**PLANT DISEASE DETECTION**

**PROJECT SYNOPSIS**

OF MAJOR PROJECT

**BACHELOR OF TECHNOLOGY**

**SUBMITTED BY:**

Akhilesh Singh (2100290100015)

Awadhesh Kumar Maurya (2100290100039)

Ayush Prakash (2100290100043)

**2025 BATCH**

Under the supervision of

Mr. Pushpendra Kumar



## **KIET Group of Institutions, Delhi-NCR,**

## **Ghaziabad (UP)**

## **Department of Computer Science and Engineering**

**Dr. A.P.J. Abdul Kalam Technical University, Lucknow**

(Formerly UPTU)

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**INTRODUCTION**

Agriculture, popularly referred to as the pillar of human nourishment and economic development, is vital to ensuring the stability and growth of societies across the globe. Despite its undoubted significance, industry continues to be besieged by numerous challenges, the majority of which compromise its potential to cater to the increasing demands of a fast-growing global populace. Of these, plant diseases are among the most rampant and destructive forces against crop productivity and. by extension. global food security. The Food and Agriculture Organization (FAO) estimates that as much as 40% of the world's crop yield is lost every year due to plant diseases. This is a staggering estimate that accentuates the severity of the issue as the losses not only erode food security but also have long-term socio-economic impacts on societies, especially where agriculture forms a key source of livelihood.

The population of the world is growing at a record level. and the world will soon be home to over 9 billion people by 2050. This demographic shift places a huge burden on agricultural systems that must deliver more food from fewer resources under the threat of climate change. Water, and shrinking arable land. Climate change is a major component that has reversed the tables against the severity and magnitude of plant diseases with unpredictable weather patterns, high temperature and humidity offering a boost to pathogen growth.

Traditional methods of disease identification such as manual inspection by experts are increasingly inadequate in addressing the scale and complexity of modern agricultural challenges. These methods are often slow, error-prone and labor-intensive and there is a growing shortage of skilled agricultural professionals, especially in developing regions. This highlights the urgent need for innovative technology-driven solutions that can bridge the gap between disease detection and timely intervention.

In response to these challenges. Disease detection represents a pioneering solution at the intersection of agriculture and technology. The project seeks to develop an intuitive mobile application that leverages state-of-the-art machine learning techniques, specifically convolutional neural networks (CNNs) to detect and predict plant diseases at an early stage. By providing farmers, agricultural professionals and stakeholders with a powerful tool for monitoring plant health. Disease detection aims to revolutionize disease management practices and enhance the overall productivity and sustainability of agriculture. The fundamental functionality of Plant Disease Detection relies on the use of CNNs, a category of deep learning algorithms that have proven to be outstanding in image recognition and classification.

**RATIONALE**

##### Image Recognition and Disease Detection:

The software takes and processes crop images via smartphones or IoT sensors. Using the help of deep learning models like Convolutional Neural Networks (CNNs), it recognizes precise diseases by cross-matching visible symptoms with a vast pre-trained database. Plant Disease Detection utilizes advanced AI methods to give accurate disease diagnoses. It does this through the following modules:

**Image Capture:**

The farmers may capture high-resolution images of the affected plant parts, i.e., leaves, stems, or fruits, using their smartphone camera or IoT-based imaging sensors.

**Image Processing:**

Using deep models like Convolutional Neural Networks (CNNs), the website identifies symptoms and patterns that match some diseases. These models get trained from multimodal datasets comprising millions of images with their corresponding labels to yield good accuracy and resistance.

**Disease Classification:**

Using pretrained architectures like ResNet or MobileNet, the web compares the input image with a vast repository of disease signatures to classify the disease and determine its severity level.

**How It Works:**

The core of Plant Disease Detection’s disease detection is its powerful image recognition capability. Users can simply capture clear images of affected plant parts through their smartphone cameras. The web’s integrated machine learning algorithms then analyzes these images, pinpointing the possible causes of plant distress such as diseases or pest infestations.

