DETECTING PLANT DISEASES USING AI

A PROJECT REPORT

Submitted by

Moksh Doshi (22BCE10131)
Prachi Tavse (22BCE10014)
Harshita Jangde (22BCE10107)
Aryan Gupta (22BCE10867)
Shreyansh Sharma (22BCE11026)

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY
in
COMPUTER SCIENCE

SCHOOL OF COMPUTING SCIENCE AND ENGINEERING

VIT BHOPAL UNIVERSITY

KOTHRIKALAN, SEHORE

MADHYA PRADESH - 466114

October, 2023

VIT BHOPAL UNIVERSITY,KOTHRIKALAN, SEHORE MADHYA PRADESH – 466114

BONAFIDE CERTIFICATE

Certified that this project report titled **“DETECTING PLANT DISEASES USING AI”** is the bonafide work of “**Moksh Doshi (22BCE10131), Prachi Tavse (22BCE10014), Harshita Jangde (22BCE10107), Aryan Gupta (22BCE10867) and Shreyansh Sharma (22BCE11026)”** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported here does not form part of any other project / research work on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

PROJECT SUPERVISOR
Dr. Faisal Rasheed Lone,
School of Computer Science and Engineering
VIT BHOPAL UNIVERSITY

The Project Exhibition I Examination is held on _______________

ACKNOWLEDGEMENT

First and foremost I would like to thank the Lord Almighty for His presence and immense blessings throughout the project work. I wish to express my heartfelt gratitude to Dr.S.Poonkuntran, Head of the Department, School of Computer Science for much of his valuable support encouragement in carrying out this work. I would like to thank my internal guide Mr. Faisal Rasheed Lone, for continually guiding and actively participating in my project, giving valuable suggestions to complete the project work. I would like to thank all the technical and teaching staff of the School of Aeronautical Science, who extended directly or indirectly all support. Last, but not the least, I am deeply indebted to my parents who have been the greatest support while I worked day and night for the project to make it a success.

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

The important topic of early disease detection in plants in the context of agriculture is the focus of this study. This topic's potential to improve food security and agricultural sustainability makes it important. The study uses artificial intelligence (AI) to accomplish this goal, focusing on convolutional neural networks (CNNs) in particular. In order to detect illnesses in their early stages and enable timely intervention to reduce crop losses, these CNNs are skilled in processing and analyzing images of plants. The study starts out by highlighting the accuracy and efficiency shortcomings of conventional illness detection techniques. It emphasizes the demand for cutting-edge methods and tools, which AI—especially CNNs—is well-positioned to provide.CNNs are a perfect tool for illness identification since they can learn complex information from photos. The utilization of datasets for CNN training is a pivotal aspect of our study. For the model to be successful, a variety of representative datasets must be available. The AI system's comprehension of plant diseases is based on several datasets, which include the PlantVillage datasets.

TABLE OF CONTENTS

1. INTRODUCTION

In this study, we tackle the pressing issue of plant diseases in apple orchards using Artificial Intelligence (AI), with a focus on harnessing advanced AI techniques, specifically Convolutional Neural Networks (CNNs), for the early identification of diseases in apple plants. We systematically gather a diverse datasets of apple plant images and employ data preprocessing techniques, including image augmentation and normalization, to prepare the data for training. Our AI model features a disease classification-optimized architecture. After rigorous experimentation, we attain remarkable results, showcasing a high level of accuracy in disease identification. The implications of our research reach beyond academia, as it offers practical agricultural applications that provide farmers with an efficient, non-invasive tool for early disease detection. This empowers targeted interventions, ultimately reducing crop losses. By delivering a cost-effective, sustainable, and accessible solution for disease detection in apple plants, our research contributes significantly to the improvement of food security and sustainable agricultural practices[1].

Challenges in the Agricultural Sector include the impending global population growth, expected to reach 9-10 billion by 2050, necessitating a significant boost in food production. Climate change compounds the issues with shifting weather patterns, extreme events, and temperature fluctuations posing threats to crop yields and causing uncertainty for farmers. Moreover, resource depletion, including soil degradation, water scarcity, and overuse of fertilizers, impacts the long-term sustainability of agriculture. Managing pests and diseases also remains a significant challenge, as they can devastate crops, resulting in substantial losses. Small-scale farmers further grapple with difficulties in accessing markets and securing fair compensation for their agricultural products[2].

