics. ImageNet consists of a variety of data for image research. The authors have pretrained a model with the subset of 10000 samples. Also pretrained model proposed in 2015 useful for transfer learning is an Inception V3 model. It is a deep convolution neural model. In less computational memory availability and complex computational problems Inception-V3 model is a good performer. This model works faster for training as the data utilised is pre-trained. It is highly useful due to its robustness. Authors X. Li et al have proposed a hybrid model to diagnose sugarcane leaf disease. In the discussion authors state that the shuffle convolution-based LViT model gives higher accuracy compared to different DL models, also the inference speed is improved for this model. The model is Lightweight ViT [LViT] blocks and a Shuffle-HDC [SHDC] network is combined to build a fast and accurate model for field sugarcane leaf disease diagnosis [8]. In this model to train the model AI challenger 2018 database is used which increases the convergence speed and accuracy. In research they studied six different models and concluded that SLVit is better than other DL models in terms of accuracy, though it is slower than ViT. This light-weight model can be further designed to assess disease severity.

Authors in the paper Digital Image Processing and IoT in Smart Health Care –A review [9] have given an idea on the application of IoT along with image processing in the medical field. Also, deep learning is a good platform to study features and helps to develop. The Internet of Things is playing an important role in connecting within the system and monitoring the system [9]. To control the assistive healthcare image processing and IOT are playing a major role. Assistive robotics in healthcare is helping to improve the quality of the specially abled. Tele medicine and automatic robotic wheelchairs are some best examples of advanced usage of developing technology. Thus, this paper elaborated on the use of Digital image processing and IoT for disease classification and several healthcare applications.

[10], The authors summarized different techniques that can be used for plant disease detection. They have discussed the effectiveness of machine learning techniques along with some drawbacks. Also, authors have reviewed some disease detection models and compared the results considering various plants for different features. According to the authors shortcomings in machine learning include a lack of effectiveness for the spatial information of an image. Thus, image Processing and segmentation, Deep learning models are briefly discussed in this paper.

Vijai Singh et al [11], in this paper authors discussed the usefulness of the different imaging technologies that can be used for detecting early-stage diseases in plants. They have focused on challenges and current trends in detecting plant diseases by using computer vision and imaging methodologies. Authors have analysed different optical techniques for the detection of plant health. This analysis shows that hyper-spectral imaging used for the avocado plant gives the highest accuracy of 98%. This paper further discusses the imaging technologies mainly hyperspectral, Thermal, fluorescence, multispectral and 3D imaging. They put forward the need to develop advanced technologies for early detection of plant diseases to avoid major loss.

[12], Authors reviewed different papers and to eliminate the shortcomings of existing models, proposed a DCNN model that reduces the training parameters and iteration time. This developed model captures the information about local spatial texture in plant leaf images. The proposed model worked for higher accuracy. An early stopping model is introduced in the experiment to avoid overfitting that occurs during the training process. The performance of this model can be evaluated with parameters accuracy, precision, recall, and F1 score are given in mathematical Eqn.- (1), (2), (3) and, (4), respectively.

$$Accuracy = \frac{tp+tn}{tp+fp+fn+tn} \quad (1)$$

$$Precision = \frac{tp}{tp+fp} \quad (2)$$

$$Recall = \frac{\mathrm{tp}}{\mathrm{tp+fn}} \quad (3)$$

$$F1\ score = \frac{2tp}{2tp+fp+fn} \quad (4)$$

Where tp, tn, fp, and fn represent true positive, true negative, false positive, and false negative, respectively.

This proposed model outperformed in terms of accuracy as well as computational efficiency. Also, the proposed model is proving distinguishing results in terms of speed. Thus, the authors concluded that this model using CNN with LBP is giving remarkable results [13]. This paper has discussed mainly hyperspectral imaging technology for agricultural usage. Variations in the surroundings like wind, intensity of sunlight, orientation of leaves, angle at which the plant is focusing the results are not affected. HSI is having major contribution in fungal disease detection, drought stress detection, weed detection and management. This paper brief on the working of a hyperspectral camera, and sensor system.

Rocío Calderón et al., 2015. This paper represents the study of an accurate and robust method for the automatic classification of V. Dahliae infection. In this remote sensing was implemented using Linear Discriminant Analysis and support vector machine methods were used [14]. The paper elaborates research on disease naming Cercospora leaf spot in sugar beet. The authors have analysed the results comparing images from thermal and hyperspectral cameras. This study was done for the early detection of diseases. The analysis shows that hyperspectral imaging gives 25% better results than thermal imaging. Though thermal imaging gives valuable data, multispectral imaging is a superior method. Due to the inability to form a clear structure on leaves as climatic changes affect crop health, the results found for thermal imaging with multispectral images are not consistent. Researchers state that KNN and SVM provide good results for different symptoms.

