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Review

Mobile Computing for Pest and Disease Management Using Spectral Signature Analysis: A Review

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Abstract: The demand for mobile applications in agriculture is increasing as smartphones are continuously developed and used for many purposes; one of them is managing pests and diseases in crops. Using mobile applications, farmers can detect early infection and improve the specified treatment and precautions to prevent further infection from occurring. Furthermore, farmers can communicate with agricultural authorities to manage their farm from home, and efficiently obtain information such as the spectral signature of crops. Therefore, the spectral signature can be used as a reference to detect pests and diseases with a hyperspectral sensor more efficiently than the conventional method, which takes more time to monitor the entire crop field. This review aims to show the current and future trends of mobile computing based on spectral signature analysis for pest and disease management. In this review, the use of mobile applications for pest and disease monitoring is evaluated based on image processing, the systems developed for pest and disease extraction, and the structure of steps outlined in developing a mobile application. Moreover, a comprehensive literature review on the utilisation of spectral signature analysis for pest and disease management is discussed. The spectral reflectance used in monitoring plant health and image processing for pest and disease diagnosis is mentioned. The review also elaborates on the integration of a spectral signature library within mobile application devices to obtain information about pests and disease in crop fields by extracting information from hyperspectral datasets. This review demonstrates the necessary scientific knowledge for visualising the spectral signature of pests and diseases using a mobile application, allowing this technology to be used in real-world agricultural settings.

Keywords: crop; disease; mobile app; pest; spectral signature

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1. Introduction

Smartphones are small, lightweight, easy-to-carry devices that can be connected to the Internet, and they make people's lives easier because most of their daily activities can be performed on a smartphone. The price of a smartphone is affordable if an individual requires only the necessary features, but if users desire additional applications on their devices, they may be required to pay a higher price for a smartphone that includes advanced functions. Today, almost everyone has a smartphone. They contain multiple functions that enable advanced computing capabilities and connectivity compared to a regular phone that only consists of basic functions such as sending or receiving calls and text messages. Applications in smartphones can help users fulfil their needs, such as sending emails for communication, playing games for entertainment, and reading the news for information [1].

Many sectors have utilized mobile applications, such as business [2], health [3], map navigation [4], and agricultural [5] industries. Specifically, precision agriculture constitutes a management practice combined with on-farm technologies employed to decrease the input of a crop, such as a pesticide and fertilizer, by applying them at the right time, right place, and in the right amount, resulting in gaining a higher profit [6]. Therefore, mobile applications are one of the technologies used in this field, used for purposes such as analysing a crop's health. A crop's health could be affected by several factors, two of which are pests and diseases that can both decrease yield production [7]. Pest and disease monitoring has often been conducted by a farmer from farmer associations or governmental agencies when the disease is severe and hard to treat. To be a professional farmer, one must have knowledge of agriculture or be advised by experts. Therefore, using mobile applications for pest and disease monitoring could help farmers observe and diagnose an infestation in its early stages [8]. Furthermore, farmers could use their smartphones to identify pests and diseases they are unfamiliar with by referring to the information in the app [9]. The survey results and observations regarding pests and diseases could guide farmers in managing other crops in the future [10].

Spectral signatures can be applied to identify the pest and disease species with higher accuracy than image identification [11]. The spectral signature of plants is vital because it demonstrates the unique values and characteristics of plant species. The same concept applies to different species of pests and diseases, as each of them has a different graph curve depending on the individual characteristics. Consequently, a spectral library may be used to compare the reflectance of pests and diseases with plants in the field and estimate the extent of the infestation [12]. Moreover, it could be employed in mobile applications to differentiate and identify the location of the pest and disease in the plant. Thus, pest and disease mapping is feasible [13]. The spectral signature graph is stored in the spectral signature library in a digital database to avoid loss of the data and provide easy access to researchers worldwide [14]. The mobile application can collect information about diseases and pests in a region and help fight or prevent the spread, helping several farmers.

In South China, a vegetation spectral library was established to record spectral data for specific growth stages of various crops and provide crop control strategy management to users [15]. Two spectral libraries have also been developed for selected plants in a tropical rainforest to store data from vegetation spectra such as leaf condition, vigour, and other physiological and biological factors [16]. Aside from that, the rubber tree disease spectral library was created to detect disease spread over a large area [17]. All spectrum libraries were created in response to particular observations and, for the most part, are inaccessible to the general public. Mobile applications help monitor pests and diseases but lack functions measuring the spectral signature between different pests and diseases. Therefore, a spectral library is an alternative approach to gathering all the spectral data for pests and diseases.

This study reviews the mobile applications for pest and disease management as a replacement for the paper-based system. Furthermore, the spectral library in the app is an alternative approach to storing the spectral signature graph of pests and diseases to be used by farmers. This review is organised in four main aspects as follows: (i) The use of a mobile application for pest and disease management, (ii) spectral signature analysis for pest and disease management, (iii) the linkage between the development of a mobile application for spectral signature analysis for pest and disease management, and (iv) the architecture of the development of the mobile application. Therefore, this review aims to show the current and future trends of mobile computing based on spectral signature analysis for pest and disease management.

2. Mobile Application for Pest and Disease Management

2.1. Role of Mobile Applications in Monitoring Pest and Disease

Technologies developed in agriculture can help farmers to increase crop yield. However, damage caused by pests and diseases increases losses in crop production. Farmers typically carry out the detection of pests and diseases when the crop is in a severe condition. The early detection of pests and diseases using mobile applications is an alternative approach. Farmers can only send a report to the app by providing information that a particular crop is infected. The area of the infected crop will also be displayed on a map, and the system will be synchronised to inform all the farmers to observe their crop and suggest a method of control to prevent the spread to other neighbouring areas.

The developed applications are mostly focused on describing pests and diseases together with their (i) causal agent, (ii) symptoms, (iii) treatment of the infection and its results, and (iv) methods to control the infection. Previously, mobile applications developed for pest and disease management were applied to different crops such as rice [18,19], palm oil [20], cocoa [21], rubber [22], coffee [23], potato [24], wheat [25], cassava [26], and barley [27]. Table 1 shows the list of mobile applications that are widely used in pest and disease management.

Table 1. List of mobile applications and their function in pest and disease management.

Name of Application	Function of Application	Country	Accuracy of Pest and/or Disease Identification	Reference
PlantifyAI	To diagnose 26 diseases across 14 crop species by offering treatment methods, common symptoms, and access to suggested cure treatments for each disease.	United States of America	Disease and crop classification: 95.7%.	Shrimali et al. [28]
Not mentioned	To identify and classify pests in images, extract characteristics of pests, and evaluate areas that prone to pests	Taiwan	Pest identification: 84%, and pest classification: 86%	Chen et al. [29]
Padi2U	To create a database of spectral signatures of weed species in rice fields	Malaysia	Weed separation species: 710 nm to 750 nm areas	Roslin et al. [30]
Mentha Mitra	To provide information about improved menthol mint types, nutrient requirements, diseases, and mechanisms for insect-pest control.	India	Not mentioned	Singh et al. [31]
Sistem Pakar Identifikasi Hama dan Penyakit Padi	To obtain a response from the user on the signs of pests and diseases that exist in rice	Indonesia	Not mentioned	Triono and Tristono [32]
e-RICE	To categorise the symptoms in order to make an accurate diagnosis of common rice diseases and problems.	Philippines	4.29 rating by respondents agree that the app is functional in detecting disease	Morco et al. [33]
Dr Lada	To identify pests and diseases in peppers and propose appropriate techniques to solve the problem	Malaysia	Pest and disease diagnosis: 97%	Adama et al. [34]
PEST APP	To provide an early warning system on the infestation of the pest at early stages in paddy	Malaysia	Not mentioned	Nasir et al. [35]
Not mentioned	To identify the extend of cold-induced injuries in zucchini in real acquisition condition	Spain	Not mentioned	Novas et al. [36]
Leaf Analysis	To identify disease in different types of crop	Spain		Picon et al. [37]
TobaccoApp	To detect any damage on tobacco leaf	Mexico	Damage caused by fungi: 97%	Valdez-Morones et al. [38]