On the positive side, AI and Machine Learning offer substantial benefits to the Agricultural Sector. These technologies enable Precision Agriculture, analyzing data from satellites, drones, and sensors to provide real-time insights into soil health, weather conditions, and crop performance. This empowers farmers to make informed, data-driven decisions that optimize resourceutilization and enhance yields. AI and ML also enhance Crop Management by identifying diseases, pests, and nutrient deficiencies in plants through image recognition and data analysis. Supply Chain Optimization through AI reduces food waste and ensures produce reaches consumers more efficiently. AI-powered platforms improve Market Access by connecting farmers to markets and promoting fair pricing. Smart Irrigation conserves water resources and reduces costs, while AI accelerates Crop Breeding by analyzing genetic data, leading to drought-resistant, disease-resistant, and high-yield crop varieties. Finally, Data-Driven Decision-Making empowers farmers and policymakers to make more informed choices, ultimately boosting overall productivity and sustainability in agriculture.

1.1 Convolutional Neural Networks (CNNs)

A plethora of deep learning models, mostly CNNs, have been employed for plant and leaf classification separately, including AlexNet, GoogLeNet, VGG, Inception, ResNet, MobileNet, etc[2]. CNNs are primarily used to solve difficult image-driven pattern recognition tasks and with their precise yet simple architecture, offers a simplified method of getting started with ANNs.
In this Experiment, We have trained a model using ImageNet and CNN and a public datasets on diseased and healthy apple leaves. The database contains 3,171 images of Apple plant leaf, this number of Apple plant leaf can be increased simply by Image preprocessing[3].

Table 1.1 Description of Apple plant Diseases

Diseases	Disease Type	Responsible Pathogen	Symptoms
Scab	Fungal	Venturia inaequalis	Light green spots on leaf
Black rot	Fungal	Diplodia seriata	Small sneaks on the upper surface of the leaf
Cedar rust	Fungal	Gym-nosporangium juniperi-virginianae	Reddish or pale yellow circular lesions appear on leaves' upper surface

2. LITERATURE REVIEW

Agriculture stands as a cornerstone of human civilization, providing sustenance and livelihoods for countless individuals worldwide. Its critical role in ensuring food security and sustainability cannot be overstated. In the face of a growing global population and the challenges posed by climate change and resource constraints, the need for innovative solutions in agriculture has never been more pressing. Among these solutions, the integration of Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), has emerged as a transformative force in the early detection of diseases in plants. This literature review seeks to delve into the role of AI, specifically CNNs, in revolutionizing plant disease detection, examine the fundamentals, applications, datasets, model architectures, performance metrics, challenges, and real-world applications in this domain. Furthermore, it will explore emerging trends, research gaps, and the potential for future innovation in the realm of AI-powered plant disease detection.

Agriculture stands as a cornerstone of human civilization, providing sustenance and livelihoods for countless individuals worldwide. Its critical role in ensuring food security and sustainability cannot be overstated. In the face of a growing global population and the challenges posed by climate change and resource constraints, the need for innovative solutions in agriculture has never been more pressing. Among these solutions, the integration of Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), has emerged as a transformative force in the early detection of diseases in plants. This literature review seeks to delve into the role of AI, specifically CNNs, in revolutionizing plant disease detection, examine the fundamentals, applications, datasets, model architectures, performance metrics, challenges, and real-world applications in this domain. Furthermore, it will explore emerging trends, research gaps, and the potential for future innovation in the realm of AI-powered plant disease detection.

