MULTIDISCIPLINARY APPLIED RESEARCH AND INNOVATION
e-ISSN: 2773-4773

MARI

Vol. 6 No. 1 (2025) 91-98
https://publisher.uthm.edu.my/periodicals/index.php/mari

Sprout-AI: Image-Based Plant Disease Detection Mobile Application

Nur Aisyah Mohamad Sulaiman, Nur Farhah Ain Ezam Shah, Nur Zulaikha Norhashim, Mazniha Berahim*

Department of Information Technology, Centre for Diploma Studies,
Universiti Tun Hussein Onn Malaysia, Pagoh Higher Education Hub, 84600 Pagoh, Johor, MALAYSIA

*Corresponding Author: mazniha@uthm.edu.my
DOI: https://doi.org/10.30880/mari.2025.06.01.013

Article Info

Received: 1 October 2024
Accepted: 30 November 2024
Available online: 15 January 2025

Keywords

Artificial Intelligence, Image Detection, Plant Diseases, Agricultural Technology and Plant Care Tips.

Abstract

This project aims to produce an image-based plant disease detection mobile application, Sprout-AI designed to revolutionise plant disease management for farmers and gardeners. While existing solutions on the market provide basic plant support, Sprout-AI goes further and provides comprehensive information and interactive support. Leveraging advanced image detection and an AI-powered chatbot, Sprout-AI provides accurate disease detection, personalised treatment recommendations, and ongoing plant care guidance. The biggest challenge Sprout-AI addresses is the lack of accessible information about plant diseases, which hinders effective plant care. By integrating machine learning models for real-time image detection, Sprout-AI enables users to quickly detect and control plant diseases. The AI chatbot improves the user experience by providing tailored advice and addressing specific questions. Developed using the ADDIE model, Sprout-AI goes through rigorous analysis, design, development, implementation, and evaluation phases to ensure functionality and effectiveness. Combining advanced technology with user-centred design, Sprout-AI emerges as a comprehensive solution for managing plant health and improving agricultural outcomes.

1. Introduction

Artificial intelligence (AI) has revolutionised numerous industries, including healthcare, education, and security, through applications like facial recognition and biometric monitoring. However, despite its potential, AI adoption in the agricultural sector, particularly in plant disease detection, has been slower. Plant diseases, caused by bacteria, fungi, and viruses, pose serious threats to crops and impact agricultural productivity at various growth stages. Infections affect plants at different stages of agricultural production [1]. Common diseases such as scab, rust, late blight, and bacterial spot, if left untreated, can result in significant yield loss, affecting food security and economic stability.

Currently, farmers and gardeners face challenges in accurately identifying plant diseases and accessing timely treatment information. Most rely on manual inspection or limited resources, which can be inefficient and prone to error. Additionally, implementing AI technology in plant disease detection faces several challenges, including ensuring the accuracy and reliability of detection algorithms and processing datasets. Many datasets, sourced from websites, contain irrelevant data or images that do not reflect local plant species, complicating the development of useful tools for beginner farmers and gardeners. Environmental variations also affect the quality of these images, making the detection process even more complex.

Therefore, the objectives of this project are to develop a mobile application that integrates AI technology, including image detection and an assistant AI chatbot. The application will feature treatment tips and provide comprehensive disease information, treatment recommendations, and plant care guidance. It will support up to 16 types of plants, using image detection to identify diseases with results displayed through text and background sound. The AI chatbot will assist users with plant-related queries and offer educational content to raise awareness about plant care. This approach aims to enhance user interaction and provide accurate, real-time information for effective plant disease management.

The remaining sections of this paper are organised as follows: Section 2 presents a literature review relevant to the project. Section 3 outlines the project methodology. Section 4 discusses the results and user evaluations. Finally, Section 5 summarises the project's achievements and explores potential future improvements. This mobile application is designed to meet the needs of farmers, gardeners, and plant enthusiasts, providing a user-friendly platform for plant health management, and fostering greater interest in gardening among new generations.

2. Literature Review

2.1 Plant Disease

Plant diseases are widespread in agricultural fields, affecting all farmers and gardeners and significantly influencing crop health and productivity. There are various types of plant diseases covered in this project which are common diseases to be found in plants such as black rot, early blight, late blight, rust, black measles, and bacterial spot. These diseases can be found in myriads of plants such as curry trees, chilli trees, apple trees, potato trees and others.

