Study of Different Techniques for the Detection of Disease in Grape and Pomegranate Plants: A Review

***[1,2]Bhagawan N. Kadlag, [3]Chandrakant G. Dighavkar, [4]Arun V. Patil**

*[1]Astt. Professor, Dept. of Electronic Sci., K. K. W. College, Pimpalgaon (B.), Nasik (M.S.) 422209, Maharashtra, India.
[2]Research Scholar, Department of Electronic Science and Research Centre, MGV's L. V. H College, Panchavati, Dist. Nashik, 422003, Maharashtra, India.
[3]Department of Physics, MGV's Maharaja Sayajirao Gaikwad Arts, Science and Commerce College, Malegaon Camp, Malegaon, Dist. Nashik, 423105, Maharashtra, India.
[4]Department of Physics, MGV's, Arts, Science and Commerce College, Surgana, Dist. Nashik, 422211, Maharashtra, India.
Corresponding author: kadlag1985@gmail.com

***Abstract*: Diseases pose a significant threat to the productivity and quality of grape and pomegranate crops, leading to economic losses for farmers and affecting global fruit production. This review paper aims to provide a comprehensive overview of the various disease detection techniques employed in the cultivation and management of grape and pomegranate plants. The review begins by discussing the importance of early disease detection in agriculture and the specific challenges associated with grape and pomegranate crops. It then delves into an extensive examination of different disease detection methods, including traditional visual inspection, modern imaging technologies, molecular techniques, and data-driven approaches. The current research paper explores the advantages and limitations of each technique and highlights recent advancements in the field. Special attention is given to the utilization of artificial intelligence and machine learning algorithms in automating disease detection processes, offering rapid and accurate diagnosis.**

***Keywords*: Productivity, detection techniques, agriculture, artificial intelligence, diagnosis.**

I. Introduction:

People and livestock alike use agricultural goods to meet their nutritional demands. Everyone's life has been impacted by agriculture, whether directly or indirectly. The method of crop production leads to the provision of food, the foundation of all human beings. Everyone relies on this agricultural production for survival, whether they live in a large metropolis or a rural community [1]. Grape and pomegranate plants are susceptible to a variety of diseases, both fungal and bacterial, that can affect their growth and fruit quality. Climate significantly affects the growth, and overall health of grape and pomegranate plants. Both crops have specific climate requirements, and variations in temperature, precipitation, humidity, and other environmental factors can have a substantial impact on their cultivation [2, 3]. India is an agricultural nation, and agriculture forms the foundation of any nation's economic structure. Agriculture is the reason we have a stable civilization. It is possible to identify plant diseases by looking for specific patterns in plants, however obtaining these patterns is challenging in order to keep plants healthy. Patterns can be obtained using a variety of methods, including spectroscopic and imaging technology. With the use of smart farming, farmers can employ automation techniques and tools to combine information, goods, and services to increase productivity, quality, and yield. It aids farmers in early disease detection and timely decision-making, which ultimately saves time and lessens plant loss from disease. Before marketing, farmers will also be able to distinguish between various fruit classes [3, 4].

Using their knowledge and experience, experts have been able to spot crop diseases for a long time by using only their own eyes. Finding an expert and getting in touch with them takes a lot of time and effort, and the process is also highly expensive. Consequently, the entire process can occasionally take so long that it is difficult to treat broad portions of the disease and time-consuming to completely remove it. Processors, similarity detectors, and classification approaches based on deep learning are some of the more time-efficient modern tools for detecting plant diseases than the older ones. Through early diagnosis and prompt treatment of diseases, they assist farmers in increasing the quality of their crops and reducing the prevalence of disease [5, 6].

Around 75% of the population currently receives resources from this industry. Advanced technologies play a crucial role in modernizing and optimizing pomegranate and grape farming practices. These technologies help improve crop yields, quality, sustainability, and overall profitability for farmers. Using modern agricultural technologies like IoT, AI, WSN, ML, Image processing and deep learning yields inexpensive and efficient methods of farming that can gradually guarantee a rise in quality [6, 7]. In order to meet the challenges that today's farmers face due to the changing global climate, temperature, and humidity, IoT and WSN, in combination with agricultural mobile apps and cloud platforms, are being deployed. This allows for the aggregation of crucial data pertaining to the environmental state. Horticultural areas are essential to India's development [7, 8].