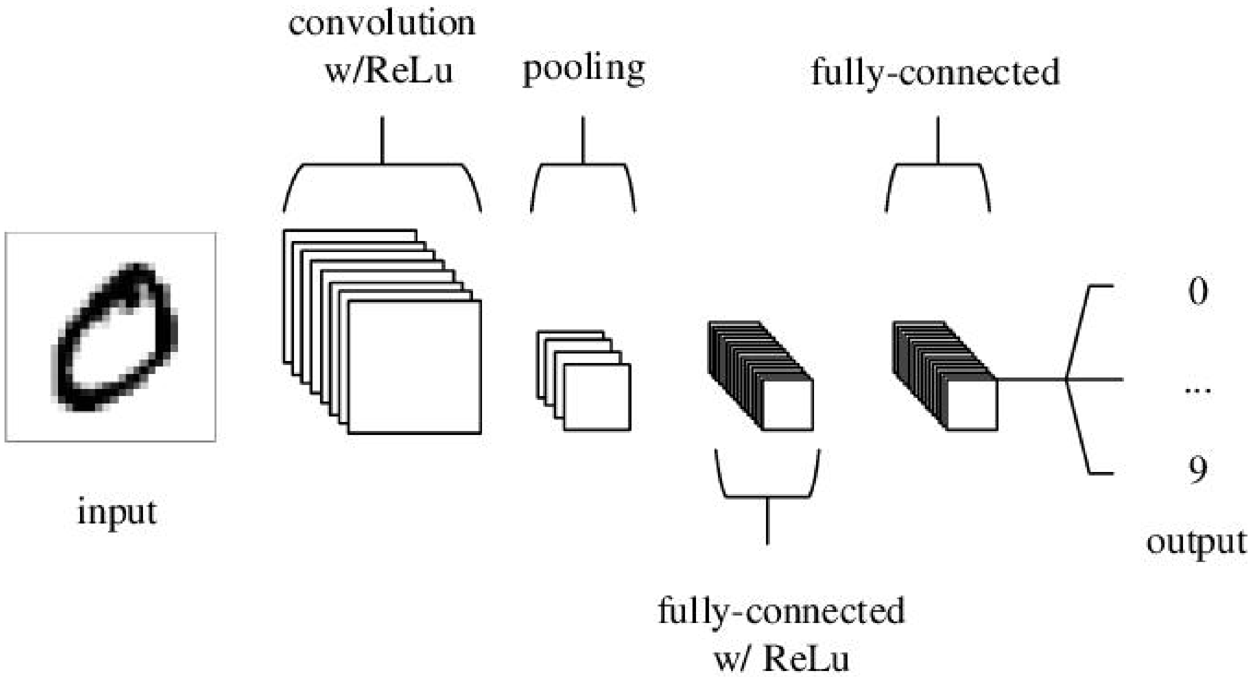


Figure 1 5-layered CNN

3. PROJECT PROCEDURE

3.1. Define the Scope and Objectives of the Research

At the outset of this research endeavor, it is imperative to clearly define the scope and objectives that will guide our exploration. We must delineate the specific plant diseases that will be the focus of our investigation and outline the precise goals of our AI-based disease detection system. This initial step sets the research's boundaries and directs our efforts toward achieving measurable outcomes in the field of plant pathology and agriculture.

3.2. Literature Review

A comprehensive literature review stands as the cornerstone of our research, enabling us to build upon existing knowledge and understand the landscape of plant disease detection utilizing AI, with a particular emphasis on Convolutional Neural Networks (CNNs). This thorough examination of the literature will afford us the insights necessary to identify gaps in current approaches, pinpoint areas where our research can make substantial contributions, and lay the foundation for our unique approach to AI-driven disease detection.

3.3 Data Collection

The next crucial phase revolves around the collection of a diverse datasets of plant images. This datasets should encompass both healthy and diseased samples, forming the fundamental building block for training and testing our AI model. The quality, diversity, and representativeness of this datasets will significantly influence the model's effectiveness and applicability in real-world agricultural contexts.

3.4. Data Preprocessing

To ensure that our datasets is primed for the training process, it necessitates meticulous data preprocessing. Tasks such as image resizing, normalization, and augmentation are essential to ready the data for model training. This step forms the bedrock of our research, ensuring that the AI system can effectively glean insights from the plant images it encounters.

3.5. Model Selection

The selection of an appropriate CNN architecture or the design of a custom model tailored to our disease detection task is a pivotal decision in our research. Common architectures like VGG, ResNet, and Inception offer established templates for building our model. The chosen architecture will serve as the computational framework that underpins our AI system.