Table 1. *Cont.*

Name of Application	Function of Application	Country	Accuracy of Pest and/or Disease Identification	Reference
Not mentioned	To control irrigation system and identify the images of plant leaf disease	India	Not mentioned	Ranjith et al. [39]
AuToDiDAC	To detect, separate, and assess the disease in cacao black pod rot	Philippines	Disease detection	Tan et al. [40]
cFertiGUAL	by calculating the amounts of fertiliser and monitoring irrigation systems, and select the best amongst the many crop growth systems and fertigation technologies	Spain	Disease detection: 97%	Pérez-Castro et al. [41]
FarmAR	To provide information about plants to farmers such as common name, scientific name of the plant, and plant diseases	Greece	Not mentioned	Katsaros and Keramopoulos [42]
Jaguza Livestock App	To improve the production and productivity of livestock by detecting livestock diseases and dealing with dangerous disease outbreaks.	Uganda	Not mentioned	Katamba and Mutebi [43]
BioLeaf	To quantify the foliar damage induced by insect herbivores on leaves	Brazil	Regular artificial damage: 25% and 50% of damaged area	Machado et al. [44]
Online at Sawah (OAS)	To detect diseases or pests that affect corn based on symptoms provided by users	Indonesia	Effectiveness: 82.5%, efficiency: 93.12%; learnability: 77.33%, and satisfaction: 73%	Simorangkir et al. [45]
Not mentioned	To identify the disease on wheat crop based on the detection of early symptom	Spain	Colour constancy algorithm of disease image: 0.81	Johannes et al. [25]
Plant Disease	To diagnose plant disease with extensible set of diseases	Greece	Disease recognition: Between 80% and 98%	Petrellis [46]

However, not all mobile applications in Table 1 used spectral signatures to detect pests and diseases. Weed is one of the components of pests and diseases. The specific characteristics of weeds can be visualized based on different wavelengths through spectral signature graphs. Hence, Roslin et al. [30] developed a new feature of the spectral signature library in mobile applications to differentiate and identify the location of weeds in the paddy field. The NIR reflectance values based on the spectral signature graph in order of highest to lowest are as follows: Jungle rice (*Echinochloa* spp.) > flower of jungle rice (*Echinochloa* spp.) > weedy rice (*Oryza sativa* L.) > red sparangletop (*Leptochloa chinensis* spp.) > saromacca grass (Ischaemum rugosum) > lesser fimbristylis (*Fimbristylis miliacea*) (Figure 1).

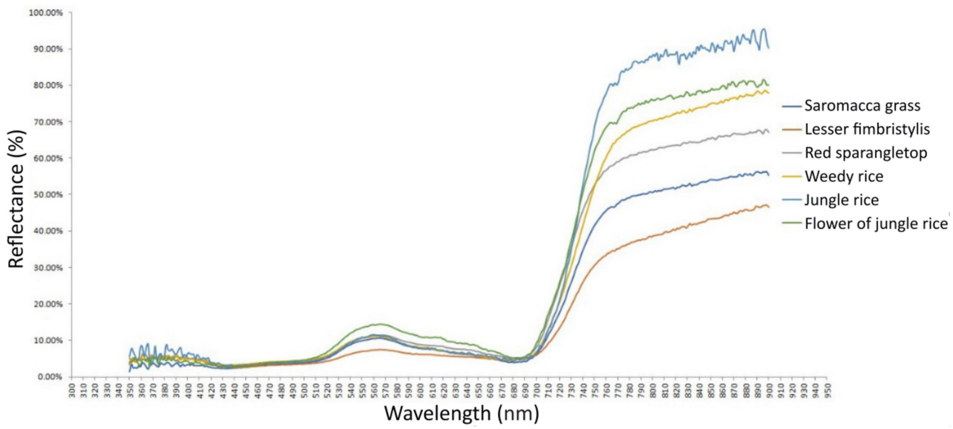

Figure 1. Spectral reflectance graph of different types of weeds in the paddy field.

One of the functionalities of mobile applications for pest and disease management is detecting early infection by taking photos and/or collecting information. For instance, PlantifyAI is a novel convolutional neural network-based mobile application that provides common symptoms, treatment methods, and proposed cure products for 26 crop diseases across 14 species [28]. On the other hand, Chen et al. [29] combined the current mature AIoT technology and deep learning YOLOv3 to develop pest identification systems in mobile applications. This application was combined with an unmanned aerial vehicle (UAV) to collect the image of *Tessaratoma papillosa*, which appeared on the back of leaves, to locate this pest in orchards.

Additionally, Padi2U is another mobile application developed by integrating multispectral imagery. This application provides a list of pests, photos of the disease and symptoms, and suggestions on how to control pests and diseases in paddy [30]. The information is explained in Malay language and is a simple way for farmers to understand the messages (Figure 2; Table 2). The photos of symptoms could be used as a reference to diagnose pests and diseases in the field. In another web application, Mentha Mitra, intended for menthol mint growers, provides information on many diseases and pests (insect). Using the feedback tool, any disease that has not yet been digitised in the app and any insect pest that is unable to be identified by the farmers can be reported together with a photo and remarks for scientific advisories [31].

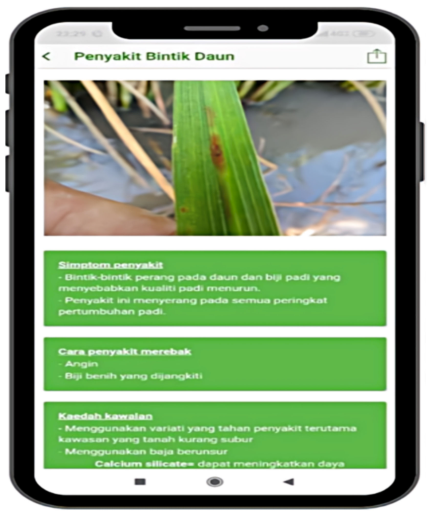

Figure 2. Example of the mobile application that displayed symptoms of disease infection on the crop.

Table 2. English translation of sentences in the mobile applications.