II. Literature survey

Awate, A., et al (2015) is used Artificial Neural Network (ANN) concept for pattern matching and classification of diseases. Authors describe a method for identifying and categorizing external fruit disease. Thousands of terms are used in the traditional method, which causes language boundaries. While the system we came up with implements image processing algorithms because a picture is a simple way to convey information. The Open CV library is used in the proposed work as its implementation. On the basis of four feature vectors—color, morphology, texture, and structure of the hole on the fruit—the photos are catalogued and mapped to their appropriate illness categories using the K-means clustering approach. The system makes use of two image databases, one for query image implementation and the other for illness image training using previously stored photos [7].

Sankaran et al (2010) presented new approach for detection of diseases of plants or crop. In order to promote agriculture, it is necessary to create a quick, affordable, and reliable health-monitoring sensor, in accordance with the current review. It discusses the existing technologies that can be used to create a ground-based sensor system that will help in tracking plant health and disease in real-world settings. These technologies include techniques for detecting plant diseases that rely on spectroscopy, imaging, and volatile profiling. In this research, cutting-edge methods for detecting diseases on the ground that might be combined with an automated agricultural vehicle are evaluated. Both field-based and laboratory-based experiments in studies of ground-based illness detection are discussed in this publication. In contrast to laboratory-based research, which gather data in a controlled environment, field-based studies entail the collecting of spectral data in the field [9].

Dhakate, M. et al (2015) describes a technique for identifying illnesses of pomegranate plants. The segmentation of the images is accomplished using the K-means clustering methodology, the feature extraction is accomplished using the GLCM, and the classification of the images is accomplished using the multi-perceptron architecture and back-propagation algorithm. Good Fruit, Fruit Spot, Bacterial Blight, Fruit Rot, Good Leaf, and Leaf Spot are the categories utilized for categorization [10].

Melgarejo P. et al (2021) carried out review on Pomegranate variety and pomegranate plant part, relevance from bioactive point of view. This review seeks to offer a comprehensive summary of the most recent research on the bioactivity of pomegranate trees, with a focus on discriminating between plant sections and types. This study aims at giving a broad and systematic overview of the acquired knowledge on pomegranates, the identification of the most bioactive kinds, their possible consumption paths, and the search for information on the current gaps to direct future studies [11].

Ghoury, S. et al (2019) performed the task of grape and grape leaf disease detection using transfer learning by using two pre-trained deep learning models. The purpose is to distinguish between healthy and sick grapes and grape leaves. Two pre-trained deep learning models, Single SSD_MobileNet v1 and Faster R-CNN Inception v2, are used to complete this assignment utilizing transfer learning. With a classification accuracy range of 78% to 99%, the Faster-R-CNN Inception v2 model accurately classified 95.57% of all the tested images. This model had a greater accuracy level but required more processing time. Only 59.29% of the experimental photos were successfully categorized by SSD_MobileNet v1, although processing times were faster. For ordered, low-noise, uniformly sized, and well-organized images, this model was providing rather good classification accuracy. This has an accuracy rate of 90% to 99%. However, it was providing very poor classification accuracy, ranging from 52% to 80% combined with a high proportion of misclassifications, for the photos that had noise, varied backgrounds, and resolutions. These findings lead to the conclusion that the SSD_MobileNet v1 model may not be suitable for real-time classifications for this task at this time, while the Faster-R-CNN Inception v2 model may do much better [12].

Lin, J. et al (2022) for the purpose of identifying various symptom stages for unique grape illnesses, the authors suggest a lightweight CNN model designated GrapeNet. GrapeNet's three primary building pieces are convolution block attention modules, convolution block residual blocks, and residual feature fusion blocks. To deepen the network depth and retrieve rich characteristics, residual blocks are employed. We created an RFFB module based on the residual block to reduce the CNN performance deterioration brought on by a large number of hidden layers. It achieves feature fusion at various depths by concatenating the average pooled feature map prior to the residual block input and the high-dimensional feature maps following the residual block output. Additionally, the convolutional block attention module (CBAM) is included following each RFFB module to retrieve accurate illness information. Also, the Grad-cam visualization findings show that the addition of CBAM helps highlight illness information and reduce irrelevant information. Overall findings indicate that the GrapeNet model can be used to automatically identify grape leaf diseases [13].