3.6. Model Training

With the model architecture in place, we embark on the training phase. During this stage, our AI model is fed with the preprocessed datasets, and its parameters, comprising weights and biases, are iteratively adjusted to minimize error or loss. The training process represents the machine learning heart of our research, where our AI system learns to detect plant diseases.

3.7. Hyperparameter Tuning

The optimization of hyperparameters becomes a vital task as we aim to improve the model's performance. Parameters such as learning rate, batch size, and dropout rates are subject to iterative adjustments. Hyperparameter tuning is an art in itself, allowing us to fine-tune our AI system for optimal results.

3.8. Model Evaluation

Once the AI model is trained, it is crucial to rigorously evaluate its performance. Metrics such as accuracy, precision, recall, and F1-score are employed to quantify its effectiveness. The evaluation stage serves as a litmus test, helping us assess how well our model performs against established benchmarks.

3.9. Testing and Validation

Beyond the evaluation, our research extends to testing and validation. Our model's performance on a separate test datasets is scrutinized to ensure its ability to generalize effectively to unseen data. This final step in the process ensures that our AI system is robust and dependable in real-world scenarios.

4. WORK DONE

Datasets is very important when working in Artificial Intelligence and machine Learning domain. The datasets we chose had apple plant leaves, the next thing to chose after choosing datasets was model to use with CNN. To find the best model for this research was very important. We ran test on the same dateset containing 3,171 images of Apple plant leaves. Then the next step was to give the parameters. We found out our model's accuracy changes with slightest change in parameter. The follow table shows different changing which gave our model 98% Accuracy.

Table 2 Parameters and values of Proposed Model

PARAMETERS	VALUES
Min_delta	0.001
Patience	10
Epochs	100
Batch size	32

Table 3 Comparing models with proposed model

Model	No. Of Parameters	Accuracy	Precision	Recall	F1-Score
ResNet-50	25,636,712	0.90	0.90	0.88	0.88
MobileNet	4,253,864	0.96	0.95	0.94	0.94
Deep CNN	121,964	0.98	0.98	0.97	0.97
Inception V3	23,851,784	0.95	0.95	0.94	0.94
Proposed Model	447,044	0.98	0.93	0.90	0.90

5. OBERVATIONS

Techniques like image augmentation, greyscale, masking can affect the efficiency and accuracy of the model[4]. We were ImageNet model and Augmentation helped us in increasing training and testing of the model as original image in Figure 2(A) and its augmented images in Figure 2(B) can be used in training which increases accuracy