**Integration of Machine Learning and Advanced AI:**

The web utilizes deep learning models trained on an extensive dataset of thousands of plant images to detect symptoms across a variety of plant species. These algorithms learn to recognize subtle visual cues, providing users with an accurate and fast diagnosis. With continuous training and updates, the web’s diagnostic accuracy improves, making it more effective over time.

**Real-Time Analysis:**

Within seconds of capturing an image, the web delivers a diagnostic result, offering immediate insights into the condition of the plant. Timely interventions become possible with early detection, preventing the escalation of diseases and saving crops from irreversible damage.

##### Multi-Crop and Multi-Region Support

Plant Disease Detection is designed to support a wide range of crops and cater to diverse agricultural regions:

**Diverse Crop Types:**

The web supports staple crops like wheat, rice, maize, and cash crops such as cotton and coffee. Additionally, it caters to fruits, vegetables, and horticultural plants.

**Regional Customization**:

Plant Disease Detection incorporates datasets from different geographical regions to address region-specific diseases. For instance, it accounts for blight in potatoes in

temperate climates and mosaic viruses in tropical zones.

**Seasonal Awareness**: The web recognizes that certain diseases are more prevalent specific seasons and adjusts its predictions accordingly.

In conclusion, Plant Disease Detection represents a significant leap forward in the integration of technology into agriculture, offering a powerful tool for early disease detection, disease management and sustainable farming practices. By addressing one of the most pressing challenges in global agriculture. It stands to make a transformative impact on food security, crop health and the livelihoods of farmers worldwide. As the web continues to evolve and expand its features, it is poised to become an indispensable tool for farmers and agricultural professionals seeking to navigate the complexities of modern agriculture. In a world grappling with food insecurity, climate change and environmental degradation. It symbolizes the potential for technology to help create a more sustainable, resilient, and food-secure future for all.

Extensive Database

Plant Disease Detection's disease database has information on many plant varieties, with each variety having information on common diseases and pests. symptoms and prevention techniques. Database is regularly updated by adding feedback from agriculture experts to include the latest research and treatments.

**OBJECTIVES**

**1. Early Disease Identification**  
The primary objective is to detect plant diseases at an early stage before they spread extensively. This helps in timely intervention and prevents crop loss.

**2. Increase Agricultural Productivity**  
By identifying diseases early and accurately, farmers can take corrective actions to ensure healthy crop growth, resulting in increased yield and productivity.

**3. Reduce Pesticide Usage**  
The system promotes targeted treatment, reducing the overuse of chemical pesticides, which are harmful to both the environment and human health.

**4. Cost-Effective Solution**  
This system helps farmers avoid unnecessary expenses on broad treatments and consultations by providing a reliable and low-cost method of disease detection.

**5. Real-Time Monitoring**  
Integration with real-time data systems (e.g., mobile apps) allows continuous plant health monitoring, improving decision-making speed and efficiency.

**6. Support Precision Agriculture**  
The technology aligns with modern precision agriculture by using image recognition and machine learning to make data-driven decisions on crop care.

**7. Assist Farmers in Rural Areas**  
The system supports untrained or semi-trained farmers by offering an automated and easy-to-use solution for disease identification without needing expert knowledge.

**8. Digital Record Maintenance**  
It maintains a digital history of plant health, helping in long-term farm planning and disease pattern analysis.

**9. Promote Sustainable Farming**  
Encourages eco-friendly agricultural practices by minimizing wastage, enhancing resource management, and ensuring crop safety.

