HOW CAN SMARTPHONE DEVICES BE INTEGRATED WITH SPECTRAL SIGNATURES TO DETECT MATAG HYBRID?
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BAGAIMANAKAH PERANTI TELEFON PINTAR DAPAT DIINTEGRASIKAN DENGAN TANDA TANGAN SPEKTRAL UNTUK MENGESAN HIBRID MATAG?

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DOI: https://doi.org/10.35633/inmateh-79-43

Keywords: *MATAG; smartphone; spectral signature; species detection*

ABSTRACT
Smartphones have become a convenient tool in agriculture due to their mobility, affordability, and capacity to enhance more efficient crop monitoring, including MATAG variety identification. Detecting MATAG hybrid varieties remains challenging because their morphological traits are difficult to differentiate macroscopically, but reflectance values can be generated using a spectral signature graph. This review aims to explore the development of an intelligent identification system for the MATAG variety based on spectral signature analysis using a smartphone device. It discusses characterisation of MATAG hybrids, spectral signature differences between each coconut species, the development of spectral signature libraries, and the potential of smartphone-spectral signature-based applications compared with manual inspection and laboratory analysis. It also highlights the mechanisms of MATAG variety detection based on spectral signature analysis using a smartphone and practical considerations for farmers. Case studies and testimonials from farmers on how smartphone devices have revolutionised crop monitoring practices were also discussed, together with the potential benefits of using this technology for the agricultural industry. It also elaborates on the opportunities and challenges of detecting MATAG variety using smartphone-spectral approaches, which will be a useful resource for app developers to solve the problems in the field. Overall, this review provides a comprehensive overview of smartphone-spectral signature integration for MATAG detection that eventually helps farmers in the plantation.

ABSTRAK
Telefon pintar telah menjadi alat yang mudah digunakan dalam pertanian kerana mobiliti, kemampuan dan keupayaannya untuk meningkatkan pemantauan tanaman yang lebih cekap, termasuk pengenalan kepelbagaian MATAG. Mengesan kepelbagaian hibrid MATAG kekal mencabar kerana ciri-ciri morfologinya sukar dibezakan melalui mikroskop, tetapi nilai pantulan dapat dijana menggunakan graf tanda tangan spektral. Ulasan artikel ini bertujuan untuk meneroka pembangunan sistem pengenalan pintar untuk kepelbagaian MATAG berdasarkan analisis tanda tangan spektral menggunakan peranti telefon pintar. Ia membincangkan ciri-ciri hibrid MATAG, perbezaan tanda tangan spektral antara setiap spesies kelapa, pembangunan perpustakaan tanda tangan spektral, dan potensi aplikasi berasaskan tanda tangan spektral telefon pintar berbanding dengan pemeriksaan manual dan analisis makmal. Ia juga menyoroti mekanisme pengesan kepelbagaian MATAG berdasarkan analisis tanda tangan spektral menggunakan telefon pintar dan pertimbangan praktikal bagi petani. Kajian kes dan testimoni daripada petani tentang bagaimana peranti telefon pintar telah merevolusi amalan pemantauan tanaman juga dibincangkan, bersama dengan faedah berpotensi menggunakan teknologi ini untuk industri pertanian. Ia juga membincangkan peluang dan cabaran mengesan kepelbagaian MATAG menggunakan pendekatan spektral telefon pintar, yang akan menjadi sumber berguna bagi pembangun aplikasi untuk menyelesaikan masalah di lapangan. Secara keseluruhan, artikel ini memberikan gambaran menyeluruh tentang integrasi tanda tangan spektral telefon pintar untuk mengesan MATAG yang akhirnya membantu petani di ladang.