[15], authors have discussed the benefits of using ML and DL to analyse hyperspectral data in real-time agriculture. Using this methodology the accuracy detecting disease and pest is improved. ML and AL algorithms need a large database to be trained also the complexity of these algorithms limit their application. However, considering DL it gives good results for complex data and identifies the relationship between input and output.

Nader Ekram Irad et. al, have applied near infrared hyperspectral imaging for early detection of disease spread in Apple trees. They have considered three varieties of apple cultivars. In their study authors have considered a feature selection algorithm, and the accuracy obtained is 91.6%. Some qualities can be studied using a hyperspectral imaging system, they are the nutritional value, texture, and flavour components. Applying the proposed system, a remote monitoring tool for quality control in the field is possible.

Table 1. Diseases in different plant [16]

Plant name	Bacterial disease	Viral disease	Fungal Disease
Cucumber	Brown blemish, Angular Blemish, Target blemish	Mosaic, Yellow blemish	Black blemish, Gray mold
Rice	Steak, blight	Black Dwarf streaked	Smut false
Maize	Streak, Stalk	Crimson, Dwarf	Rust
Tomato	Canker	Curl leaf yellow	Late/ early blight

Table 2. Summary of Literature review

Reference	Contribution	Limitation	Research Gap
[17]	Lightweight deep learning model integrating multisource data	Tested mainly on controlled datasets; limited crop diversity	Validation on diverse, real-world farm conditions and multiple crop types
[6]	Mobile Net-based CNN for automated leaf disease detection	Focused only on RGB image datasets	Integration with multimodal data [thermal, hyperspectral, IoT]
[13]	Overview of hyperspectral imaging applications	High cost and limited scalability	Affordable, portable hyperspectral solutions for smallholder farmers
[16]	Comprehensive review of AI and CV methods	Literature-based, lacks experimental validation	Standardized benchmarks and comparative studies across modalities
[3]	IoT-based smart agriculture implementation	Limited integration with AI disease detection	IoT + AI pipelines for real-time disease management
[1]	Fuzzy-based function networks for disease detection	Narrow dataset scope; limited scalability	Hybrid fuzzy + deep learning approaches

[12]	CNN + LBP feature fusion for multi-class classification	Relies on image-only features	Fusion with contextual data [soil, weather, crop stage]
[10]	Survey of plant leaf disease detection approaches	Lacks practical deployment insights	Field-level validation and farmer-centric usability studies
[8]	Lightweight Vision Transformer for sugarcane leaf disease diagnosis	Crop-specific; limited generalization	Cross-crop transformer models for broader applicability
[7]	CNN-based identification of plant diseases	Relies only on RGB datasets	Expansion to multimodal datasets and early detection methods
[18]	Hybrid CNN using simulated thermal imaging	Simulation-based; lacks real-world validation	Field trials with actual thermal imaging data
[15]	Systematic review of hyperspectral imaging	Highlights potential but limited adoption	Cost-effective, scalable hyperspectral deployment
[2]	Smart farming for agricultural management	Focused on management, not disease detection	Integration of disease detection into smart farming frameworks
[11]	Review of imaging techniques for plant disease detection	Limited focus on multimodal integration	Comparative evaluation of imaging modalities [RGB, hyperspectral, thermal]
[19]	GAN + hyperspectral imaging for early detection of cotton Verticillium wilt	Crop-specific; expensive technology	Affordable early detection methods across crops

3 Methodology

Data Collection

- Public datasets [Plant Village, PHENOMICS, UAV-based field datasets].

Preprocessing

- Image normalization, noise reduction, and spectral calibration.

- Augmentation techniques [rotation, scaling, color jitter] to improve model robustness.

Model Development

- CNN architectures [ResNet, Efficient Net] for RGB and multispectral data.
- 3D-CNN and spectral feature extraction for hyperspectral datasets.
- Random Forest and SVM baselines for comparison.
- Augmentation techniques [rotation, scaling, color jitter] to improve model robustness.

Evaluation Metrics

- Accuracy, precision, recall, F1-score.
- Cost-effectiveness and scalability assessed qualitatively.