Malay Language	English Language
Penyakit Bintik Daun	Lead spot disease
Simptom penyakit Bintik-bintik perang pada daun dan biji padi yang menyebabkan kualiti padi menurun. Penyakit ini menyerang pada semua peringkat pertumbuhan padi	Symptoms of the disease Brown spots on the leaves and seeds of rice that cause the decline of rice quality. The disease attacks at all stages of rice growth.
Cara penyakit merebak Angin Biji benih yang dijangkiti	Methods on the spread of disease Wind Infected seeds
Kaedah kawalan Menggunakan variati yang tahan penyakit terutama kawasan yang kurang subur. Menggunakan baja berunsur cancium sillicates	Control methods Using disease-resistant varieties in less fertile areas Using calcium silicates fertilizers

Sistem Pakar Identifikasi Hama dan Penyakit Padi (Paddy Pest and Disease Specialist Identification System) is another mobile application that identifies pests and diseases in paddy. The information was displayed in tabular form, including the causal agent, common and scientific names of the pest, a picture of the pest, symptoms, and the control method [32]. Firstly, the user needs to enter the consultation menu from the app and select which types of consultation the user needs, i.e., disease or pest. Secondly, the user needs to insert their name and answer all the questions generated in the system according to the symptoms that appear on the rice. Finally, the result of the consultation will appear, and the user can print or visualise the output through the application. e-RICE is another mobile application that provides information to farmers about pests and diseases in paddy. It uses a rule-based algorithm to classify rule generation based on the knowledge and information provided by experts in paddy to classify the symptoms given by a farmer for an actual diagnosis. Each evaluation of the disease diagnosis will be reviewed again by the developers, other farmers and agricultural officers [33].

In Malaysia, researchers from Universiti Kebangsaan Malaysia developed a mobile application named Dr Lada [34]. This application was used to detect pests and diseases in pepper. Users could diagnose the pest or disease infection from this application by answering questions, which minimised farmers' dependency on an agricultural officer because they were able to diagnose diseases themselves. Furthermore, a research team from the International Rice Research Institute at the University of Queensland, Australia, the Philippine Rice Research Institute in the Philippines, and the Research Institute for Rice in Indonesia developed a mobile application to diagnose pest and disease infestation in crops by answering questions based on the symptoms that appeared. This application was called Rice Doctor and was used to identify the possible ways for the disease to spread and provide suggestions on how to diagnose/treat and overcome the infection. Furthermore, researchers from the National Rice Research Institute in India also developed a mobile application called riceXpert to provide information on the disease, pest, weed, and other possible causal agents that cause an infestation in paddy fields [47]. Using those mentioned applications, farmers could transfer the data from the field in a user-friendly way in a shorter timeframe to conduct decision making for pest and disease prevention. Therefore, this study contributed to the body of new research in terms of developing mobile applications in detecting pests and diseases.

2.2. Image Processing for Pest and Disease Monitoring Using the Mobile Application

Mobile applications require the user to capture an image of the infected part of the plant. Image preprocessing analyses the image with an algorithm built into the system [48]. The preprocessing step ensures that the image captured analyses the infected part only and excludes the background and healthy part, which is referred to as the separation technique.

The colour of the image will be corrected based on colour constancy and uniformity [49]. The infected part will then be extracted and checked with the pest and disease image model to confirm the infection. The user will receive the results with the name of the pest and disease, the causal agent, a method to control the infection, and prevention guidelines to overcome the infection [50].

Additionally, the mobile application guides farmers to diagnose the infection and further process the application [51]. For cassava crops, AdSurv collected the infected crop images and labelled them on the images as evidence [52]. The disease diagnosis is also used to detect major diseases based on the symptoms that appear on the leaf, such as Cassava Mosaic Disease, Cassava Brown Streak Disease, Cassava bacteria blight, and Cassava green mite. The collection of images is divided into five categories of healthy plants. Another four types are based on each disease because each disease has distinct symptoms on leaves [53]. Therefore, farmers can use this application to diagnose the infected plant and assess the severity of the infection. Hence, image processing is one of the most common methods to visualize the infected plant using mobile applications.

2.3. Systems for Extraction of Disease Using the Mobile Application

A mobile application was developed to identify disease in crops, for example, paddy, using fuzzy entropy [54]. Fuzzy entropy is a system capable of modelling non-statistical imprecision and works well for disease extraction. The result showed that fuzzy entropy has more than 90% accuracy in detecting disease in paddy, except for tungro disease, with an accuracy of only approximately 70%. There are four diseases in paddy identified in the study, namely bacterial leaf blight, tungro disease, brown spot, and leaf blast. The camera captures the infected plant for image preprocessing that involves cropping, converting, and enhancement. For image extraction, fuzzy entropy is used to extract the disease. After that, image classification used a Probabilistic Neural Network to classify the disease. The results are shown in the mobile application. As a consequence, various systems in image processing could be used to extract pests and diseases on plants.

3. Spectral Signature Analysis for Pest and Disease Management

3.1. Spectral Reflectance in Monitoring Plant Health

Reflectance is a measure of electromagnetic energy that bounces back from the surface of a material. It is a wavelength-dependent ratio of reflected incident energy. Leaf reflectance in the visible (400 to 700 nm), near-infrared (NIR, 700 to 1100 nm), and shortwave infrared (SWIR, 1100 to 2500 nm) ranges are influenced by a variety of interactions. These interactions involve radiant energy absorption stimulated by leaf chemistry, light scattering due to the leaf surface and internal cellular structures, and radiant energy absorption caused by leaf water content, proteins, or carbon content [55].

Numerical knowledge of the canopy size is important for efficient farm management. Precision agriculture applications that seek to estimate this commonly use canopy health maps, i.e., as expressed by leaf area per unit (such as plant or meter of cordon), the leaf area index, or other canopy parameters (vegetation fraction and biomass) as a proxy. To correctly map the spatial variability of such farm features, remote sensing data from satellite, aircraft, or drone platforms is needed [56]. In the case of vertical shoot-positioned canopies, a substantial proportion of soil (bare or with cover crops) is exposed to nadir-viewing remote sensing from the inter-row area. Surface reflectance is subject to fluctuations caused by the canopy structure and its illumination at suggested spatial resolutions, equivalent to plant or row spacings [57].

Green vegetation of spectral signature feature basins in the visible range of the spectrum has shown pigmentation in plant tissues. Chlorophyll is the major photosynthetic pigment in green vegetation, and it is significantly absorbed in the chlorophyll absorption spectral bands at red (670 nm) and blue (450 nm). When a plant is pressured to the extent that chlorophyll growth is decreased, the amount of reflectance in red (670 nm) regions increases [58]. Water's spectral response has different substances characteristic of light absorption NIR and beyond. The suspended sediments and increase in chlorophyll levels are two common elements influencing the spectral response of water. In each situation, the spectral response will change to indicate the presence of suspended sediments or algae in the water [59].

Detection anomalies in the photosynthetic parameters are crucial in remote sensing approaches. Changes in pigment, nutrients, cell structure, water intake, chemical concentrations, and gas exchange are subsequently displayed in the reflectance characteristics of the leaf or canopy [60]. The anomalous behaviour is then attributed to abiotic or abiotic stress. Indirectly, the observed and measured changes in spectral reflectance are related to plant stressors [61]. The data collected by the sensors are often compared using one of the various vegetation indices and subjected to extensive data analysis to be categorised as healthy or unhealthy and between different types of pests and diseases. Every extra step introduces uncertainty into the technique.

As most of the previous studies are specific to the combination of the crop and a pest or disease and relate to external factors, the findings in the literature are non-uniform and it is challenging to compare them quantitatively. As an example, extrinsic factors such as the leaf internal structure, surface features, and water content could influence the pigment absorption of plants. Hence, no single wavelength is associated with a single pigment concentration [62]. Due to the failures of this method, researchers have turned to correlation analyses to establish unique pathogen-specific spectrum signatures, such as a spectral index and ratio with discriminant analyses [63,64], but they do not provide conclusive optimal spectral signatures. However, the same findings indicate that the sensitivity of particular spectral areas with significant absorption corresponds to abiotic and biotic factors such as pigmentation [65]. Figure 3 depicts a framework of plant health monitoring employing spectral signature analysis.