2.2 Image Detection and TensorFlow Lite

With advanced technology, we embedded the AI field in this proposed mobile application, which allows farmers and gardeners to capture the real-time image detection of infected plants using their smartphones. It can be analysed using object detection with deep learning techniques by using Convolutional Neural Networks (CNNs) to identify potential diseases. CNN is a type of artificial neural network used primarily for image detection and processing, due to its ability to recognise patterns in images. For the model development process, we created a custom CNN model from scratch to tailor plant disease detection excels in accurately classifying diseases based on image analysis. Its precision in identifying subtle visual cues specific to plant health issues demonstrates its capability to reliably distinguish between various disease symptoms captured in images.

Since the proposed project is a mobile application, TensorFlow Lite has been used in the developed mobile application. TensorFlow Lite is a lightweight version of TensorFlow, which is Google's open-source framework for machine learning and deep learning. TensorFlow Lite is specifically designed to run on mobile and embedded devices, making it possible to deploy machine learning models on smartphones, tablets, microcontrollers, and other devices with low computational resources. Several projects such as EfficientNet were developed using TensorFlow by researchers at Google AI in 2019, achieving top 1 accuracy of over 84% on the ImageNet dataset. Other than that, BERT (Bidirectional Encoder Representations from Transformers) has been implemented using TensorFlow and achieved state-of-the-art results in various NLP benchmarks. BERT achieved impressive results on the General Language Understanding Evaluation (GLUE) benchmark score of 80.5% [2].

In SproutAI, we are using image detection to detect plant diseases using real-time image detection. Image detection for plant disease, also known as plant disease detection using computer vision, is a technique that leverages machine learning models to identify diseases or pests affecting plants based on images of their leaves. Once the images are captured, preprocessing techniques are applied to enhance the quality and suitability of the images for analysis. This may involve operations such as resizing, normalisation, and colour adjustment to standardise the images. This approach holds promise for revolutionising agriculture by enabling early and accurate detection of diseases, thereby facilitating timely treatment and management practices.

Existing applications that also use similar approaches are PlantVillage [3], and Plantix [4]. However, specific accuracy metrics may vary, but generally, these applications strive for high accuracy rates. Accuracy in these applications can be influenced by factors such as the quality and diversity of the training data, the robustness of the machine learning models used and the conditions under which the models were evaluated such as types of plants, variations in lighting and environmental conditions.

2.3 AI Chatbot

This application is also integrated with an AI chatbot called SproutBuddy. SproutBuddy is tailored specifically for plant-related inquiries such as disease identification, treatment options, overall plant health assessment, and plant identification based on images. This chatbot enhances user interaction by providing comprehensive and accurate information through natural language processing (NLP).

We leverage Gemini's framework and develop this feature to ensure robust functionality and reliability. By integrating Gemini, we capitalise on its advanced capabilities in understanding and responding to diverse plant-related queries, thereby offering users a seamless and informative experience. This approach not only enhances user engagement but also underscores our commitment to leveraging state-of-the-art AI technologies for practical agricultural and botanical applications.

3. Methodology

Sprout-AI mobile application necessitates a methodology to serve as a framework for planning, developing, and executing it. The selected project management methodology will dictate the progression of our project. Align with our goal to enhance the image detection feature, we adopt Agile[5] principles for iterative progress and combine them with a proposed methodology comprised of several key stages: data collection, data preprocessing, development of the classification model, development of the mobile application, classification of user-selected images, and reporting of classification results to the user. The flowchart of our proposed method is illustrated in Fig. 1.