Image processing is the step-by-step process of collecting the data in the form of an image, applying the algorithm to get detailed information. Figure 1 represents the steps involved in image processing. MATLAB software is used in Image processing.

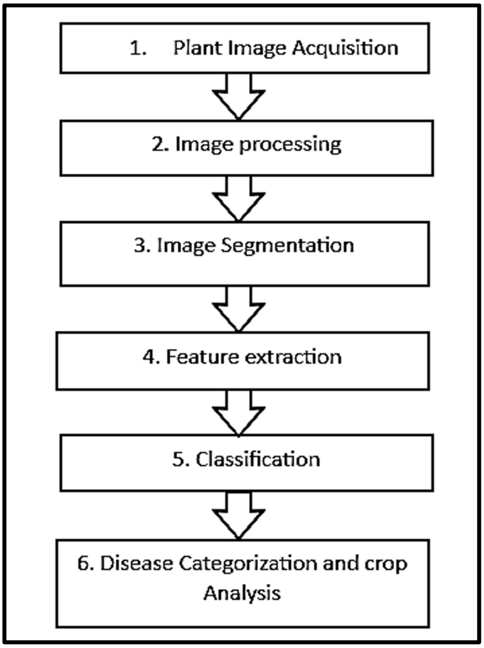

Fig.1. Image processing steps

Some image processing techniques, such as hyperspectral, thermal imaging, multi-spectral imaging, and fluorescence imaging, can be used for plant disease detection.

Multi-spectral Imaging:

In multi-spectral imaging, the data information as an image is captured within a specific wavelength across the electromagnetic spectrum. Using this method extraction of additional information, which is limited to the human eye for red, green, and blue, can be overcome. This method was developed for military applications. It is used in painting and document analysis. [17].

Figure 2 represents the steps involved in multi-spectral imaging

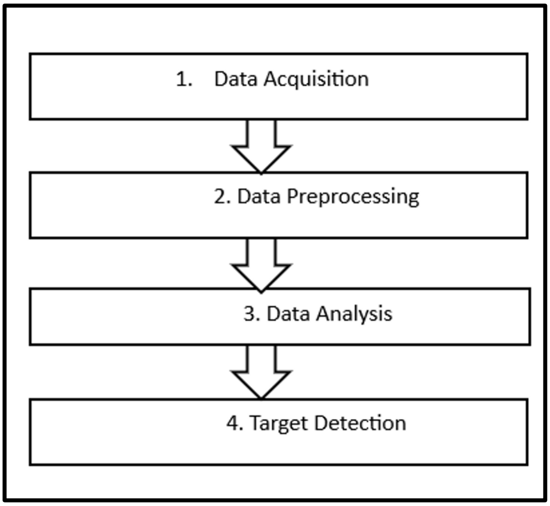

Fig.2. Multi-spectral Imaging steps

Thermal Imaging:

In thermal imaging techniques involve scanning of infrared radiation emitted from an object. The collected data is processed, and the output is provided in a graphical representation. Output data is presented in the temperature distribution across the object. Temperatures are between -20 °C to +1500 c is measured. It is a passive technique useful for imaging in both daytime and night-time conditions. [18]. Figure 3 represents the steps involved in Thermal imaging**.**