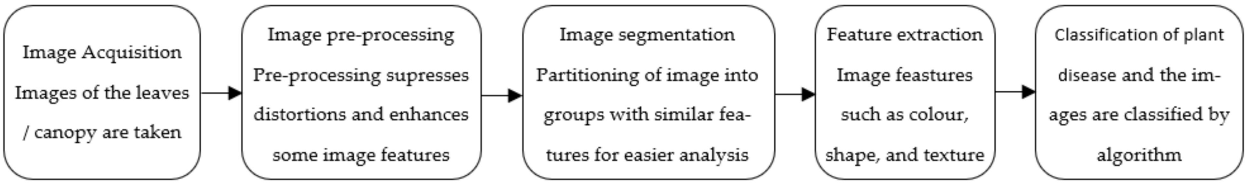

Figure 3. Steps in spectral signature analysis for plant health monitoring.

The use of spectral signatures for pest and plant diseases in the parametric analysis is limited. Non-parametric techniques such as Principal Component Analysis, Cluster Analysis, Support Vector Machines, Partial Least-Squares, and Artificial Neural Networks (ANNs) have been widely adopted by researchers [66–68]. For example, in general terms, PCA is one kind of feature extraction method that helps to find the highest contribution of points, and the highest contribution of points can be identified through the highest eigenvalues with principal component during PCA analysis. Therefore, the lowest contributions amongst those points can be omitted and only the points with the highest contribution are selected for further processing/analysis. Generally, a comparison between thermal, fluorescence, and hyperspectral imaging supports a multi-sensor data fusion method to measure plant health [69]. A comprehensive study [70] on head blight on wheat highlighted each system's main benefits and drawbacks and subsequently studied the individual sensor combinations. Using IR in the 7.5–12 m wavelength region, thermography-based sensors showed temperature differences between crops influenced by biotic and abiotic stresses. While chlorophyll fluorescence-based approaches in the visible spectrum are widely utilised, they are inhibited by the need for dark adaptation to minimise the effect of sunlight on the measurement. Hence, spectral reflectance could be used in monitoring plant health.

3.2. Spectral Signature of Pest and Diseases in the Crop Field

Both hyperspectral imaging and non-imaging sensors are effective techniques for detecting changes in plant health [71]. Changes in reflectance are caused by plant tissue's biophysical and biochemical properties. Plant diseases can alter tissue colour and leaf shape, transpiration rate, crop canopy morphology and density, and the interaction of solar radiation with plants [72]. They cause changes in the optical characteristics of leaf tissue. As there are changes in pigmentation, the hypersensitive response, and cell wall deterioration, leaf reflectance is thus susceptible to plant stress [73]. Pest and disease-specific symptoms, such as the succession of chlorotic and necrotic tissue with different optical properties and composition, as well as typical fungal structures such as powdery mildews, rusts, and downy mildews, may be identifiable.

When plants are subjected to infections that cause chlorotic and necrotic symptoms, the composition and content of leaf pigments change. The type of host–pathogen interaction influences the pattern of responses and the degree of up- and down-regulation of physiological systems. Necrotrophs rapidly kill plant cells and then feed on the nutrients generated by the dead tissue, whereas biotroph pathogens create haustoria to take nutrients from living cells [74]. Because the characteristics of the symptoms vary, different wavebands may be appropriate for detecting various diseases. Using sensing techniques, identifying a disease, its discrimination from other diseases, and abiotic stressors is still a challenge in vegetation monitoring. The interpretation of spectral reflectance data without knowledge of the spectral characteristics of leaves and typical symptoms is impossible at present. The highest findings of disease detection were found in the visible and NIR ranges of the spectrum. For example, reflectance spectroscopy was employed to identify the wilt induced by the vascular fungus Fusarium oxysporum from that caused by drought in tomatoes [75].

Differences in spectra, ratios, or derivations can be used to distinguish changes in spectral reflection and differences in spectral signatures [76]. This method can compare the spectra of healthy and unhealthy plants. Meng et al. [77] discovered various important regions of different spectra between healthy plants and plants infected with Cercospora leaf spot, powdery mildew, and sugar beet rust. Based on an understanding of reflectance properties, spectral algorithms for remote sensing of vegetation have been created, which use specific wavelengths of spectral signatures. They are linked to various biochemical and biophysical plant factors that indicate plant health. Spectral vegetation indices are frequently used to monitor, analyse, and map temporal and spatial variation in vegetation.

Disease symptoms can be seen at specific wavelengths and might include any number of changes in the plant's colour, shape, or functioning as it responds to disease. The disease symptoms vary depending on the pathogen and include leaf spots, chlorosis, necrosis, wilting, or overgrowth. Plant stress other than diseases can activate protective mechanisms that result in suboptimal development, chlorophyll loss, or changes in surface temperatures [78]. These changes cause noticeable modifications in the spectral signature compared to a healthy plant and may be detected using several approaches [79].

Based on Figure 4, visible light can be applied to evaluate variations in the colour and morphology of infected plant tissue. Changes in water content, leaf thickness, and photosynthetic efficiency could be detected using infrared and short-wave infrared, whereby long-wave infrared can be used to monitor plant surface temperatures. Multiple images are captured using hyperspectral sensors over its wavelength range of 300–2500 nm. Furthermore, imaging devices measure the absorption, transmission, and reflectance of input electromagnetic radiation interacting with the plant surface. Compared to healthy tissue, infected plant tissue generally has a lower reflectivity. Image analysis algorithms determine the contrast between diseased and non-diseased leaf areas [31].

