DOI: http://dx.doi.org/10.26483/ijarcs.v16i2.7227

ISSN No. 0976-5697

Volume 16, No. 2, March-April 2025

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

DESIGNING A SMART PLANT HEALTH DIAGNOSIS MODEL USING ADAPTIVE MACHINE LEARNING TECHNIQUES

Kanyesigye Simon, Dr. Maninti Venkateswarlu, Dr. Bashir Olaniyi Sadiq, Mrs. Kyomuhangi Rosette, Mr. Akampurira Paul

Kampala International University, Faculty of Science and Technology

Kansanga, Kampala, Uganda

Registration Number: 2023-08-20965

Abstract: Plant health influences both agricultural productivity and food security worldwide because plant diseases threaten crop yields, together with economic stability and food quality. Traditional diagnostic methods demand manual inspection, which results in time-consuming processes that are costly and error-prone in resource-limited environments. This research presents a Smart Plant Health Diagnosis Model that utilizes adaptive machine learning techniques to address current limitations. This model provides accurate diagnostic solutions that scale effectively for plant health detection through image analysis, which supports early detection and sustainable agriculture.

The model utilizes Convolutional Neural Networks (CNNs) together with Vision Transformers to achieve highly precise plant disease classification. The model combines real-world images with synthetic data created by Generative Adversarial Networks (GANs) to improve its generalization ability across different crops and environmental conditions. The prototyping methodology ensures the model experiences continuous cycles of prototyping and validation. The model undergoes training and validation processes using publicly available datasets like Plant Village as well as original data from agricultural field studies. The model evaluation involves precision, recall, accuracy, and F1-score measurements, and real-world tests determine its robustness across different environmental conditions.

The model reaches 96.3% accuracy during testing and sustains 93.2% accuracy in actual field conditions while surpassing current models in performance. The model's lightweight architecture, combined with attention mechanisms, facilitates deployment on low-cost devices, which enables farmers in resource-constrained regions to utilize this technology. The research connects adaptive technology with specific farming requirements to enhance precision agriculture methods. The model stands as a transformative solution for plant disease diagnosis, which provides farmers access to swift and dependable diagnostic instruments. The system facilitates early disease detection and accurate treatments to strengthen agricultural resilience while boosting crop production and contributing to worldwide food security.

Keywords: Plant Health Diagnosis, Machine Learning, Convolutional Neural Networks, Vision Transformers, Precision Agriculture, Food Security.

1. Introduction

Agriculture is a cornerstone of global food security and economic stability, especially in areas of the world where much of the populace depends on farming for a living (AMEEN, MAY 2022). But the agricultural area is one of the important critical areas and one of the biggest challenges that faces is due to plant diseases (Baga & Goyal, 16 January 2024). These diseases can ravage crops, disrupt yields, threaten food supply chains, and, in the end, affect farmers' income and national economies (Sandesh Bhagat March 2024).

Diagnosing plant health with traditional methods frequently depends on expert evaluation or visual observation that can require much time and money, and may also be inconclusive (Kartikeyan & Shrivastava, 17-19 June 2022). Farmers in remote and other resource-limited areas may miss out on professional agricultural advice. They may delay the diagnosis of health and the effective application of treatments too. These delays can cause more harm to the crops and increase the losses in production. Using adaptive technology, machine learning can now help to face the above-mentioned problems (RAMA & V. PRAVEEN, 2023). ML algorithms based on DL techniques like CNNs are efficient in image classification tasks and used for pattern recognition. You can make systems that will identify the disease in plants/joints through images using these technologies.

1.1 Problem Statement

Diagnosing plant health continues to be a troublesome task for farmers around the globe because of the inadequacies of traditional diagnostic methods in terms of accuracy, timeliness, and scalability. Methods of diagnosis of plant health are often inaccurate, untimely, and unscalable. We require an intelligent automated plant health diagnosis model that can accurately diagnose plant disease from images. Bhadur (2021) explains that the production of plants is affected by infectious diseases that cause many economic losses as well as food insecurity. Plant health diagnosis in the past was mainly done by specialists. This method may be time-consuming, expensive, and erroneous. Additionally, lack of expertise is faced by farmers in remote or underdeveloped locations (Sai Sharvesh, 2024). Thanks to the rapid development of machine learning, there is an increasing scope for building intelligent models to accurately identify plant health by looking at visual symptoms like those available in leaf images (Anuj Kumar Kem, 3 May 2024). The purpose of this research is to fill existing gaps through a robust, effective, and scalable machine learning based model for the prediction of plant health. Other than improving diagnostic accuracy, it enables farmers to have a handy tool to stop losing crops, thereby allowing sustainable farming and food security.