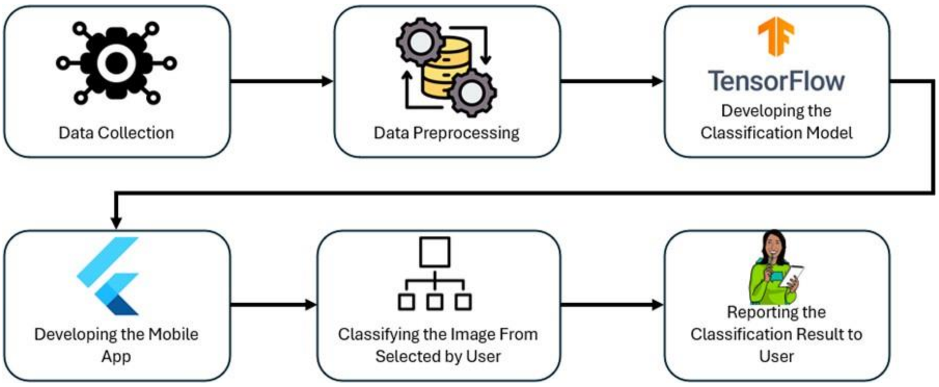


Fig. 1 *Flowchart of the proposed method*

3.1 Data Collection and Preprocessing

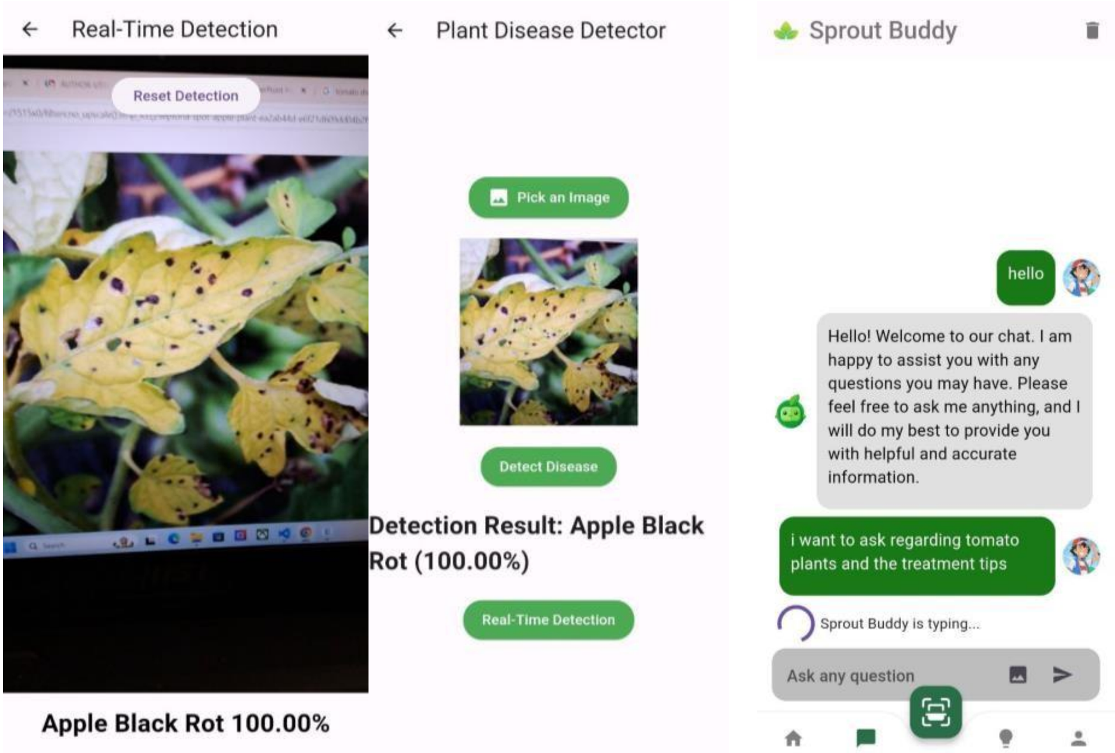
In the data collection phase for developing Sprout-AI, we will primarily utilise the open-access PlantVillage [6] dataset, which consists of 14 crop plants and includes diverse images of healthy and diseased leaves. Not just that, we have incorporated images of curry and chilli plants to improve the dataset's accuracy and relevance for a broader range of crops. Next, we moved to the data preprocessing phase, which required steps such as augmentation, standardisation, and folder structuring. Image augmentation is essential to expand the dataset by flipping, cropping, or adjusting the hue of the images, thereby increasing the variability and robustness of the model. For standardisation, images will be resized to 224x224 pixels and converted to JPG format to ensure uniformity and compatibility with the neural network input requirements. Lastly, the images will be divided into training and validation datasets, and organised into folders corresponding to disease categories to facilitate efficient model training and evaluation. This structured approach ensures that our dataset is comprehensive, balanced, and ready for effective machine learning application.