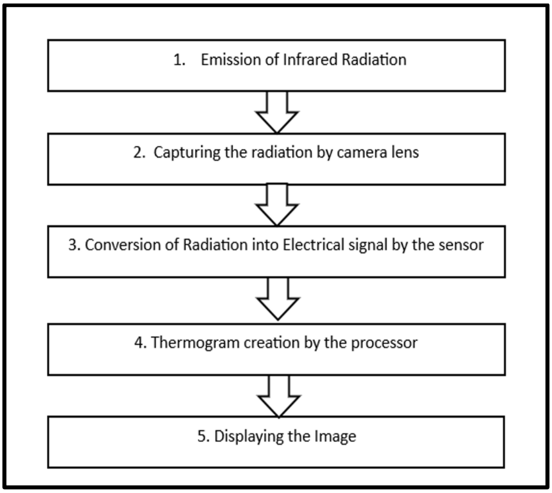

Fig.3. Thermal Imaging Steps

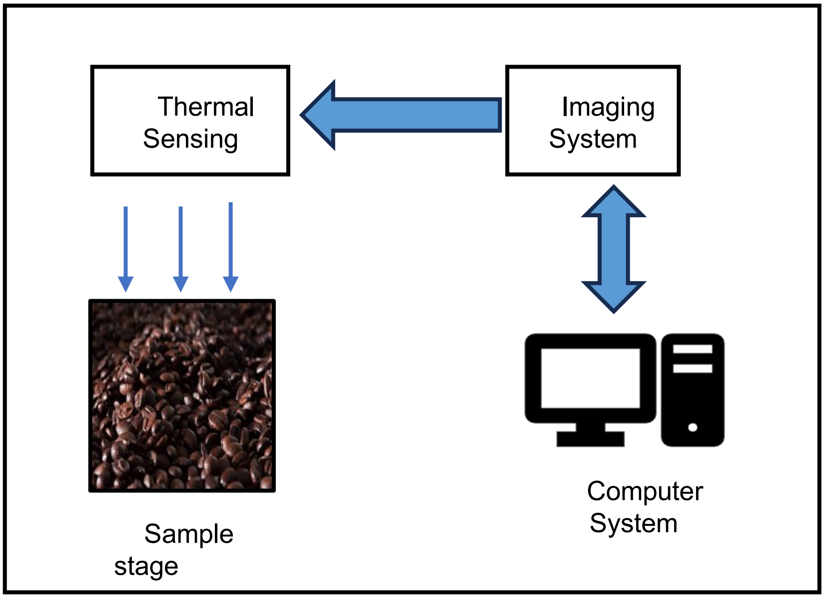

Fig.4. Schematic of Thermal imaging method

Hyper-spectral Imaging:

Hyper-spectral imaging is a technique that captures and processes a spectrum of light across many wavelengths. The detailed analysis of the surface in complex areas where other imaging methods may be insufficient [7]. Hyperspectral cameras have a high spatial resolution [~ 1–30 m] and regular sampling [~ 4–15 nm] of a broad spectral range. It has applications in astronomy, agriculture, biomedical imaging, and physics [19]. Figure 5 represents the steps involved in hyper-spectral imaging.

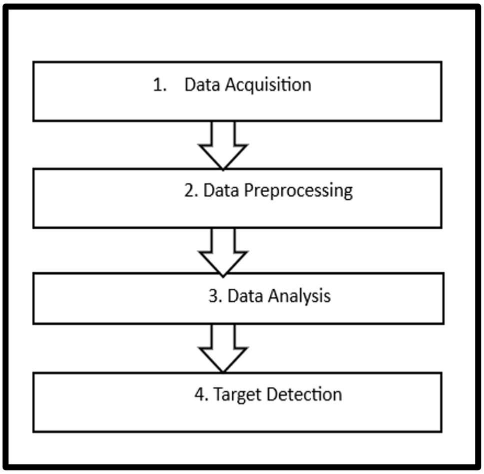

Fig.5. Hyper-spectral Imaging Steps

Figure 6 gives the Schematic of the Hyperspectral Imaging system

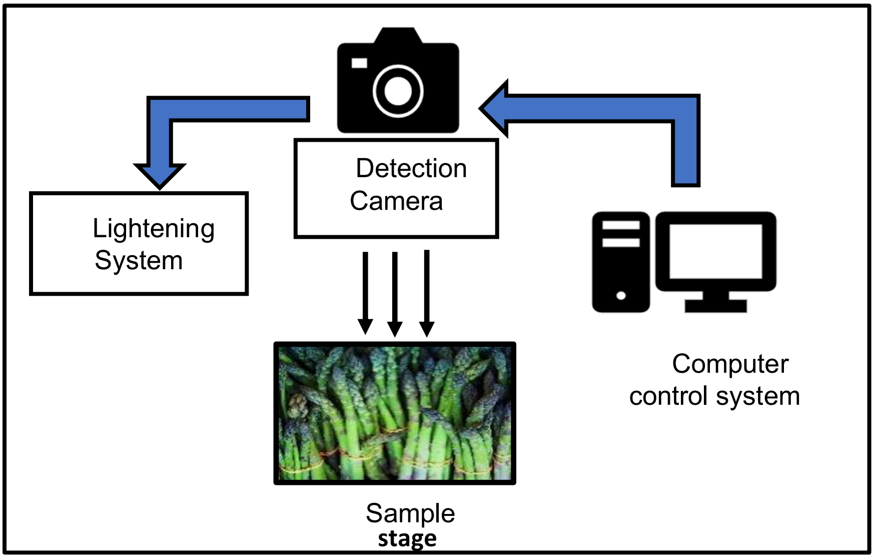

Fig.6. Schematic of a Hyperspectral Imaging system [13]