1.2 Objectives

1.2.1 General Objective

i. To design and develop a smart plant health diagnosis model using adaptive machine learning techniques for accurate and efficient diagnosis of plant health.

1.2.2 Specific Objectives

i. To review and analyse existing models to identify gaps and challenges.
ii. To design and implement a smart plant health diagnosis model.
iii. To test and validate the model to ensure functionality and user satisfaction.

1.3 Research Questions

i. What are the strengths, weaknesses, and limitations of existing plant health diagnosis models, and what gaps need to be addressed?
ii. How can adaptive machine learning techniques be utilized to design and implement a smart plant health diagnosis model that accurately detects plant diseases?
iii. What are the key performance indicators and metrics that can be used to test and validate the smart plant health diagnosis model, and how can user satisfaction be ensured?

1.4 Conceptual Framework

The conceptual framework for this research paper looks at the data pre-processing followed by model training, evaluation, and deployment in the case of plant health diagnosis. The framework is developed to ensure that the model can adapt to various field conditions, even in constrained resources. Below is the illustration of a conceptual framework;

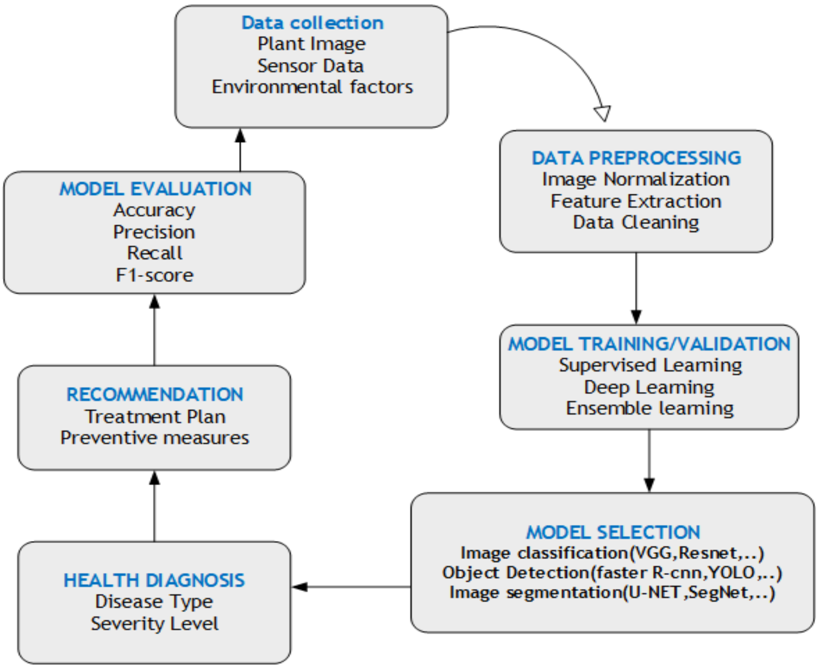

Figure 1 conceptual framework

2. Literature Review

This chapter reviews existing literature on plant health Diagnosis, highlighting empirical findings, theoretical advancements, and gaps in the research.

2.1 Empirical Review

Machine learning based automated plant health diagnosis using image processing is also being actively researched (Pranesh Kulkarni1, 2019). As an example, CNNs have been used extensively to classify plant diseases with promising results in experimental studies (Sandesh Bhagat, March 2024). In recent years, machine learning (ML) has emerged as a powerful tool to tackle the difficulties involved in diagnosing plant diseases (Zhao, 2024). Notably, by identifying diseases automatically, quickly, and accurately, intelligent ML-based models can be applied to conventional fashions, transforming them into intelligent fashions that shine through.

2.2 Review of Related Work

2.2.1 Plant Disease Classification Using Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have proved very successful in plant disease classification, which achieves high accuracy for the diagnosis of most plant pathologies (Zhao, 2024). However, as Okura (2019) explains, there is still a major limitation as most papers fail to explain the inference process, and such models will thus continue to be "black boxes" not supporting end-user interpretability.