**LITERATURE REVIEW**

**Research Paper 1**

**PLANT DISEASE DETECTION USING CNN- BASED DEEP LEARNING MODELs**

Author:- Akhilesh Singh1 , Awadhesh Kumar Maurya2 , Ayush Prakash3

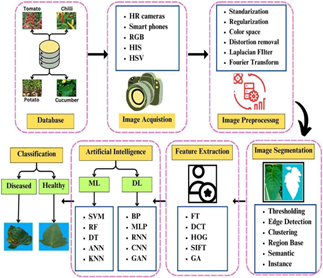
Training and Placement Cell Objectives

1. To enhance students’ employability through soft skills and technical training.
2. To organize campus placement drives for final-year students.
3. To arrange internships and industrial visits for practical exposure.
4. To bridge the gap between academia and industry needs.
5. To collaborate with companies for recruitment and training.
6. To guide students in career planning and decision-making.
7. To prepare students for competitive exams and interviews.
8. To keep students updated with current industry trends.
9. To encourage industry-academic partnerships.
10. To ensure maximum placement opportunities for students.
11. To enhance students’ employability through soft skills and technical training.
12. To organize campus placement drives for final-year students.
13. To arrange internships and industrial visits for practical exposure.
14. To bridge the gap between academia and industry needs.
15. To collaborate with companies for recruitment and training.

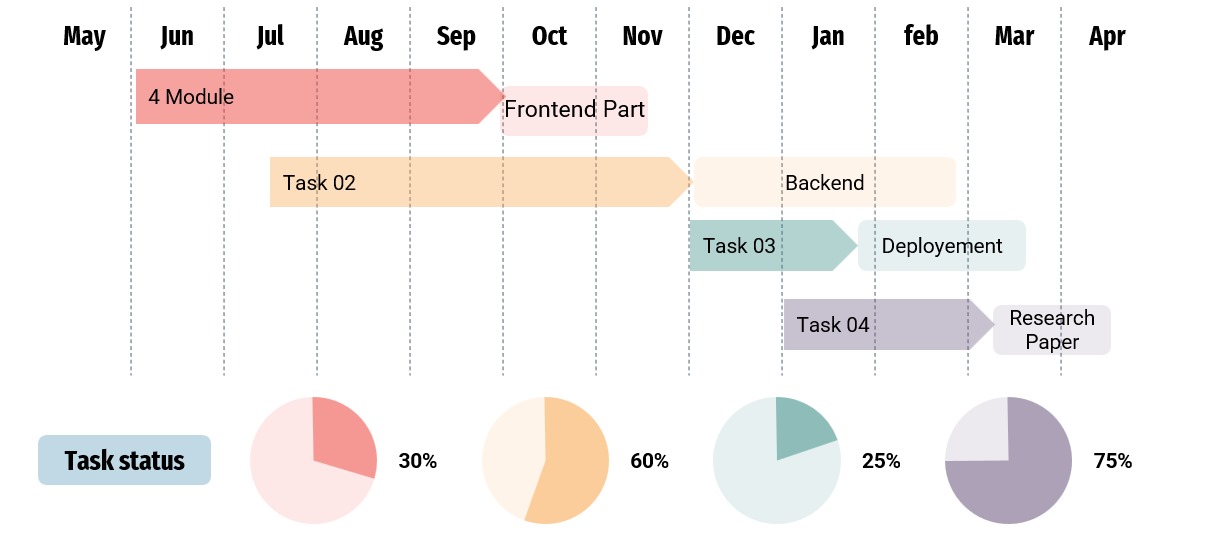
**METHODOLOGY**

Automated leaf disease identification is a step-by-step procedure that involves the use of image processing and artificial intelligence (AI) in machine learning (ML) and deep learning (DL) algorithms. Proper identification and detection of plant disease are identified by the system based on computational powers, hence resulting in successful disease management and improved crop production. Image acquisition, preprocessing, segmentation, feature extraction, and classification based on AI algorithms are the basic steps used.

1. Image Acquisition Disease diagnosis starts with proper image acquisition of the plants' leaves. It is a digital image acquisition process using cell phones or digital cameras that are stored in standard image formats such as JPEG, PNG, or TIFF. The images need to be of good quality because it would directly affect the efficiency of the subsequent process and classification process. Any degradation in image quality due to low light, motion blur, or noise in the background can severely hamper the performance of the models. Agricultural scientists therefore employ field images and open-source databases like PlantVillage, Plant Doc, and IPM Images that provide a huge dataset of leaf images labelled according to various plant species and disease types.