3.2 Classification Model Development

In the classification model development phase, we proposed a customised convolutional neural network (CNN) to classify plant diseases. The model consists of three convolutional layers with max pooling, followed by a flattened layer and two dense layers. The CNN technique will effectively distinguish between healthy and diseased plants. We aim to create a highly accurate model capable of real-time plant disease detection therefore the iterative process will be set to 90 epochs to ensure optimal performance. Our development process involved utilising Dart and Python for machine learning and dataset training, supported by TensorFlow & Keras frameworks for deep learning to build robust back-end systems capable of handling the complexities of our application's machine learning components. Scalability, security, and performance optimisations were ensured throughout this process, laying a solid foundation for future iterations and expansions.

3.3 Mobile Application Development and Classification Result

For the mobile application development, we utilised Flutter as our IDE to develop the application, integrating features such as an AI chatbot. The plant disease detector offers real-time image detection and image uploading functionalities. This stage involves evaluating the correctness of image classification, ensuring that the application accurately identifies plant diseases based on user-submitted images. Additionally, it focuses on the usability of the user interface, confirming that it is intuitive and easy to navigate. Users perform various tasks, such as uploading images for disease classification and navigating through different features. Fig. 2 (a) illustrates the real-time and uploaded image. Real-time detection enables users to scan a plant leaf through the camera and display the result of the plant's condition. Meanwhile, the second functionality of image detection which is image upload which allows users to select a specific image for plant disease detection. Fig. 2 (b) showcases the Sprout-AI chatbot's functionality, featuring a text input box for user queries and an option to send images. The chatbot responds accordingly, with a 'Send' button for submitting questions and a 'Delete' button on the app bar to clear the chat.



(a) (b)

Fig. 2 *Integrated AI technology (a) Plant disease detector; (b) Chatbot*

By integrating classification results into the mobile application development, we can conclude decisions about design and functionality, ensuring that the application not only meets technical requirements but also aligns with user expectations.

4. Results and Discussion

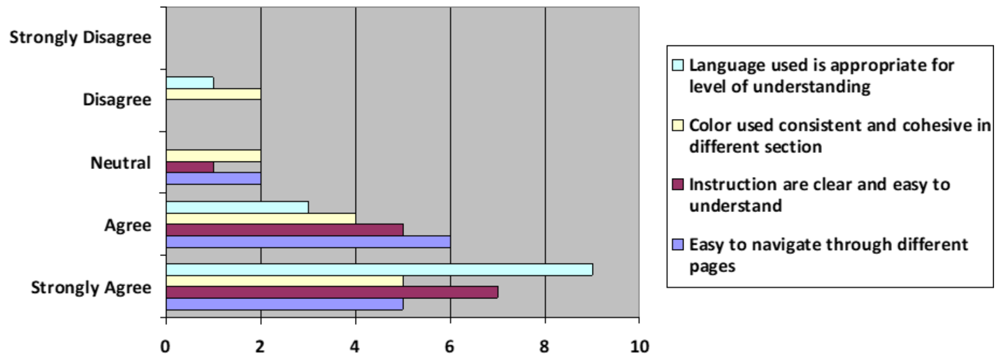
This section will summarise the conducted survey regarding the proposed project which was conducted via a Google Form provided to participants. Users were given a brief explanation of the application before answering the survey, ensuring they understood its objective and flow. This survey is categorised into four parts: the first part covers user information, the second part focuses on design and functionality, the third part discusses features and accuracy, and the fourth part evaluates overall satisfaction. In the first and fourth parts, the evaluation will be conducted using a Dichotomous scale, while the second and third parts will be evaluated by a Likert scale from strongly agree to strongly disagree. This survey was distributed to the farmers, gardeners, and others. Table 1 represents the distribution of respondents' occupations, from farmers, gardeners, and respondents from other backgrounds.