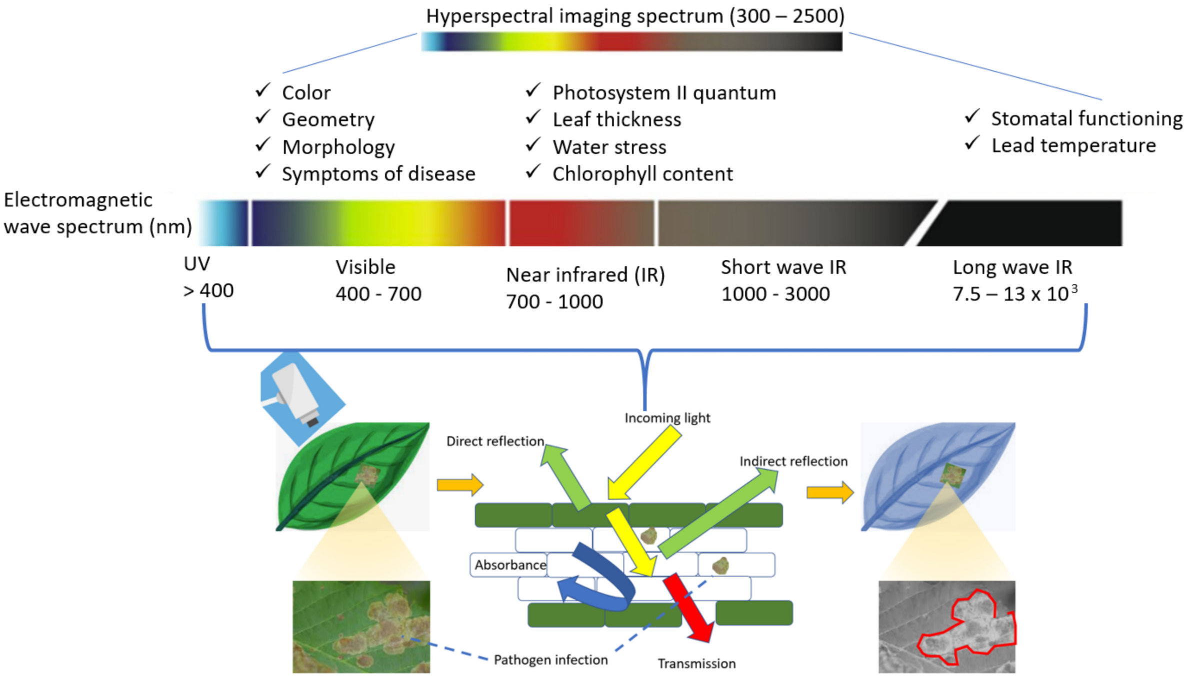

Figure 4. Techniques for high-throughput phenotyping of plants and diseases.

A great deal of research has shown that textural and phrenological differences can also be considered as a viable technique using hyperspectral data for the remote identification of invasive plants such as the Nile rose or water hyacinth (*Eichhornia crassipes*). In contrast to previous broadband multispectral sensors, new-generation sensors such as Sentinel 2 and Landsat 8 sensors of invasive plants such as the Nile rose or water hyacinth (*Eichhornia crassipes*) with superior sensing properties have presented untapped prospective options [80]. The spectral reflectance of the Landsat 8 operational land imager OLI was used to distinguish the water hyacinth's spectral signature from other plants. These indices revealed the highest reflection of the water hyacinth plant compared to other plants.

As each vegetation species has similar spectral signatures, spectral classification of vegetation types in complex environments is difficult [81]. However, other researchers discovered that water hyacinth has a specific spectral or textural signal that allows it to be distinguished from surrounding native flora [82]. Textural and phonological variations were efficient approaches for identifying water hyacinth. Another contribution showed that hyperspectral data constitute an appropriate strategy for detecting invasive plants based on differences in spectral signatures [83]. Water hyacinth displayed higher NIR reflectance values than related plant species and water, owing to the high reflectance of the internal spongy leaf structure (700–1000 nm) [84]. The spectral signatures of hyacinth detected typical characteristics with low reflectance in the visible part of the spectrum due to high concentrations of chlorophyll-a, which is an indicator of healthy aquatic vegetation conditions [85].

Despite the use of non-imaging sensors with a field of view of 10 mm, it was feasible to detect diseases on the leaves and trace the variations in the spectral signatures of different diseases as the disease severity increased. Each disease has a specific spectral signature, allowing for disease differentiation based on spectral vegetation indicators. These findings are consistent with Cesarano et al. [86], who found that symptoms on sugar beet leaves caused by *Heterodera schachtii* and root rot induced by Rhizoctonia could be accurately detected using several vegetative indicators. Based on training datasets, Di Gennaro et al. [87] employed vegetative indices and classification via the support vector machine technique to detect and distinguish three distinct diseases on sugar beets, i.e., Cercospora leaf spot, sugar beet rust, and powdery mildew. Data from remote sensing and ground observations were examined to detect disease in its early stages before visual detection. This study proposes a novel way of analysing the quantitative and qualitative regional distribution of symptomatic plants. The technology could also be used to investigate the physiological basis of grapevine leaf stripe disease and anticipate its development. A broad scope of research has used spectral signature analysis in pest and disease management (Table 3). This review found it could be extended into future studies using different classification techniques and algorithms for spectral signature analysis in pest and detection.

Table 3. Example of applications for spectral signature analysis in pest and disease management.

Previous Studies	Purpose	Research Findings
Fanti et al. [88]	To determine a spectral signature for the Asian soybean rust (*Phakopsora pachyrhizi*) and quantify the number of urediniospores in a water sample.	*Phakopsora pachyrhizi*'s spectral signature ranged from 1500 cm^{-1} to 1550 cm^{-1}. The quantification yielded high values for calibration coefficients (R^2 = 0.95), cross-validation coefficients (R^2 = 0.93), and prediction coefficients (R^2 = 0.92), demonstrating the accuracy of estimating the amount of urediniospores.
Wei et al. [89]	To select the optimal wavelengths to be used as disease spectral signatures in order to distinguish between healthy and diseased peanut infected with *Athelia rolfsii*.	Two or more feature selection methods were used to choose wavelengths of 501–505, 690–694, 763, and 884 nm. These wavelengths can be used to create optical sensors for automated stem rot detection in peanut fields.
Soca-Muñoz et al. [90]	To examine the spectral reflectance signatures of brown rust (*Puccinia melanocephala*) and orange rust (*Puccinia ku-ehnii*) in surgarcane.	The difference in reflectance among healthy and contaminated leaves in the red and near-infrared bands of the electromagnetic spectrum means it is able to determine contamination with both orange and brown rust by combinations of these bands.
Żelazny et al. [91]	To investigate the impact of spectrum pre-processing on the severity of *Fusarium* spp. head blight infection in winter wheat.	Milk-ripening phase predictions based on mean-aggregated spectra obtained at the same crop developmental stage can be beneficial through standard normal variate pre-processing.
Cordon et al. [92]	To develop indices based on the reflectance spectral signature of the plants for detecting tomato plants infected by bacterial canker before symptoms appear.	Three shortwave-infrared zone indices enabled the detection of bacterial canker-inoculated plants in a faster and non-destructive manner, up to one week before symptoms arose: Normalized Difference Water Index, Simple Ratio of Water Index, and Water Index 1 180 (WI_{1180}).
Mirandilla et al. [93]	To differentiate the spectral responses of the three principal pests and diseases, blast, bacterial leaf blight, and rice tungro disease.	The three diseases are particularly sensitive to the red and red-edge ranges. As the disease progressed, NIR wavelengths were reduced. During the early stages of tungro, the yellow-orange region (550–620 nm) is highly sensitive.
de Oliveira et al. [94]	To investigate the spectral signature of rust incidence in the coffee field.	In the visible, SWIR-1, and SWIR-2 spectral regions, rainfed areas had higher reflectance values than irrigated areas during wet seasons.
Furlanetto et al. [67]	To create a procedure for early and reliable identification and differentiation of soybean under different levels of Asian rust disease according to spectral analysis.	The spectral signature of the leaves revealed a significant increase in reflectance of the vegetation indices region as disease levels increased, which was associated with a lower pigment concentration. More than 97.00% of the spectral variance in the first and second principal components, and the stepwise procedure selected from 87 spectral bands.
Manganiello et al. [95]	To detect the spectral signatures of *R. solani*-assayed wild rocket including green baby lettuce, red baby lettuce, and *R. rolfsii* and *S. sclerotiorum.*	OSAVI, SAVI, TSAVI, and TVI were found to be highly correlated to disease severity, are promising for all pathosystems analysed, and capable of tracking biological control activity against multiple soil-borne pathogens of baby leaf vegetables, based on significant changes in spectral signatures between healthy, infected, and bio-protected plants.