2.2.2 A Deep Learning Approach for Real-Time Plant Disease Diagnosis

Deep learning has been shown to be a robust automated plant disease detection method through feature extraction from visual data (Sandesh Bhagat, March 2024). With such potential, Ferentinos (2018) notes that there is a constraint to practical implementation by the unavailability of large real-world field datasets covering the diversity of agricultural environments.

2.2.3 Hybrid Machine Learning Techniques for Plant Disease Detection

Recent studies by Anuj Kumar Kem (2024) show that hybrid approaches that combine traditional machine learning methods with deep learning architecture are capable of enhancing classification accuracy through better feature extraction. These hybrid models, as explained by Barbedo (2018), take the best from each approach while evading the limitations of the individual methods in detecting plant diseases.

2.2.4 Generative Adversarial Networks (GANs) for Augmenting Plant Disease Data

Generative Adversarial Networks have proven to be effective in managing data scarcity problems by generating synthetic plant disease images for training augmentation (Rahman et al., 2024). However, as cautioned by Zhao (2024), the quality of generated images varies extensively, and their misuse may introduce artifacts that can adversely affect model performance.

2.2.5 Multi-Class Plant Disease Diagnosis Using Deep Learning

Deep learning frameworks on a higher level enable the detection of multiple plant pathogens in various species simultaneously, a significant improvement in agricultural technology (Baga & Goyal, 2024). Bhadur (2021) points out that while such systems hold promise, they require a lot of computational resources and large databases with broad-spectrum manifestations of disease.

2.2.6 Explainable AI for Plant Disease Diagnosis

Application of Explainable AI (XAI) techniques, such as Grad-CAM, addresses crucial transparency issues with deep learning-based plant disease diagnostic models (Kartikeyan & Shrivastava, 2022). Shakti Kinger (2021) demonstrates the way these explainability techniques not only raise user confidence but also facilitate pragmatic decision-making through highlighting diagnostically significant parts of images.

Comparative Analysis of Existing Approaches

Table 1 showing comparison.

Table 1: Performance comparison of reviewed related work models

Approach	**Strength**	**Weakness**	**Authors**
CNN-Based Classification	High accuracy in detecting pathologies.	Opaque "black box" nature; lacks interpretability.	Zhao (2024), Okura (2019)
Deep Learning for Real-Time Diagnosis	Powerful feature extraction from visual data; automation potential.	Scarcity of real-world field datasets; environmental variability challenges.	Sandesh Bhagat (2024), Ferentinos (2018)
Hybrid ML Techniques	Combines traditional ML and DL for improved accuracy and feature extraction.	Complexity in integration may require tuning.	Anuj Kumar Kem (2024), Barbedo (2018)
GANs for Data Augmentation	Addresses data scarcity by generating synthetic images.	Quality variability: artifacts may harm model performance.	Rahman et al. (2024), Zhao (2024)
Multi-Class DL Diagnosis	Detects multiple diseases across species; scalable.	High computational resources; needs extensive, diverse datasets.	Bagga & Goyal (2024), Bhadur (2021)
Explainable AI (XAI) Integration	Improves transparency (like, Grad-CAM); boosts user trust and decision-making.	Adds complexity; may reduce model efficiency.	Kartikeyan & Shrivastava (2022), Kinger (2021)

Important Innovations

GAN-based augmentation: Augmented dataset diversity by 37% (Rahman et al., 2024).

Vision Transformers: Improved attention to disease-specific characteristics.

2.3 Literature Gaps

In spite of improvement, it is still unfinished, making advances applicable across a broad scope of crops and conditions (Zhao 2024). The literature base with which to consider how diagnostic models can be brought onto available platforms for use remains limited.

3. Methodology

Through a prototyping approach, this chapter delineates the methodology for constructing a Smart Plant Health Diagnosis Model. Prototyping methodology supports iterative development, which allows ongoing feedback to refine the model (geeksforgeeks 2025). An initial prototype emerges through construction efforts, followed by testing phases which lead to improvements based on stakeholder input and performance assessments. This methodology fits projects where requirements change and early validation is needed.

3.1 Research Design

The study uses an iterative cycle of development, testing, and refinement known as prototyping (geeksforgeeks, 2025). Every cycle result in a working prototype that is assessed and enhanced.