**TimeLine of Project**

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**FEASIBILITY STUDY**

A feasibility study is a process of evaluating the viability of a proposed project, taking into account its economic, technical, and operational feasibility.

**Feasibility Study for Plant Disease Detection System (300 Words, Heading by Heading):**

**1. Technical Feasibility**  
The project is technically feasible due to the availability of advanced tools and technologies such as Convolutional Neural Networks (CNNs), Python libraries (like Torch, OpenCV, and TensorFlow), and smartphone cameras for image acquisition. Existing datasets (e.g., PlantVillage) support model training. Cloud-based platforms and mobile applications can be integrated for real-time usage. Thus, the technical infrastructure required is accessible and reliable.

**2. Operational Feasibility**  
Operationally, the system is user-friendly and can be deployed on mobile or web applications, making it accessible even to farmers in remote areas. Automated detection eliminates the need for expert consultation, saving time and effort. With a minimal learning curve, even users with limited technical knowledge can operate the system, enhancing its practical utility.

**3. Economic Feasibility**  
The development and deployment costs are reasonable, using open-source frameworks and existing datasets. Since it reduces the cost of frequent expert visits and minimizes pesticide use by providing early alerts, it proves to be a cost-effective solution in the long run. Also, the investment required for development can be recovered through governmental or NGO support or by offering the app as a subscription-based service.

**4. Legal Feasibility**  
The project does not violate any legal boundaries. Data used for training is open-source and publicly available. However, user data and privacy must be protected under data protection laws if mobile apps are used for deployment.

**5. Schedule Feasibility**  
With proper planning and a defined roadmap, the system can be developed, trained, tested, and deployed within a realistic timeline of 4–6 months. The schedule is practical and manageable, considering standard academic or professional project durations.

**6. Social Feasibility**  
The system has high social acceptance, especially in agriculture-dependent communities. It empowers farmers, improves crop health, reduces food insecurity, and supports sustainable agriculture practices.

**FACILITIES REQUIRED**

**1. Hardware Facilities**

* **High-Performance Computer:** Required for training deep learning models, preferably with GPU support for faster computation.
* **Smartphones or Cameras:** For capturing clear images of plant leaves in real-time.
* **Internet Connectivity:** Needed for data collection, model updates, cloud integration, and real-time prediction if deployed online.

**2. Software Facilities**

* **Programming Environment:** Python with libraries like PyTorch, TensorFlow, OpenCV, NumPy, and Matplotlib.
* **Integrated Development Environment (IDE):** Tools like Jupyter Notebook, PyCharm, or VS Code for writing and debugging code.
* **Database:** For storing user inputs, image data, and prediction history.
* **Cloud Services (Optional):** AWS, Google Cloud, or Firebase for storage, model hosting, and mobile app backend.

**3. Dataset Resources**

* **Image Datasets:** Large labeled datasets like PlantVillage for training the model with various plant disease images.

**4. Human Resources**

* **Developers/Researchers:** For coding, training models, testing, and deployment.
* **Domain Experts (Optional):** For verifying disease predictions and ensuring accuracy.

**5. Deployment Tools**

* **Mobile/Web Application Platform:** Android Studio (for mobile) or Flask/Django (for web).
* **Version Control:** GitHub or GitLab for managing source code.

These combined facilities ensure smooth development, testing, and deployment of the plant disease detection system.

**EXPECTED OUTCOME**

**Expected Outcome of Plant Disease Detection System (300 Words):**

**1. Accurate Disease Identification**  
The system is expected to accurately identify plant diseases using image classification techniques. By analyzing leaf images through a trained deep learning model, it can classify whether the plant is healthy or infected, and specify the type of disease. This improves early detection and minimizes crop damage.

**2. Increased Crop Yield and Quality**  
Early and precise diagnosis allows farmers to apply timely and targeted treatment. This reduces the spread of disease, thereby preserving the health of crops and significantly improving yield and quality, which directly benefits food production and farmers' income.

**3. Cost Reduction in Farming Practices**  
By detecting diseases early, the need for excessive pesticide use and expert consultations is reduced. This lowers the overall cost of farming while also protecting the environment from chemical overuse.