3.3. Image Processing for Pest and Disease Diagnosis Based on Spectral Signature

Pest and disease detection by capturing images of crops with symptoms could be conducted using a camera in the mobile application. The camera can capture the image via image processing and detect the condition of the plant containing the pest or disease based on light reflectance, with certain restrictions [96]. One of the solutions to improve the restrictions is implementing hyperspectral sensors in mobile applications. A hyperspectral sensor measures up to hundreds of electromagnetic spectrum bands in the range of the sensor. Each of the spectral bands of the hyperspectral sensor measures only a few nanometers of the electromagnetic spectrum, resulting in a high-spectral-resolution wavelength [97]. Therefore, each pixel in a hyperspectral image receives a specific collection of data regarding the reflectance (or transmittance) of each spectral band [98].

The sum of these data is known as a spectral signature (or spectral profile), and a non-imaging hyperspectral sensor (i.e., point spectroscopy) captures it without any additional spatial information [99]. Hyperspectral sensors measure the spectral bands for each pixel in an image and combine the spectrum and spatial resolutions. Accordingly, each pixel in the image has its spectral signature, which includes reflectance values for all spectrum bands measured by the hyperspectral sensor [100]. From another viewpoint, the resulting image is a hyperspectral data cube with two dimensions of spatial information and one size considering the spectral information. Generally, hyperspectral sensors can measure the NIR (700–1000 nm) and SWIR (1000–2500 nm) as parts of the electromagnetic spectrum (400–700 nm) [101].

The connection between spectral signature information and ground data proved that the rate of pest and disease infestation can be determined in the crop. At certain wavelengths, pest and disease variations could be displayed based on spectral reflectance. Roslin et al. [30] found that in the visible spectrum (450 nm to 700 nm), many weed spectral signatures were quite similar, and several overlapped. Undoubtedly, not all weeds have a similar spectral signature on the crop, therefore calibration and validation are still required to identify weeds in cropland. At the same time, in the infrared region (700 nm to 990 nm), various species' spectra are distinguished by their wavelengths. Since each weed is unique, the significant bands for each plant can be found in the particular area (710 nm to 750 nm). The affected area could be an indicator of differentiating weed species using spectral signatures. Hence, there is a need to store the information on the spectral signature of the weed, as well as other types of pests and diseases, in a user-friendly way.

Red, green, and blue (RGB) will be used for the image data collection, and then by using image processing, the weeds can be identified based on the shape and colour. Thus, by using a smartphone, the user can identify the weeds through the apps that will be connected to the data processing machine in the cloud. The spectroradiometer will collect the spectral signature (hyperspectral data) that can be used as reference data for weed classification. Thus, the RGB and spectral and hyperspectral information can be used to identify and reference data for the hyperspectral data.

Certain mobile applications only record the RGB imagery. However, by using artificial intelligence (AI) in the cloud server, they can process the RGB information to generate the results. The spectral signature of plants is already stored in the spectral library that can be used if the user has the hyperspectral sensor, and they can compare it with the spectral library in the mobile application. Those spectral signatures are conveniently accessible via mobile devices that have installed the online datasets. The mobile applications have a database of the problems encountered, including a spectral signature graph, which differentiates it from other existing mobile applications such as WeedID and Padi2U that simply provide an image of the pest, a detailed description, and the control method [102,103]. In the future, mobile applications could be used as a reference for the user to view the spectral signature for each pest and disease. The mechanism of using spectral signatures in mobile applications is explained below (Section 4).

4. The Linkage between the Development of the Mobile Application for Spectral Signature Analysis in Pest and Disease Management

The leaf pigments, water content, and cell structure differ between species. Pest and disease species can also be identified based on these differences [104]. However, most farmers cannot identify them in the field due to a lack of access to the most up-to-date data and information on pest control, particularly weed control. Rahman et al. [105] and Haug et al. [106] utilized images to identify weeds and make treatment recommendations. These images are useful for weed control; unfortunately, there is a lack of spectral information about weed species. Compared to image identification, the spectral signature can be employed to determine weed species with high accuracy [11].

Two spectral libraries were developed for a select tropical rainforest to store data from vegetation spectra, including leaf condition, health, and other physiological and biological factors [16]. In addition, the rubber tree disease spectral library was created to detect the disease spread over a vast area [107]. All spectral libraries were compiled based on particular observations and were mainly inaccessible to the public. However, a spectral library for various pest and disease species in crop cultivation is a great place to start, gathering all spectral signatures for current and future usage. Visually detecting pests and diseases in a wide crop field area is difficult and time-consuming for farmers. As a result, a mobile application for pest and disease management could replace the paper-based system, providing a spectral signature database of weed species accessible via mobile application. Using mobile applications, farmers can take an image of the pest or disease, and through image processing, the application can measure and store the amount of light that reaches the sensor. In this approach, mobile application usage helps the user effectively manage weeds.

Integrating the spectral signature library with mobile applications could be a potential use of modern technology for pest and disease management in the field. The mobile application can visualise the spectral signature graph of the pest or disease and recommend chemical control methods. Furthermore, the spectral signature can be used as a reference to detect pests and diseases with a hyperspectral sensor in a shorter time period than the traditional method, which takes much longer to comprehensively detect the entire rice field. Farmers may simply view the pests and diseases that affected their crops with the information provided in the mobile application. Eventually, a mobile application that incorporates a spectral signature library can display pest and disease information in a crop field.

For instance, Roslin et al. [30] created a spectral signature graph of weeds, a common type of pest in rice fields, and developed a mobile application for the spectral signature of weeds. Using Master AppsBuilder, all spectral signatures were kept in a spectral database and displayed on smartphones. Figure 5 shows the website's main menu, which includes a list of applications, and Figure 6 demonstrates the content of menus, pictures, a description, the control method, and a spectral signature graph. The main menu includes weed information, the spectral signature of weeds, and suggestions for weed control. Users can install the mobile application on their devices. The mobile application operates by displaying an image of the weed species, its general name, scientific name, description, a method of control using a chemical application, and a graph of the weed species' spectral signature. This mobile application stores a database of weed information, including spectral signatures, and provides a spectral signature graph.

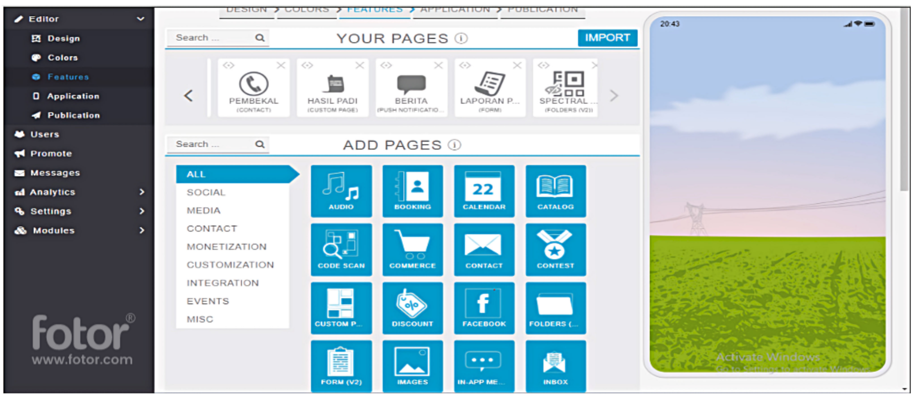

Figure 5. The application Editor tool and Feature menu in MasterAppBuilder Application. (PEMBEKAL: SUPPLIER, HASIL PADI: RICE YIELD, BERITA: NEWS, LAPORAN: FORM).