Multidisciplinary Applied Research and Innovation Vol. 6 No. 1 (2025) p. 91-98

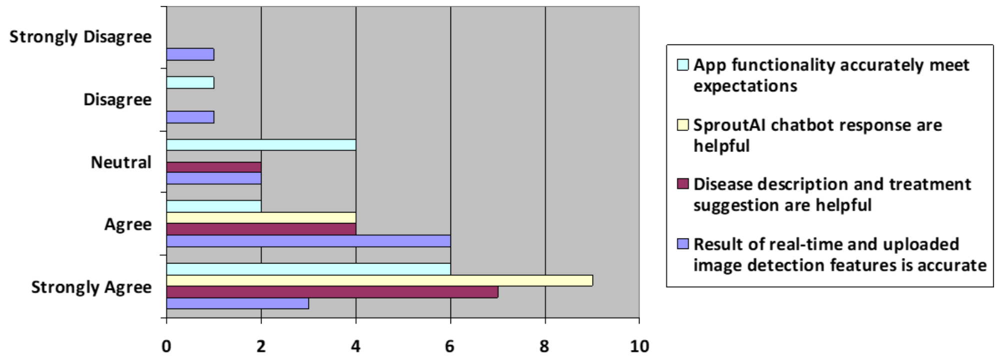
Table 1 *Quantity respondents based on occupation*

Occupation	Quantity
Farmer	3
Gardener	5
Others	5

Fig. 3 presents the survey results in a bar chart, indicating that the total number of respondents is 13. Most respondents strongly agree with Part 2 and Part 3 of this survey that the design and functionality of this mobile application use appropriate language for the level of understanding and the features and accuracy accurately meet expectations.



(a)



(b)

Fig. 3 *Evaluation of surveyed (a) Design and functionality; (b) Features and accuracy*

4.1 Evaluation of Design and Functionality

Fig. 3 (a) illustrates and summarizes the survey responses on the design and functionality of the apps. Most respondents strongly agree and agree that it is easy to navigate through different pages, while some feel neutral.

This results in our app delivering a good navigation experience. Besides that, most respondents strongly agree and agree that the instructions are clear and easy to understand. However, some respondents answered neutral, suggesting that there might be an opportunity to make it more accessible and straightforward for all users. Additionally, some respondents answered strongly agree and agree regarding the colour used consistently cohesive in different sections. However, there are also some neutral and disagreeing responses regarding this. Lastly, most respondents only answered strongly agree and agree that the language used in the application is appropriate for their level of understanding. Using a global language ensures that everyone can use this application.

4.2 Evaluation of Features and Accuracy

Fig. 3 (b) shows responses regarding the features and accuracy of the apps. Regarding the real-time and uploaded image detection features being accurate, a few respondents strongly agree, while the majority and most respondents agree. Some respondents chose neutral, and there were a few responses in both the disagree and strongly agree categories. This clearly proves that image detection features have some shortcomings, but they can still perform well. Most respondents strongly agree and agree that features disease descriptions and treatment suggestions are helpful. However, there are certain responses to neutral. Besides that, most respondents strongly agree that the responses from the Sprout-AI chatbot are helpful, with a few more respondents agreeing. This indicates that our app's features have met users' expectations. Lastly, most respondents strongly agree that app functions accurately meet their expectations, with a smaller number agreeing. However, there are also responses indicating neutrality and a few indicating disagreement.

4.3 Overall Satisfaction

We used a table to summarize the overall satisfaction of respondents. Table 2 simplifies the feedback regarding the overall satisfaction of the apps. 100% of respondents answered "Yes" to using the apps in the future. Our app offers a virtual assistant for the users especially the farmers and gardeners to prevent plant disease. This indicates that it can attract users to rely on the apps. They are also 100% the recommend the apps to family and friends. This level of support shows the app meets the needs of its users. Besides that, only 84.6% of respondents answered "Yes" regarding the satisfy using the apps' features and the left 15.4% answered "No". This indicates that our app is performing well overall, even though some users are not completely satisfied. About 84.6% of respondents answered "Yes" and 15.4% answered "No" regarding the helpfulness of the tips and suggestions. While the treatment and suggestions might not meet all users' expectations, our apps still give the best performance. Hence, the overall satisfaction positively proves that our apps provide the best value to the users.

Table 2 *Overall Satisfaction*

Question		Yes	No
a)	Will you use this app in the future?	100%	0%
b)	Will you recommend the apps to your family and friends?	100%	0%
c)	Are you satisfied using all the apps' features?	84.6%	15.4%
d)	Are all the treatments and suggestion helpful?	84.6%	15.4%

Fig. 4 *User testing of the app*

In conclusion, this survey was conducted alongside user testing to gather comprehensive feedback from the users. This approach ensured the quantitative data were collected and provided a holistic view of user's experiences. Fig. 4 presents the snapshot of user testing of the proposed application. This figure demonstrates two gardeners from Kolej Kediaman Kampus Pagoh using the Sprout-AI application to scan the diseased plants in their garden. This figure highlights key moments during the testing process and insight gained from the survey and user testing in identifying areas for improvement of the application.