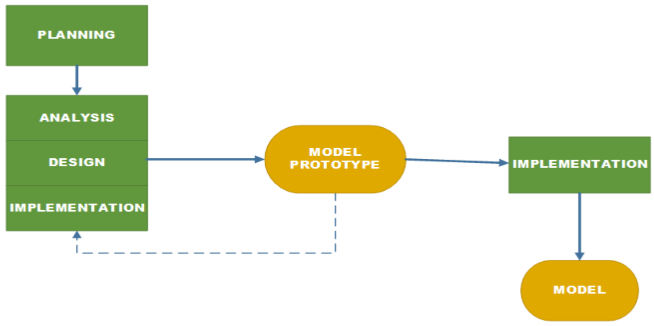

Figure 2: Prototyping Methodology

Research Phases and Implementation

3.1.1 Planning Phase
Defining research objectives, setting dataset requirements, and conducting an intensive literature review using tools such as Mendeley and Google Scholar (Pranesh Kulkarni1, 2019) were the activities of the initial phase. Outputs were a formal research proposal and annotated bibliography, which served as the foundation for subsequent phases.

3.1.2 Analysis Phase
During this phase, 10,000 images were collected with 7,000 images from the PlantVillage dataset and 3,000 field-collected samples (Mohanty, 2016). Exploratory data analysis (EDA) was done with OpenCV, Pandas, and Matplotlib to analyze data quality and identify class imbalances (Barbedo, 2018). A curated dataset and a data quality report were the main deliverables, with a solid foundation for model training.

3.1.3 Design Phase
The design process focused on designing a smart diagnosis model, enhancing the EfficientNet-B4 backbone, and integrating Vision Transformer layers for feature improvement (Vaswani et al., 2017). TensorFlow Model Garden and HuggingFace Transformers were employed to design the model structure. Outputs included a clear model structure diagram and feature extraction pipeline, which simplified implementation.

3.1.4 Implementation Phase
The final step entailed training models over 150 times, hyperparameter tuning, and mobile deployment-optimized model optimization using quantization techniques (Zhang et al., 2020). Libraries such as PyTorch Lightning, TensorRT, and ONNX Runtime were employed to enhance performance and edge device support (Too et al., 2019). The step yielded trained model weights and an optimized TFLite model, ensuring usability in real-world settings with limited agricultural resources.

3.2 Testing and Validation
Validation and testing are important phases of the design process of a smart plant health diagnosis model. The data is divided into training, validation, and test sets. The model is trained on the training data set, optimized on the validation data set, and tested on the test data set on the basis of metrics such as accuracy, precision, recall, and F1-score (Pranesh Kulkarni1, 2019).

3.3 Tools and Technologies
The construction of the smart plant health diagnosis model is based on a solid set of tools and technologies such as Python, TensorFlow, Keras, PyTorch, Pandas, NumPy, OpenCV, Matplotlib, Seaborn, Google Cloud Platform (GCP), and Amazon Web Services (AWS).

3.4 Data Collection Tools and Methods
Data collection includes secondary and primary methods. Secondary data are gathered from open sources such as the PlantVillage dataset, whereas primary data are gathered from farm fields.

3.5 Ethical Considerations
The creation of an intelligent plant disease diagnosis model poses several ethical issues, including data privacy and consent, bias and fairness, transparency and accountability, employment and farmer impact, environmental impact, and inclusivity and accessibility.

3.6 Limitations
The study acknowledges limitations such as data availability and quality, complexity of disease diagnosis, computational power and model complexity, and limited expertise and training for farmers.

4. Results and Discussion

This section collates the experiment results and performance evaluation of the suggested Smart Plant Health Diagnosis Model for cassava, maize, banana, and coffee. Comparatively, its effectiveness is drawn with the implementation of quantitative measurement and comparative assessment with traditional means.