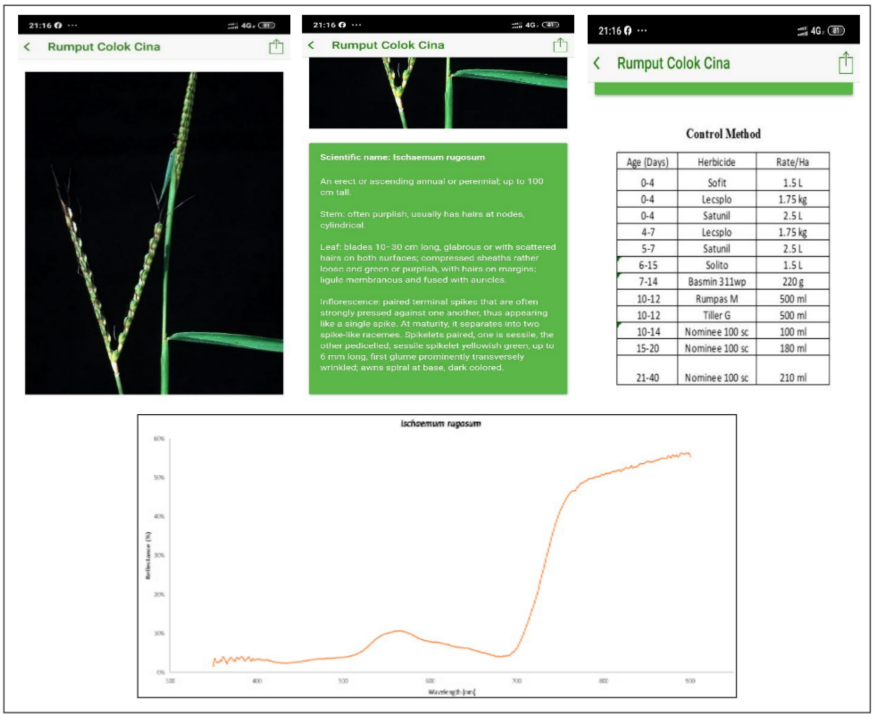

Figure 6. The content of menus, pictures, description, control method, and spectral signature graph.

Many challenges must be addressed, such as the limitations in obtaining raw data of the spectral signature of the pest and disease in the crop rice field, the differences in control methods for each type of pest and disease, and the farmers' ongoing use of traditional methods in detecting pests and diseases. Mobile phone cameras have a limited range of spectra, which imposes a limitation on using mobile phones for spectral analysis since mobile applications only have three bands. However, by using the AI algorithm, we can process the RGB image using the cloud server and can also retrieve the spectral signature from the spectral library. In other words, pests and diseases are detected by a sensor such as RGB and transmitted to a UAV detector based on AI. The expert system uses an algorithm to recognize the presence of UAVs through spectral signature analysis in which there are multiple spectral bands and a wide range of the electromagnetic spectrum. The spectrograms are extracted from the detected reflectance value of the pest or disease, which are then sent to a specified algorithm that recognizes the patterns by generating an image.

Hyperspectral data have the ability to provide adequate spectral information for discriminating within-class roofing materials and conditions. Accordingly, utilizing field spectroscopy data as fundamental in analysing the roofing spectral signature is more efficient compared to using airborne hyperspectral data due to the expensive cost of data acquisition. Furthermore, handling hyperspectral data requires an effective method to reduce the redundancy of data yet maintain useful information. Statistical analysis and vegetation indices for spectral reflectance analysis, such as discriminant analysis, a support vector machine, a convolutional neural network, and ANN, could improve the classification results. In summary, the construction of a spectral library in a mobile application can enhance the visualization of spectral signature graphs of pests and diseases.

5. Structure of Steps in Developing a Mobile Application That Can Incorporate Spectral Signature Analysis for Pest and Disease Management

5.1. Collection of Hyperspectral Reflectance Data and Spectral Signatures

Initially, hyperspectral reflectance data and spectral signatures of pests and diseases should be collected. The task of spectrum data collection consists of two major steps, namely spectral sampling (Figure 7) and spectral library compilation. Throughout the spectral range, the white panel diffuses approximately ~99% of the incident light during the calibration process. Particularly, the white reference panel's reflectance value is almost one for each wavelength [108]. Each pest and disease should be selected at random for 10 samples at a distance of 5 cm between the optical sensor and the sample. Hence, this method is used to avoid inaccuracy and noise when recording data [109].

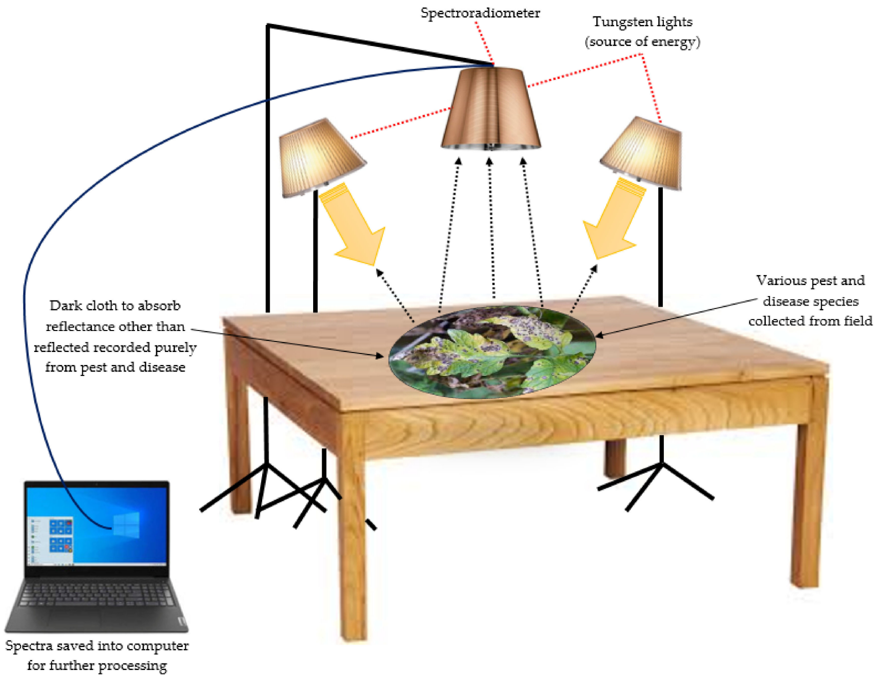

Figure 7. Configuration of spectral sampling in agriculture.

5.2. Generation of Spectral Signature Graph

Applications for crop species identification or pest and disease detection should be based on the ability to acquire a spectral signature that is related to tree characteristics and plant health status. Therefore, a spectral signature graph could be linked to various parameters including tree characteristics such as age category, varietal difference, density, and composition of shade. Other parameters include healthy and unhealthy trees, whereby spectral signature values may differ depending on the plant's health status. For data analysis, all raw data were transferred to a computer. The data were saved in a Microsoft Excel file. Additionally, the data should be binned into 10 nm spectral bands, in comparison with the original value of 1 nm (Figure 6). The spectral signature could be visualised in the spectral reflectance graph for each species of pest and disease. The first derivative is able to be run and visualised based on the techniques outlined below:

(i) Visualization of Spectral Reflectance. Create a graphic representation of the spectral reflectance for pest and disease species.
(ii) First Derivative Analysis. Calculate the first derivatives using Equation (1) and display the spectral signature graph and first derivate graph.

$$FD = \frac{R}{R} = \frac{Ry_2 - Ry_1}{\lambda x_2 - \lambda x_1} \tag{1}$$

where:

FD = First Derivative.
$Ry_1,\ Ry_2$ = Reflectance of the first and second reflectance pairs n1 and n2.
$\lambda x_1, \lambda x_2$ = Wavelength of first and second reflectance pairs n1 and n2.
n = Position of reflectance.