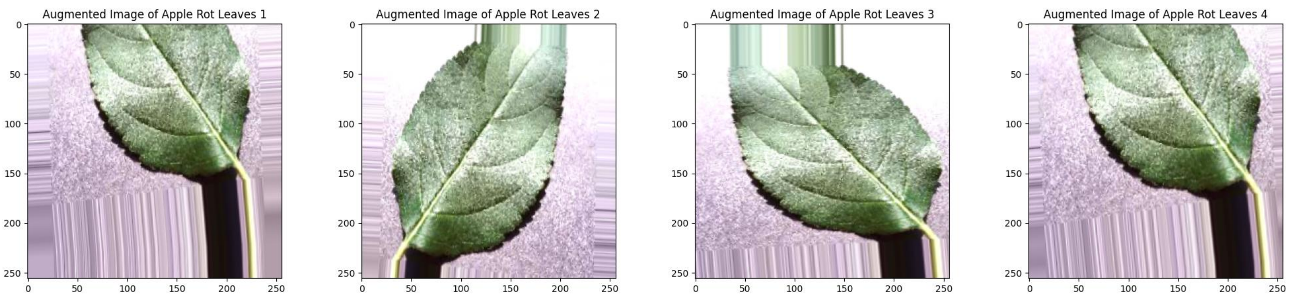


Figure 2(A) Augmented Image

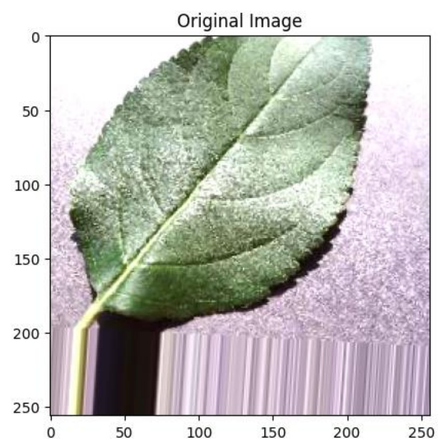


Figure 2(B) Original image

As we increased epochs from 25 to 100, we started getting more improved accuracy I.e. the variation in accuracy after each epoch decrease drastically and although losses in first few epochs are high, it gradually reduced to a very low percentage. But on increasing epochs more than 100 gave us very little to no improvement. Furthermore, We gave a strange relation between recall and precision on increase epochs from 25 to 100, the graph got stable outcomes.