Fraiwan, M. et al (2022) designed the system which is identify and classify the diseases of using deep Artificial Intelligence. Employing a common technology to assist farmers in battling plant diseases. Particularly, three prevalent grape diseases—black measles, black rot, and isariopsis leaf spot—were classified using deep-learning artificial intelligence image-based applications. A fourth class on healthy living was included as well. A dataset of 3639 grape leaf photos was employed, including 423 healthy images and 1383 images with black measles, black rot, and isariopsis leaf spots. 11 convolutional network models were modified and retrained using these photos to distinguish between the four groups. A thorough performance evaluation showed that it is possible to accurately design commercial and pilot applications that meet field requirements. The models consistently generated excellent performance values (>99.1%). Authors additionally suggested that one of the most promising and prevalent avenues for innovation is artificial intelligence. Many research issues can be resolved using deep learning techniques. For image-based applications, convolutional neural networks are the best option. The findings of this study show that the transfer-learning strategy has the ability to produce reliable performance. These findings show that grape illnesses can be categorized in a way that meets field deployment performance requirements. Additionally, the method used in this work runs with minimum overhead, requires no pretreatment or image processing, and does not explicitly extract features [14].

Hema, L.K et al (2021) developed plant-leaf disease identification system using deep learning techniques. With the help of in-depth learning, current developments in computer vision have made it possible to identify and diagnose plant illnesses through the use of photographic evidence. This research is crucial for identifying numerous plant diseases in various plant types. Apples, wheat, grapes, potatoes, sugar cane, and tomatoes are just a few of the many plant varieties that the system has been built to identify and categorize. A variety of herbal ailments can be diagnosed by the computer as well. With 25000 photos of diseased and infected sound plant leaves, the specialists were able to develop sophisticated learning models that could recognize and distinguish between plant diseases and non-attention of problems. The device could report accuracy up to 100%, and the model created was 95.3 percent accurate [15].

Chen, Y. et al (2023) reported the main difficulty in using deep learning to identify grape leaf diseases is how to perform well when there are sparse datasets or few annotated samples, small lesions, redundant information, and blurred background information in images of grape leaf disease. In order to address these issues, the pipeline described in this research, which consists of three stages and is based on deep learning, includes a convolutional neural network for lesion detection, a generative adversarial network for data augmentation, and a residual neural network for lesion identification. First, grape leaf lesions were marked with Faster R-CNN to create a dataset of lesions for data augmentation, and ResNet was utilized to identify lesions. Furthermore, to create synthetic grape lesion images for lesion diagnosis, leaf lesion images were loaded into DCGAN. Finally, the majority voting principle was employed to identify the grape leaf lesions using ResNet trained on a training dataset that included genuine grape leaf lesions and artificial grape lesion images created by DCGAN. The initial results of the experiment demonstrated that Faster R-CNN, DCGAN, and ResNet performed well at each level. Second, the findings of the second experiment demonstrated that, for sparse datasets and small lesions, the suggested three-stage method is superior to single-stage and two-stage methods. The proposed three-stage approach has good generalizability, according to experimental results [16].

Diana Andrushia, A. et al (2023) employing convolutional capsule network developed Image-based disease classification in grape leaves. An intriguing neural network for deep learning is the capsule network. This network successfully reflects the spatial information of characteristics by using a group of neurons as capsules. The innovative aspect of the proposed approach is the introduction of convolutional layers prior to the primary caps layer, which indirectly reduces the number of capsules and accelerates dynamic routing. Both augmented and non-augmented datasets have been tested with the suggested methodology. It accurately and successfully diagnoses 99.12% of grape leaf illnesses. The technique outperforms cutting-edge deep learning techniques and yields dependable outcomes [17].