1. INTRODUCTION

Coconut (*Cocos nucifera L.*) is one of the most important plantations, particularly in tropical countries. Indonesia, the Philippines, and India are the world's biggest coconut producers, accounting for up to 75% of global production (*Halim et al., 2018*). Almost every part of the coconut tree can be consumed for human benefit. There are three types of coconut trees: tall, dwarf, and hybrid. Hybrids have earlier flowering, higher fruit yield, higher copra production, and higher copra and oil quality than the parent. The most popular hybrid is the 'MATAG' cultivar. The 'MATAG' results from intervarietal crosses between 'Malayan Yellow Dwarf' or 'Malayan Red Dwarf' with 'Tagnanan Tall'. The MATAG could generate drinking fruit juice, whereas the husk fibres are denser and more suitable for coir production.

MATAG is also widely used in the industry of processing products. Therefore, the agro-based ministry of the respective countries is always trying to increase the amount of MATAG trees planted (*Halim et al., 2018*). Thus, seedling producers attempt to keep up with the high demand. However, MATAG plantations need help in producing uniform and high-quality seedlings, resulting in a shortage of plantations for farmers (*Hassan et al., 2021*). The reasons for this issue are a less true-to-type MATAG variety identification and poor seedling quality caused by non-systematic and imprecise nursery management, which enhances the inefficient distribution of water and nutrients to seedlings (*Yusof et al., 2017*).

The standard MATAG variety detection technique in coconut nurseries is expert visual assessment based on the parent's colour. This approach is time-consuming and prone to human error (*Bisi et al., 2020*). Therefore, the seedlings will be culled based on the assessor's visual ability and experience. MATAG variety detection could be improved using computer vision techniques, including machine learning and support vector machines (*Che'Ya et al., 2022*). The efficiency for plant species identification using machine learning could reach up to 99.8% (*Borraz-Martínez et al., 2022*). As a result, the cost of production can be reduced, and the nursery's output of high-quality MATAG seedlings could be increased.

Nevertheless, the differences between MATAG varieties are hard to distinguish by visual comparison due to their similar shapes and colours. Because different substances have specific spectral signatures and reflectance, remote sensing techniques can be used with high altitude imaging sensors to obtain spectral information of the Earth's surface, including MATAG varieties. Therefore, spectral signatures can identify each MATAG according to its unique value and characteristics, which are displayed through the spectral signature graph (*Ahansal et al., 2022*).

Some farmers cannot identify MATAG variety and their characteristics in the field because they need up-to-date data related to MATAG, including leaves information for sensor imagery such as its width, length, area, perimeter, area of white space, area of the bounding box, area of hull, the perimeter of the hull, colour, texture, morphology, and structure, as well as seedling information for spectral signature analysis such as only germinated, normal seedlings, and seedling age (*Zaki et al., 2023*). As an alternative, a spectral library can be developed to compare the reflectance of the MATAG variety and include other applications such as image processing, estimating the infestation percentage, identifying the trees' location, and providing information on managing crops from planting to harvesting (*Rosle et al., 2019*). The spectral signature graph can be stored in the library using an online database and a mobile app to avoid losing data and allow researchers to access it worldwide easily (*Roslin et al., 2021*). The apps could help the farmers to process the image on the sensor via smartphone and visualise the MATAG variety mapping in the nurseries.

Some digital databases of the spectral library for crop variety identification, including the Johns Hopkins Spectral Library, United States Geological Survey (USGS) Spectral Library, ASTER Spectral Library, MedSpec, Jet Propulsion Laboratory Spectral Library, and LILIAN, were inaccessible to the public (*Kokaly et al., 2017; Adam, 2012*). While general crop monitoring apps exist, none specifically address MATAG variety detection through spectral signatures. Developing a spectral library for the MATAG variety is a proactive starting point for storing spectral signatures for future usage. Therefore, this review aims to discuss and elaborate on developing an intelligent identification system for the Matag variety based on spectral signature analysis using a smartphone device. Rather than being separate approaches, smartphones, UAVs, and sensors form a complementary ecosystem. Data collected across different spatial and temporal scales are integrated, analysed, and communicated back to the farmer via the smartphone platform, creating a seamless workflow for precision MATAG detection and farm management.