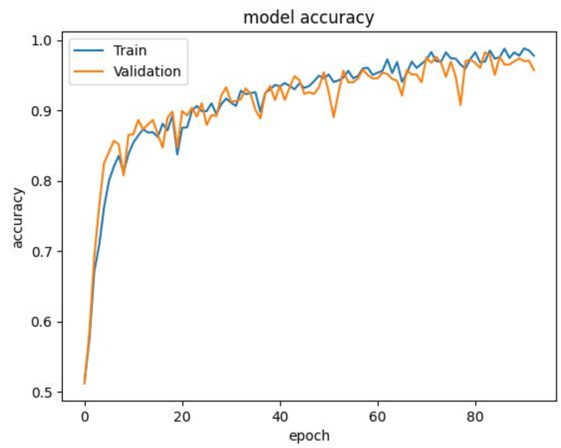


Figure 3 Model's accuracy with increasing epochs

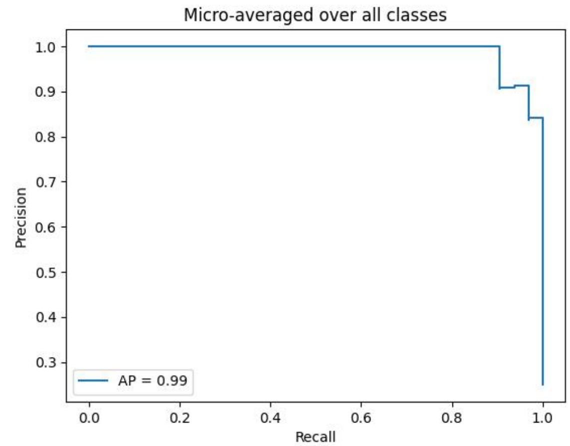


Figure 4 Precision verse Recall

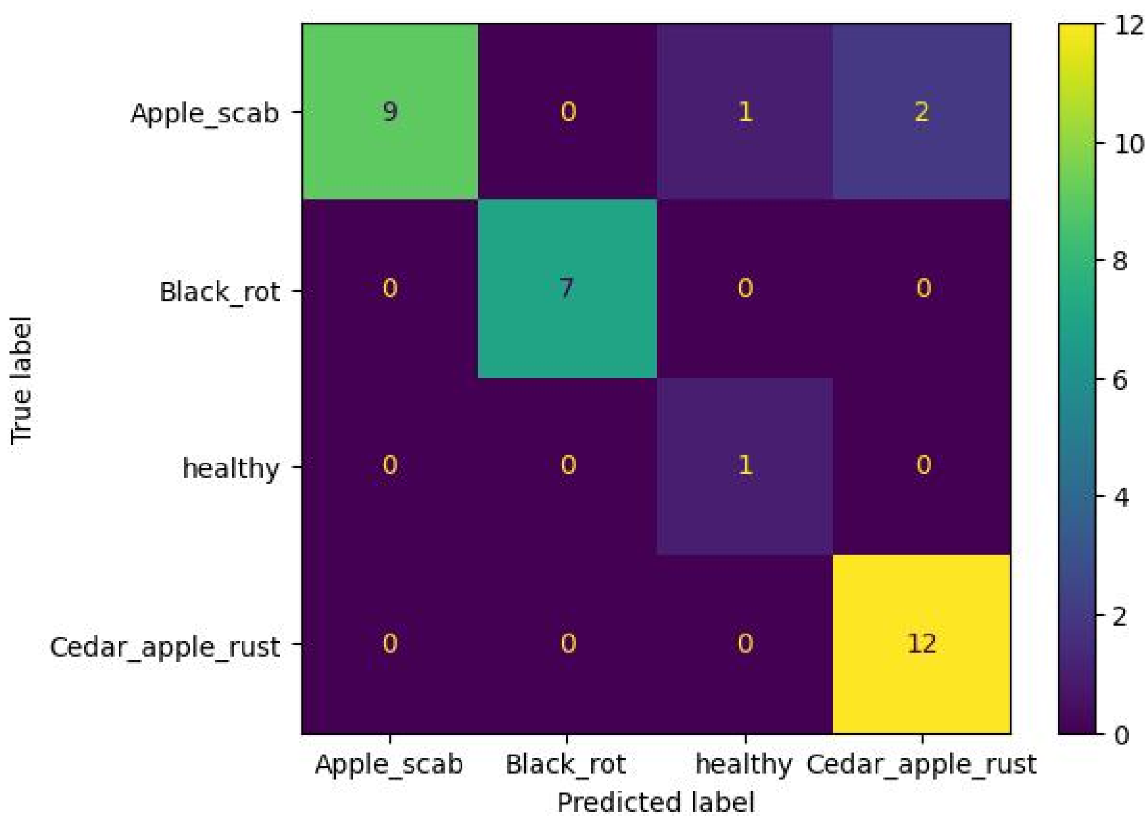
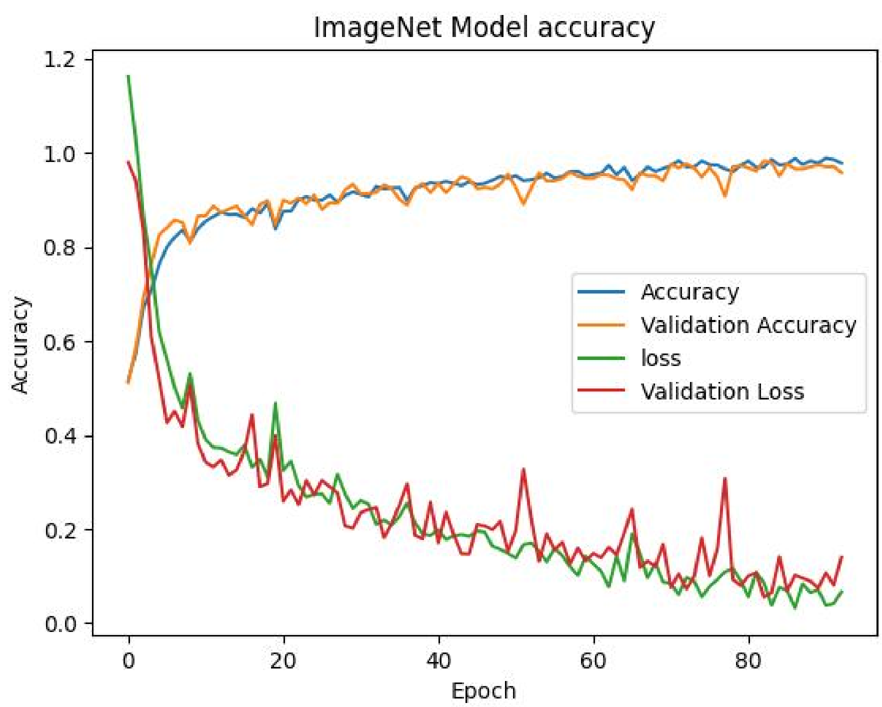


Figure 5 Confusion Matrix of proposed model

6. RESULT & CONCLUSION

We Achieved 98% accuracy CNN model for detection of Apple plant leaves with high precision in identifying apple plant diseases. In conclusion, this research underscores the transformative potential of AI, particularly CNNs, in revolutionizing plant disease detection, thus contributing to enhanced food security and sustainable agricultural practices. By summarizing key findings and suggesting areas for future research and innovation, this research seeks to shape the trajectory of AI applications in agriculture and horticulture.Looking to the future, We are looking to explores emerging trends and potential areas of improvement, such as multi-sensor data integration and ensemble models. Simultaneously, this research identifies research gaps as opportunities for future innovation and expansion in this dynamic field.