5.3. Incorporation of Spectral Libraries into the Mobile Application

The purpose of developing a spectral library is to store the spectral data of the pest, identify the different disease severities in a large area, and provide an action plan for users to control pests and diseases. The spectral library also includes normatively measured and processed situation parameters of background information for the specified pest and disease species. The five components of the spectral library system are (i) a knowledge database, (ii) a measured spectral library, (iii) an auxiliary library, (iv) spectral analysis, and (v) an end-user application demonstration (Figure 8). Certain information, i.e., background knowledge on pest and disease species, could be identified in a knowledge database. Then, all of the calculated spectra of different species could be saved in the measured spectral library, and the auxiliary library can store several of the ancillary data of the species measured. The spectra gathered in the spectrum analysis could be pre-analysed to verify the accuracy of the library before it is used by end-users in practical tasks. Figure 8 presents an example of the data model of the Spectral Library System of pest and disease species.

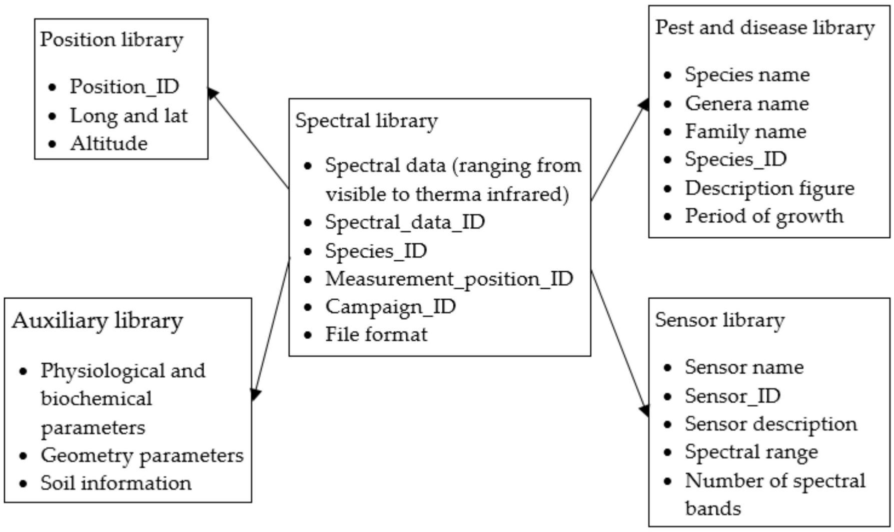

Figure 8. The data model of Spectral Library System of pests and species [16].

Therefore, the spectral signature graph could be stored in the spectral signature library through a multipurpose database, i.e., mobile applications, that users can interface with, as well as providing convenient access to researchers [14]. After that, the spectral signature could be displayed as a spectral reflectance graph for each pest and disease. A spectral library for pest and disease species in the crop field using mobile applications is an excellent start to store all spectral signatures for current use and the future.

5.4. Design of Mobile Applications Containing the Spectral Libraries

The design of mobile applications can be divided into two parts, namely the system architecture (i.e., back-end) and menu design (i.e., the graphical user interface). The system architecture consists of the presentation layer, logic layer, and data layer. At the presentation layer, users can view and interact with the mobile application, in which the flow should allow them to move features intuitively and each menu should have its own target. On the other hand, the logic layer is the application programme interface (API) through which farmers receive data from the database layer and send back the request to the user in the presentation layer. The data are subsequently transferred to the presentation layer. The data layer is the basis of the mobile application and is where all data are saved and retrieved. Each request for information in the presentation layer will be directed through the logic layer and then to the data layer. The information will be passed through the logic layer, and then displayed to the user in the presentation layer. A list of the main menus in the mobile applications is illustrated in Table 4. Figure 9 is the theoretical framework for generating the spectral signature graph for detecting pests or diseases using mobile applications.

Table 4. List of main menus of the mobile applications.

Menu	Details Information
Location	Research site, area of crop field, and total plot that being used for the research
Planting schedule	Planting activities
UAV images	Hyperspectral images
Field problems	Images of condition at the field
Pest and disease	List of pest and disease, its spectral signature graph, and suggestion of methods to control
Weather forecast	Weather condition at the field
Yield	Amount of harvested yield
Report	Farmers can use and send report about pest and disease

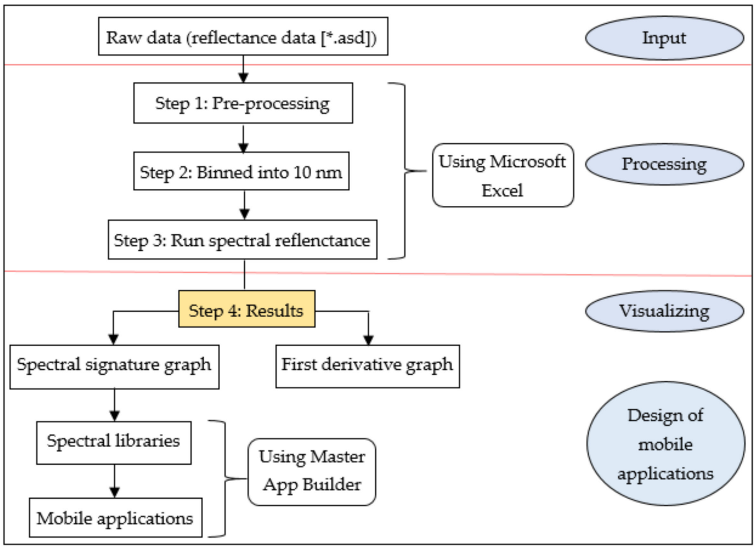

Figure 9. Theoretical framework for generating the spectral signature graph for detecting pests or diseases using mobile applications.

6. Conclusions

The development of mobile applications in agriculture has greatly impacted farming and aided in the monitoring of crop status by farmers and agricultural officers. It can be concluded that mobile applications are essential in agriculture due to their specific function in managing pests and disease, which can help farmers manage their farms effectively compared to conventional methods. No training is required to use the applications, and farmers can easily use them. In fact, farmers can diagnose the infection themselves based on the mobile applications and identify control methods to prevent the infection from becoming severe or happening again if information about the crop, disease, and precision is provided in a database of the spectral library. Information on the ecological characteristics of plant communities also allowed mobile applications with different features to distinguish between similar spectral signatures and reduce the commission and omission errors. However, they may misdiagnose the infection and apply the wrong treatment before using the application if the symptoms are identified late or the plant is already sick. Therefore, mobile applications in pest and disease management that function by visualising spectral signatures are needed for farmers.

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Abbreviations

AI	artificial intelligent
ANN	artificial neural network
NIR	near-infrared
RGB	red, green and blue
SWIR	short wave infrared
UAV	unmanned aerial vehicle

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