2. CHARACTERISATION MATAG HYBRID

MATAG is currently the most commercialised coconut variety planted in Malaysia, followed by Aromatic Dwarf, known as PANDAN and other dwarf varieties. The name “MATAG” refers to a new hybrid coconut, based on the original coconut from Malaysia, which is Malayan Yellow Dwarf (MYD) or Malayan Red Dwarf (MRD), a female parent crossing with Tagnanan Tall coconut (from the Philippines) as a male parent. MATAG produces large, rounded fruits that mature rapidly and provide high yields. Due to the increasing demand for raw materials in cooking and virgin coconut oil, MATAG has been identified as a suitable source for commercial cultivation in several states in Malaysia (*Raj et al., 2024*). The main producing states are Johor, Perak, Selangor, and Kelantan, where the favourable climatic conditions are well suited to coconut cultivation (*Man and Shah et al., 2020*).

MATAG can reach a height of 15 m, has orange or green leaves, and may initiate to bloom mostly in the third year of cultivation. The MATAG is a new variety of coconut that can produce more coconuts annually than other hybrid or normal coconut trees, up to 40,000 coconuts per hectare. MATAG begins bearing fruit in the third year after planting and can be harvested at approximately 48 months *(DOA, 2016)*. Compared with other hybrid cultivars, MATAG produces a higher number of coconuts, typically about 10–22 fruits per bunch. MATAG has a high nut production rate, yielding approximately 25,000-30,000 nuts per hectare yearly, which is more than the other hybrid types (*PRESSREADER, 2016*). Its average output yield during the first six years of harvest is 18,467, compared to 5,050 nuts for Malayan Tall.

The benefits of MATAG coconuts include their ability to produce higher copra per yield, i.e., 53.9%, because they have thicker plump fruit than other hybrids such as Aromatic Green Dwarf (AGD), CAMMA, and normal coconuts (*Kingimi et al., 2023*). When compared to a normal coconut, the size of the coconut is also larger, which makes the copra thicker and, thus, increases the production of grated coconut and coconut milk (Fig. 1). The MATAG hybrid is more flexible in terms of suitability for both tender and dry nuts due to its ease of dehusking for dry nut purposes, larger nut size that results in a higher amount of water, and reduced husk thickness. In addition, the MATAG coconut’s flavour is tastier because the coconut water is sweeter than regular or other hybrid coconuts, making it more pleasant to drink.

Fig. 1 - Nursery centre for the MATAG variety at DoA, Jorak (Johor)

3. OVERVIEW OF MATAG VARIETY DETECTION BASED ON SPECTRAL SIGNATURE LIBRARIES

Plant pigments absorb light primarily within the photosynthetically active radiation range of 400–700 nm. For example, chlorophyll strongly absorbs blue-violet and red light while reflecting green light, which gives leaves their characteristic green appearance *(Virtanen et al., 2020)*. Carotenoids, in contrast, reflect light in the yellow, orange, and red regions of the spectrum while absorbing mainly blue-green and violet light *(Liu and Van Iersel, 2021)*. Different coconut cultivars often have similar shapes and colours, making visual discrimination difficult. However, they can be differentiated and identified based on their distinctive spectral signatures. Each plant pigment exhibits a characteristic spectral response defined by its reflectance across different spectral bands. Plant spectral signatures generally show low reflectance in the visible region of the electromagnetic spectrum because photosynthetic pigments strongly absorb visible light *(Kutser et al., 2020)*.

Coconut tree fronds with varying degrees of Coconut Scale Insect (CSI) infestation are healthy (young), slightly healthy, moderately healthy, and severely infected. Therefore, the identification of CSI in spectral signatures, even at low level, can evaluate the efficacy of control measures (biological and chemical) (*Franco et al., 2018*). Furthermore, a previous study (*Noor Azmi et al., 2020*) found that various degrees of disease infestation on coconut can be differentiated based on spectral signature using 8-band Worldview-2 satellite imagery, with the NIR-1 and NIR-2 bands, followed by the Red Edge band.