Graph 1 Model Accuracy and Losses

7. REFERENCES

1. M. M. Kabir, A. Q. Ohi, and M. F. Mridha, “A multi-plant disease diagnosis method using convolutional neural network,” CoRR, vol. abs/2011.05151, 2020.

2. J. Yao, S. N. Tran, S. Garg, and S. Sawyer, “Deep learning for plant identification and disease
classification from leaf images: Multi-prediction approaches,” 2023.

3. P. Sharma, P. Hans, and S. C. Gupta, “Classification of plant leaf diseases using machine learning and image prepossessing techniques,” in 2020 10th international conference on cloud
computing, data science & engineering (Confluence), pp. 480–484, IEEE, 2020.

4. I. K. K. B. K. S. M. VIBHOR KUMAR VISHNOI, (Member and A. A. KHAN, “Detection of apple plant diseases using leaf images through convolutional neural network,” pp. 1–59, 2022.

5. H. T. Rauf, B. A. Saleem, M. I. U. Lali, M. A. Khan, M. Sharif, and S. A. C. Bukhari, ‘‘A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning,’’ Data Brief, vol. 26, Oct. 2019, Art. no. 104340, doi: 10.1016/j.dib.2019.104340.

6. S. Kodors, G. Lacis, O. Sokolova, V. Zhukovs, and I. Apeinans,‘‘Apple scab detection using CNN and transfer learning,’’ Agron omy Res., vol. 19, no. 2, pp. 507–519, 2021. [Online]. Available: http://hdl.handle.net/10492/6447

7. D. P. Hughes and M. Salathe, ‘‘An open access repository of images on plant health to enable the development of mobile disease diagnostics,’’ 2015, arXiv:1511.08060.

8. J. Shin, Y. K. Chang, B. Heung, T. Nguyen-Quang, G. W. Price, and A. Al-Mallahi, ‘‘A deep learning approach for RGB image-based pow dery mildew disease detection on strawberry leaves,’’ Comput. Electron.Agricult., vol. 183, Apr. 2021, Art. no. 106042.

9. C. Bi, J. Wang, Y. Duan, B. Fu, J.-R. Kang, and Y. Shi, ‘‘MobileNet based apple leaf diseases identification,’’ Mobile Netw. Appl., vol. 27, no. 1, pp. 172–180, Aug. 2020, doi: 10.1007/s11036-020-01640-1.

10. M. B. Tahir, M. A. Khan, K. Javed, S. Kadry, Y.-D. Zhang, T. Akram, and M. Nazir, ‘‘Recognition of apple leaf diseases using deep learning and variances controlled features reduction,’’ Microprocess. Microsyst., 2021, doi: 10.1016/j.micpro.2021.104027.

11. D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, and N. Batra, “Plantdoc: A dataset for visual plant disease detection,” in Proceedings of the 7th ACM IKDD CoDS and 25th COMAD, pp. 249–253, 2020.

12. S. D.M., Akhilesh, S. A. Kumar, R. M.G. and P. C., "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight," 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, pp. 0645-0649, doi: 10.1109/ICCSP.2019.8698007.

13. G. Shrestha, Deepsikha, M. Das and N. Dey, "Plant Disease Detection Using CNN," 2020 IEEE Applied Signal Processing Conference (ASPCON), 2020, pp. 109-113, doi: 10.1109/ASPCON49795.2020.9276722.

14. Mohanty SP, Hughes DP and Salathé M (2016) Using Deep Learning for Image-Based Plant Disease Detection. Front. Plant Sci. 7:1419. doi: 10.3389/fpls.2016.01419

15. R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural Features for Image Classification," in IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, no. 6, pp. 610-621, Nov. 1973, doi: 10.1109/TSMC.1973.4309314.

16. Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324.