Table 3. Summary of hyperspectral image classification by different authors [16]

Disease	**Algorithm**	**Accuracy**
Rust	QDA	94.50
Rot	3DCNN	95.73
Head blight	SVM	99.00
Plant village	Adaptive coherence logistic regression	97.41

Fluorescence Imaging:

It is an imaging technique used to observe biological processes in living beings. It is a type of non-invasive imaging that includes an Excitation source, Filtration of emitted light, Detection, amplification, and visualization. Figure 7 gives the steps involved in Fluorescence imaging

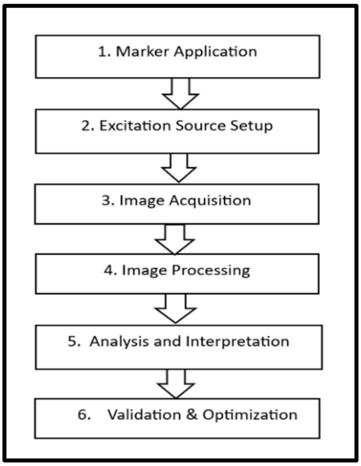

Fig.7. Fluorescence Imaging steps

Figure 8 represents the fluorescence imaging technique.

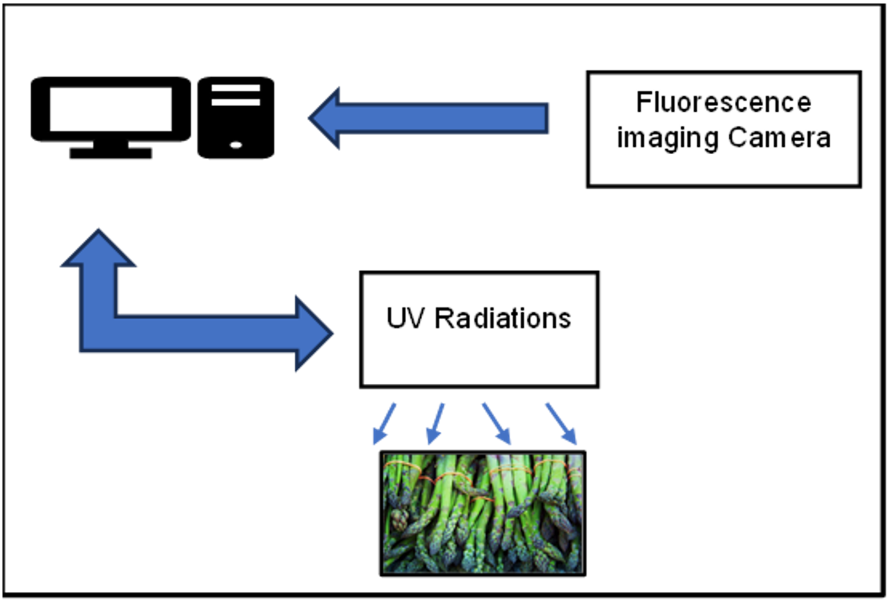

Fig.8. Schematic of Fluorescence Imaging

From the study, results for accuracy obtained for different crops using thermal, hyperspectral, and fluorescence imaging are analyzed. Comparison of Thermal, hyperspectral, and fluorescence imaging methods is given in Table 4.

Table 4. Comparison of Thermal, hyperspectral, and fluorescence imaging methods

Plant	**Imaging Type Accuracy**		
	Thermal	Fluorescence	Hyperspectral
Rice	90- 95	75-85	60-75
Tomato	90-96	80-90	65-75
Cucumber	85-92	75-85	60-70

Table 5. Comparison of different imaging methods

Imaging Modality	**Accuracy [avg]**	**Scalability**	**Field Applicability**	**Remarks**
RGB	85–90%	High	Excellent	Accessible via smartphones/drones
Multispectral	88–92%	Medium	Good	Balanced cost vs. spectral detail

Hyperspectral	92–97%	Low	Limited	Best accuracy, but expensive
Thermal	80–85%	Medium	Moderate	Useful for water-stress diseases

4 Conclusion

To detect pests and identify diseases on plants, image processing is a robust methodology in different aspects, and when combined with IoT, it can achieve better results in sustainable agriculture. Applying the Spectral Angle Mapper, disease can be classified with 91% accuracy. To decrease the complexity of calculation, spectral subsets are approachable. Use of hyperspectral imaging in agriculture is giving higher accuracy compared to other imaging methods. Image processing plays a role in clinical and healthcare for the early detection of disease.

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