**4. Easy-to-Use Interface for Farmers**  
The system will be deployed via a simple mobile or web application, allowing farmers—even with limited technical knowledge—to capture images and get disease predictions easily. This democratizes access to agricultural technology.

**5. Real-Time Monitoring and Reporting**  
With real-time image analysis, the system can provide instant feedback. It may also maintain a record of past diagnoses, helping farmers track the health of their crops over time.

**6. Educational and Advisory Support**  
Along with disease detection, the system can provide brief information about the disease and recommend possible treatments or preventive actions, acting as a basic digital advisor for farmers.

**7. Contribution to Smart Farming and Research**  
The system promotes precision agriculture and data-driven farming practices. It also opens new research opportunities in agri-tech, AI, and remote sensing.

Overall, the project aims to create a scalable, affordable, and intelligent solution that supports sustainable agriculture and empowers the farming community.

**REFERENCES**

1. H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik and
2. Z. ALRahamneh, Fast and Accurate Detection and Classification of Plant Diseases, International Journal of Computer Applications, Wageningen Academic publishers, vol. 17, no.1, pp: 31-38, March 2018.
3. F. Argenti,L. Alparone,G. Benelli ,” Fast algorithms for texture analysis using co-occurrence matrices” Radar and Signal Processing, IEE Proceedings , vol. 137, Issue 6, pp:443-448 , No. 6, December 2020.
4. P. Revathi, M. Hemalatha, Classification of Cotton Leaf Spot Diseases Using Image Processing Edge Detection Techniques, pp-169-173, Tiruchirappalli, Tamilnadu, India, 2019.
5. A.Menukaewjinda, P.Kumsawat, K.Attakitmongcol, A.Srikaew, Grape leaf disease detection from color imagery using hybrid intelligent system, Proceedings of electrical Engineering/electronics, Computer, Telecommunications and Information technology (ECTI- CON), vol 1. pp: 513-516, Krabi, Thailand, 2018.
6. Haiguang Wang, Guanlin Li, Zhanhong Ma, Xiaolong Li
7. , Image Recognition of Plant Diseases Based on Principal Component Analysis and Neural Networks, 8th International Conference on Natural Computation, pp- 246-251, Chongqing, China, 2012 .
8. G. Koch, ‘‘Siamese neural networks for one-shot image recognition,’’
9. B. Wang and D. Wang, ‘‘Plant leaves classification: A few-shot learning method based on Siamese network,’’ *IEEE Access*, vol. 7,pp. 151754–151763, 2019.
10. D. Das and C. S. G. Lee, ‘‘A two-stage approach to few- shot learning for image recognition,’’ *IEEE Trans. Image Process.*, vol. 29, no. 5,pp. 3336–3350, Dec. 2020.
11. L. Fei-Fei, R. Fergus, and P. Perona, ‘‘One-shot learning of object categories,’’ *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 4,pp. 594–611, Apr. 2006.
12. Dheeb Al Bashish, M. Braik, and S. Bani-Ahmad, A Framework for Detection and Classification of Plant Leaf and Stem Diseases, 2010 International Conference on Signal and Image Processing, pp: 113-118, Chennai, India, 2010.
13. Sladojevic, Srdjan,and others. ”Deep neural networks based recognition of plant diseases by leaf image classification.” Computational intelligence and neuroscience 2016 (2016)
14. S. D. Khirade and A. B. Patil, ”Plant Disease Detection Using ImageProcessing,” 2015 International Conference on Computing CommunicationControl and Automation, 2015, pp. 768-771, DOI: 10.1109/ICCUBEA.2015.153
15. Singh, G., and Yogi, K. K. (2023). Performance evaluation of plant leaf disease detection using deep learning models. Arch. Phytopathol. Plant Prot. 56, 209–
16. Vishnoi, V. K., Kumar, K., and brajesh, k. (2021). Plant disease detection using J. Plant Dis. Prot. 128, 19–535. doi: 10.1007/s41348-020-00368-0