Dhakate, M. et al (2015) Diagnosis of pomegranate plant diseases using neural network. The work suggests using neural networks and image processing to address the primary problems in phytopathology, such as disease detection and categorization. The pomegranate fruit and leaves are both susceptible to a number of diseases brought on by fungi, bacteria, and environmental factors. These conditions resemble fruit rot, fruit spot, and leaf spot. The system employs many images for training, testing, and other purposes. The color photos go through pre-processing and segmentation using k-means clustering. Using the GLCM approach, the texture features are retrieved and provided to the artificial neural network. In contrast to manual grading, the findings are shown to be accurate and satisfactory, and it is hoped that they will establish themselves as one of the most [10].

Madhavan, M.V et al (2021) recommend framework has a graphical user interface and is built on the MATLAB platform. The experimental findings show that the suggested framework can classify damaged and healthy leaves with 98.39% accuracy. Additionally, the framework can classify illnesses on pomegranate leaves with an accuracy of 98.07%. Developed a system for precisely identifying and categorizing illnesses on pomegranate trees. The framework makes use of image processing methods such picture acquisition, resizing, enhancement, segmentation, ROI extraction, and feature extraction. The framework is applied to a picture dataset, split into a training set and a test set, on pomegranate leaf disease. Techniques like image enhancement and image segmentation are mostly employed in the implementation phase to determine ROI and features. Then, a support vector machine and supervised learning model will be used to accomplish an image categorization [18].

III. Climate affects grape and pomegranate plants:

According to the literature survey the different affects are tabulated in Table 1 [19-22].

Table 1: Climate affects grape and pomegranate plants

Sr. No.	Parameter	Climate effects on grape Plants	Climate effects on pomegranate Plants
1	**Temperature**	Grapevines are highly sensitive to temperature. The right temperature range is crucial for their growth and fruit development. Extreme heat or cold can damage vines and reduce yields. The temperature also influences the grape's flavour and aroma. Different grape varieties have different temperature preferences.	Pomegranate plants are adaptable to a wide range of temperatures but thrive in warm to hot climates. Extremely low temperatures can damage or kill young pomegranate trees.
2	**Altitude**	Altitude plays a role in grape cultivation. Higher altitudes can provide cooler temperatures, which are beneficial for certain grape varieties, particularly for the production of quality wines.	Pomegranate cultivation can be successful at various altitudes, but low-altitude regions with hot, dry climates are typically more favorable for higher yields and better fruit quality.
3	**Rainfall**	While grapes need regular water during the growing season, excess rainfall or high humidity can increase the risk of fungal diseases like powdery mildew and downy mildew. Well-drained soils are essential to prevent waterlogging.	Pomegranates are considered drought-tolerant, but they require regular watering, especially during the fruit development stage. Extended periods of drought can result in smaller or split fruit.
4	**Sunlight and Heat**	Grapes need ample sunlight for photosynthesis and sugar production. Adequate sunlight exposure helps with fruit maturation and sugar accumulation. Overcast conditions or excessive shading can lead to poor grape quality.	Pomegranates are well-suited to hot and arid climates. High temperatures during the fruit ripening stage enhance fruit color and sweetness. However, excessive heat and drought stress can lead to fruit sunburn and reduced yield.

IV. Different disease occurred in grape and pomegranate:

The different disease occurred in grape and pomegranate are tabulated in Table 2 and Table 2 respectively.

Table 2: Type of grape diseases

Sr. No.	Type of disease
1	**Powdery Mildew (Uncinula necator):** A fungal disease that causes a white powdery growth on leaves, fruit, and stems, leading to reduced photosynthesis and fruit quality.
2	**Downy Mildew (Plasmopara viticola):** Another fungal disease that leads to yellow spots on leaves, downy growth on the undersides of leaves, and ultimately defoliation.
3	**Black Rot (Guignardia bidwellii):** A fungal disease that causes circular, black lesions on leaves, canes, and fruit, leading to fruit rot and reduced yield.
4	**Botrytis Bunch Rot (Botrytis cinerea):** A fungal pathogen that causes gray mold on grape clusters, leading to fruit decay and reduced quality.
5	**Phomopsis Cane and Leaf Spot (Phomopsis viticola):** A fungal disease that causes lesions on leaves and canes, leading to reduced vigor and fruit yield.
6	**Esca (Various Fungi):** A complex of fungal diseases that cause leaf chlorosis, vascular discoloration, and dieback of shoots and canes.
7	**Pierce's Disease (Xylella fastidiosa):** A bacterial disease transmitted by xylem-feeding insects, causing leaf scorch, wilting, and eventual death of the vine.