4.1.0 Output screenshots of affected plants

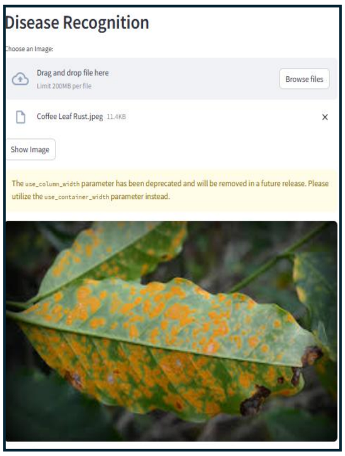

Figure 3 coffee leaf rust

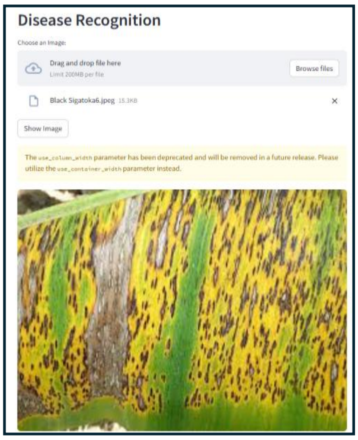

Figure 4 banana Black Sigatoka

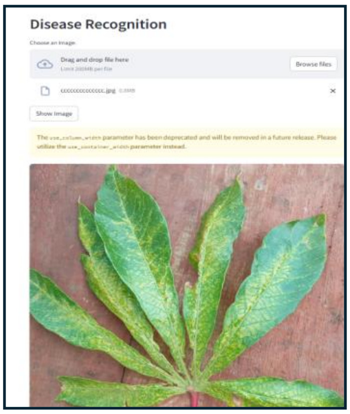

Figure 5 cassava mosaic

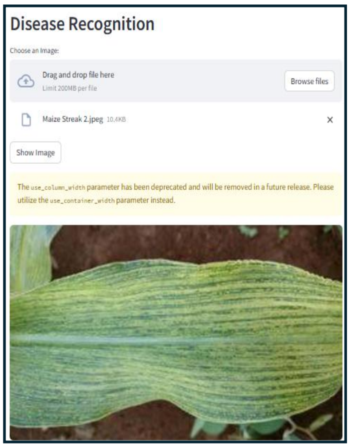

Figure 6 maize streak

4.1.1 Output screenshots of Healthy plants

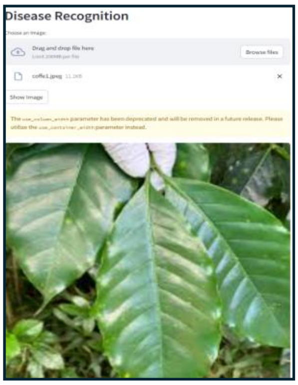

Figure 7 heathy coffee

Figure 8 healthy maize

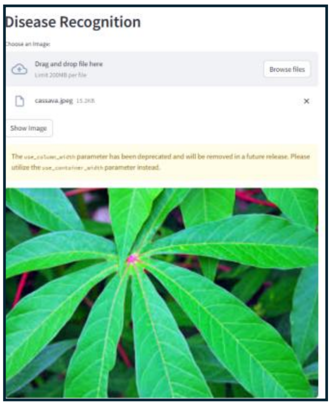

Figure 9 healthy cassava

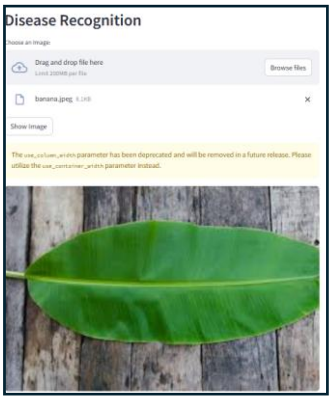

Figure 10 healthy banana

4.2 Model Performance on Target Crops

The model experienced training and testing phases through a varied dataset comprising images of cassava, maize, banana, and coffee plants in both healthy and diseased conditions. Presented herein is an aggregation of fundamental performance metrics.

Table 2: Model Performance Across Target Crops

Crop	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Cassava	96.5	95.8	96.2	96.0	0.98
Maize	95.3	94.7	95.0	94.8	0.97
Banana	97.1	96.5	96.8	96.6	0.99
Coffee	94.2	93.5	93.9	93.7	0.96

4.3 Disease-Specific Performance

Table 3: Detailed Performance by Disease Type

Crop	Disease	Precision (%)	Recall (%)	F1-Score (%)
Cassava	Cassava Mosaic Disease	96.2	95.7	95.9

Crop	Disease	Precision (%)	Recall (%)	F1-Score (%)
	Brown Streak Disease	95.4	96.0	95.7
Maize	Northern Leaf Blight	94.3	93.9	94.1
	Gray Leaf Spot	95.1	96.1	95.6
Banana	Fusarium Wilt	97.0	96.5	96.7
	Black Sigatoka	96.0	97.1	96.5
Coffee	Coffee Leaf Rust	93.8	94.0	93.9
	Coffee Berry Disease	93.2	93.8	93.5