5. Conclusion

In conclusion, this application enables farmers and gardeners to detect plant diseases and acquire plant-related knowledge in a more engaging and time-efficient manner. Its emergence is driven by the preference of the new generation for mobile platforms, which offer accessibility and interactive interfaces that enhance learning experiences. Ensuring proper treatment and care guidance for plants is crucial to fostering healthy growth and preventing detrimental impacts on other plants. Neglecting these aspects may result in the destruction of individual plants or, in severe cases, entire farms or gardens.

Acknowledgement

The authors would like to thank the Centre for Diploma Studies, University Tun Hussein Onn Malaysia for its support.

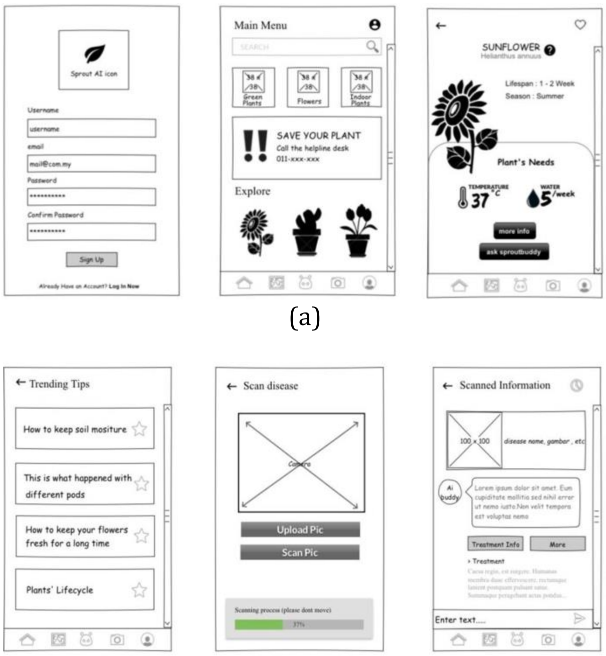
Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm their contribution to the paper as follows: study conception and design: Nur Zulaikha Norhashim; data collection: Nur Aisyah Mohamad Sulaiman; analysis and interpretation: of results by Nur Farhah Ain Ezam Shah, Nur Zulaikha Norhashim, draft manuscript preparation: Nur Aisyah Mohamad Sulaiman; supervision throughout research process: Mazniha Berahim. All authors reviewed the results and approved the final version of the manuscript.

Appendix A: Application Storyboard



(a) (b)

Fig. 5 *Application storyboard (a) Login page and home page; (b) Tips page, scan image disease page and chatbot image*

Penerbit UTHM

References

[1] P. A. Nazarov, D. N. Baleev, M. I. Ivanova, L. M. Sokolova, & M. V. Karakozova, "Infectious Plant Diseases: Etiology, Current Status, Problems and Prospects in Plant Protection", *Acta naturae,* vol.12, no. 3, pp.46, Jul 2020.

[2] K. A. Garrett, D. P. Bebber, B. A. Etherton, K. M. Gold, A. I. Plex Sulá, & M. G. Selvaraj, "Climate change effects on pathogen emergence: Artificial intelligence to translate big data for mitigation," *Annual Review of Phytopathology*, vol. *60, no.* 1, pp. 357-378, August 2022.

[3] M. Aleedy, H. Shaiba, M. Bezbradica, "Generating and Analyzing Chatbot Responses using Natural Language Processing. In IJACSA)," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 9, 2019.

[4] N. Rane, S. Choudhary, & J. Rane, "Gemini versus ChatGPT: applications, performance, architecture, capabilities, and implementation," *Journal of Applied Artificial Intelligence*, vol. 5, no. 1, pp. 69–93, February 2024.

[5] geeksforgeeks, "What is Agile Methodology?," GeeksforGeeks, Dec. 13, 2023. [Online]. Available: https://www.geeksforgeeks.org/what-is-agile-methodology/

[6] D. Hughes and M. Salathe. "An open access repository of images on plant health to enable the development of mobile disease diagnostics," April 2016.