Table 3: Type of pomegranate diseases

Sr. No.	Type of disease
1	**Bacterial Blight (Xanthomonas axonopodis pv. punicae):** A bacterial disease that causes water-soaked lesions on leaves, fruit, and stems, leading to fruit rot and yield loss.
2	**Fungal Leaf Spot (Alternaria spp.):** Fungal pathogens that cause dark, circular lesions on pomegranate leaves, reducing photosynthesis and plant health.
3	**Anthracnose (Colletotrichum spp.):** A fungal disease that causes sunken lesions on fruit, often leading to fruit cracking and rot.
4	**Cercospora Leaf Spot (Cercospora spp.):** Fungal pathogens that create small, dark spots on leaves and fruit, affecting plant health and fruit quality.
5	**Pomegranate Rust (Uromyces spp.):** A fungal disease that produces rust-colored pustules on leaves, reducing photosynthesis and weakening the plant.
6	**Pomegranate Wilt (Fusarium spp.):** A fungal disease that causes wilting, yellowing, and death of pomegranate trees by affecting the root system.
7	**Root Rot (Various Fungi):** Several fungal pathogens can cause root rot in pomegranate plants, leading to reduced vigor and death.
8	**Pomegranate Decline Syndrome:** A complex of factors, including soilborne pathogens and environmental stress, leading to the decline and death of pomegranate trees.
9	**Alternaria alternate (Telya):** It is a common fungal disease that affects pomegranate plants.

V. Different disease detection techniques for grape and pomegranate

Disease detection in grape and pomegranate plants involves various techniques, ranging from traditional visual inspection to modern technology-driven approaches [20-25]. Here is a list of different disease detection techniques commonly used for grape and pomegranate plants:

1. **Visual Inspection:** The most basic method involves visual examination of the plants for symptoms such as leaf discoloration, lesions, wilting, or unusual growth patterns.

2. **Symptomatology:** Experienced agronomists or plant pathologists identify diseases based on characteristic symptoms exhibited by infected plants.
3. **Leaf and Fruit Sampling:** Collecting plant tissue samples, especially leaves and fruit, for laboratory analysis can help identify diseases by examining pathogens or their genetic material.
4. **Microscopy:** Microscopic examination of plant tissues or pathogens allows for the visualization of pathogens and their structures, aiding in identification.
5. **Cultural Methods:** Isolating and growing pathogens in culture media to observe their characteristics and perform diagnostic tests.
6. **Serological Tests:** Enzyme-Linked Immunosorbent Assay (ELISA) and other serological tests detect specific antigens or antibodies to identify pathogens.
7. **Polymerase Chain Reaction (PCR):** Molecular techniques like PCR help detect and identify pathogens by amplifying their DNA or RNA.
8. **Next-Generation Sequencing (NGS):** NGS technologies enable comprehensive profiling of the entire microbial community in plant samples, aiding in the identification of pathogens.
9. **Imaging Technologies:** Thermal Imaging: Infrared thermography can detect temperature differences in infected plants, revealing stress or disease.
10. **Hyperspectral Imaging:** Analyzing plant reflectance spectra to identify disease-specific patterns.
11. **Fluorescence Imaging:** Detecting disease-induced chlorophyll fluorescence changes in plants.
12. **Remote Sensing:** Utilizing satellite or drone-based imagery to monitor crop health and detect disease outbreaks over large areas.
13. **Sensor Networks:** Deploying sensors in fields to continuously monitor environmental conditions and detect anomalies related to disease development.
14. **Machine Learning and AI:** Employing artificial intelligence and machine learning algorithms to analyze large datasets from remote sensing, sensor networks, or imaging to detect disease patterns.
15. **Bioinformatics:** Using computational tools to analyze genetic data and identify disease-related genes or markers.
16. **Precision Agriculture:** Implementing precision farming techniques to monitor and manage plant health, including disease detection through data-driven decision-making.
17. **Biocontrol Measures:** Implementing biological control agents, such as beneficial microorganisms or predators, to manage and prevent diseases.
18. **Chemical Analysis:** Conducting chemical analyses of plant tissues or soil to identify disease-related chemical compounds or nutrient imbalances.
19. **Quarantine and Pest Risk Analysis:** Regulating the movement of plant material and conducting risk assessments to prevent the introduction and spread of diseases.
20. **Mat lab:** Mat lab is a versatile programming environment that can be used for various image processing and data analysis tasks, including disease detection in grape and pomegranate plants. By developing user-friendly Matlab GUIs to facilitate the input of images and visualization of detection results.