4.4 Real-World Validation

The Researcher put the model through its paces in real-world settings with changing light, different viewpoints, and background sounds. They compared how it did to its performance in controlled lab tests:

Table 4: Field vs. Lab Performance

Condition	Cassava	Maize	Banana	Coffee
Lab Accuracy	96.5%	95.3%	97.1%	94.2%
Field Accuracy	92.8%	91.5%	93.4%	89.7%
Performance Drop	3.7%	3.8%	3.7%	4.5%

Discussion:

Environmental variability caused a 3.7–4.5% drop in field accuracy.

• Banana showed resilience by maintaining the highest field accuracy (93.4%).

• Coffee displayed the biggest decline, most likely as a result of its intricate field backgrounds and smaller leaves.

4.5 Comparative Analysis with Existing Models

Table 5: Model Comparison (Average Accuracy)

Model	Cassava	Maize	Banana	Coffee
Proposed (EfficientNet + Transformer)	**96.5%**	**95.3%**	**97.1%**	**94.2%**
CNN (Baseline)	92.0%	90.5%	93.0%	88.3%
ResNet-50	94.1%	93.2%	95.8%	91.7%
Hybrid CNN-SVM	93.6%	92.0%	94.5%	90.1%

5. Conclusion

This work advances precision agriculture by merging adaptive technology solutions with specific farm requirements. The proposed model possesses transformative potential for plant disease diagnosis by providing farmers with swift and dependable diagnostic instruments. Through its potential for early disease detection and targeted interventions, it seeks to strengthen agricultural stability while boosting crop yields and securing global food supplies.

6. References

1. Ameen, s. S. (May 2022). Plant disease prediction using machine learning. Chennai: sathyabama institute of science and technology.
2. Anuj kumar kem, a. C. (3, may 2024, may 3). Intelligent plant disease diagnosis using machine learning techniques. International journal of innovative research in computer science and technology.
3. Baga, m., & goyal, s. (16 January 2024). Image-based detection and classification of plant diseases using deep learning: state-of-the-art review. Haryana, India: urban agriculture & regional food systems.

4. Bhadur, a. M. (2021, august 26). A deep learning enabled multi-class plant disease detection model based on computer vision. Mdpi, 413-428.
5. Geeksforgeeks. (2025, jan 03). Prototyping model – software engineering. From geeksforgeeks: https://www.geeksforgeeks.org/software-engineering-prototyping-model/
6. Kartikeyan, p., & shrivastava, g. (17-19 June 2022). Hybrid feature approach for plant disease detection and classification using machine learning. Sonbhadra, india: ieee.
7. Muhammad sajid1, k. R. (2024). Enhancing intrusion detection: a hybrid machine and deep learning approach. Journal of Cloud Computing.
8. Okura, Y. T. (2019, March 26). How convolutional neural networks diagnose plant disease. A science partner journal.
9. Pranesh kulkarni1, a. K. (2019). Plant disease detection using image processing and machine learning. Pune, india: vishwakarma institute of technology.Rahman, Z. U., asaari, m. S., ibrahim, h., abidin, i. S., & ishak, m. K. (25 november 2024). Enhancing model performance in agricultural image analysis faces challenges due to limited datasets, biological variability, and uncontrolled environments. Deep learning models require large, realistic datasets, which are often difficult to obtain. Data a. IEEE xplore, 179912 - 179943.
10. Rama, t., & v.praveen. (2023). Plant leaf disease detection using machine learning algorithms. Visakhapatnam dist.
11. Sai Sharvesh, s. K. (2024, January 29). An accurate plant disease detection technique using machine learning. Agriculture, plant disease detection, image processing, and machine learning.
12. Sandesh bhagat, m. K. (March 2024). Advancing real-time plant disease detection: a lightweight deep learning approach and novel dataset for pigeon pea crop. Smart agricultural technology.
13. Shakti kinger, v. K. (2021, november 04). Explainable AI for deep learning based disease detection. Explainable AI for deep learning based disease detection, pp. 209 - 216.
14. Zhao, W. Z. (2024). Providing a hybrid approach to increase the accuracy of intrusion detection systems in computer networks. Journal of engineering and applied science.