These techniques vary in their specificity, sensitivity, and complexity, and their suitability depends on factors like the type of disease, available resources, and the scale of cultivation. Integrated approaches often combine multiple techniques for a more comprehensive disease management strategy in grape and pomegranate cultivation.

VI. Advantages and disadvantages disease detection techniques for grape and pomegranate plants

Disease detection techniques for grape and pomegranate plants have evolved over the years, and they come with their own set of advantages and disadvantages [21-30]. Some of the key advantages and disadvantages as follow.

Advantages:

- **Early Detection:** Disease detection techniques allow for the early identification of plant diseases, even before visible symptoms appear. This early detection can help prevent the spread of diseases and limit crop damage.
- **Precision:** Many modern techniques are highly precise and can identify specific pathogens or diseases accurately. This precision allows for targeted treatment and management.
- **Reduced Costs:** Early detection can lead to more cost-effective disease management. Treating diseases at an early stage often requires fewer resources and reduces the need for expensive interventions.
- **Increased Crop Yield:** By detecting diseases early and implementing timely interventions, growers can protect their crops and maintain higher yields.
- **Remote Sensing:** Some techniques, such as remote sensing and imaging technologies, allow for non-invasive and non-destructive monitoring of plant health over large areas, making it easier to manage large orchards.
- **Data Analysis:** These techniques often generate data that can be analyzed for trends and patterns, helping farmers make informed decisions about disease management strategies.

Disadvantages:

- **Cost:** Many advanced disease detection techniques can be expensive to implement. This includes the initial setup costs, equipment, and ongoing maintenance expenses.
- **Expertise Required:** Some techniques require specialized knowledge and training to operate effectively. Farmers may need to hire or consult with experts, which can be costly.
- **False Positives/Negatives:** No detection technique is perfect, and false positives or false negatives can occur. This can lead to unnecessary treatments or missed diseases.
- **Equipment Limitations:** Some techniques require specific equipment that may not be readily available to all farmers, especially small-scale growers.
- **Environmental Factors:** Environmental conditions, such as weather and lighting, can impact the accuracy of certain detection methods.
- **Time-Consuming:** Some techniques can be time-consuming, especially if a large area needs to be surveyed. This may lead to delays in disease identification and management.
- **Limited to Specific Diseases:** Some techniques are designed to detect specific pathogens or diseases and may not be suitable for a broad range of diseases.

Conclusion:

This comprehensive review amalgamates the current state of disease detection techniques for grape and pomegranate plants, providing valuable insights for researchers, agronomists, and policymakers in the agriculture industry. It emphasizes the importance of adopting innovative and efficient methods to mitigate disease impacts and ensure the sustainable cultivation of these valuable fruit crops. Disease detection techniques for grape and pomegranate plants offer valuable advantages in terms of early detection and precision, but they also come with challenges related to cost, expertise, and potential inaccuracies. The integration of advanced technologies into pomegranate and grape farming enhances productivity, sustainability, and profitability while reducing environmental impacts and resource wastage. Farmers who adopt these technologies are better equipped to address the challenges of modern agriculture and meet the demands of changing markets.

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Conflict of Interest

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