Reflectance generally decreases across the measured wavelength range as leaf health declines from healthy to infected. However, the spectral curves may show substantial variability because infection affects only part of the leaf area, often up to 50%, and measurements may randomly include both infected and healthy tissue within the sensor's field of view *(Rodríguez Machado et al., 2020)*. These differences can be visualized using reflectance-wavelength curves. Reflectance is measured at discrete intervals over a specified wavelength range. The width of these intervals represents the spectral resolution of the sensor, while the reflectance recorded within each interval corresponds to an individual spectral band. A spectral signature is characteristic of a material because its reflectance and emittance properties vary with its physical condition and surrounding environment *(Meerdink et al., 2019)*.

The real-time monitoring of spectral signatures has been improved by using field-based devices. The portable spectrometer is a device that can measure the spectral signature of plants, in which the signature can be used to recognise the plant species. Accordingly, because reflectance readings rely on incident sunlight, the device can only capture valid spectral signatures throughout the day under a clear skyline view with no significant cloud cover or precipitation (*Musiol-ková et al., 2021*). This aspect is why comparing the spectral signature graph of the same plant species between earlier studies is challenging and depends on the sampling environment during the measurement, such as humidity, cloud cover, type temperature, wind speed and direction, and aerosols (*Torresani et al., 2024*) The other reasons are viewing geometry (fore optic degree and field of view or FOV and instantaneous-field-of-view or IFOV, fore optic height above terrain, and ground), and illumination geometry, such as date, azimuth and orientation, position and sun altitude, time, and smoke and haze (*Jafarbiglu and Pourreza, 2023*). Hence, different conditions that influence the spectra of vegetation are shown in Fig. 2.

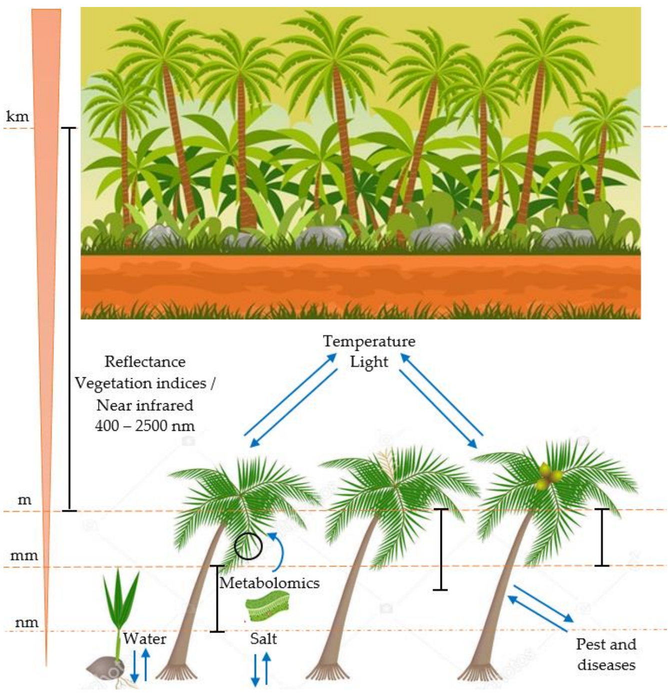

Fig. 2 - Different conditions which influence the spectra of vegetation

Plant reflectance can be measured using a handheld device, such as a spectroradiometer, to measure canopy spectral reflectance. These devices have developed into a helpful alternative for identifying or differentiating objects pertaining to spectral information using conventional methods, such as texture analysis and colour segmentation (*Soca-Muñoz et al., 2020*). Regarding vegetation, they can be used in the field to measure the spectral signatures of the visible light spectrum of various plant species, including different coconut species, i.e., MATAG. The spectral signature of the crop is attributed to low reflectance values in the visible zone of the electromagnetic spectrum due to significant light absorption by photosynthetic pigments (*Kutser et al., 2020*). The absorption maxima for chlorophyll a and b are in the blue (400 nm to 500 nm) and red (around 670 nm) zones, respectively, whereby carotenoids (i.e., xanthophylls and carotenes combined) absorb in the blue range as well (*Agostini et al., 2024*). Any disease that causes pigment degradation, chlorosis, or tissue necrosis may result in visible reflectance changes. Near-infrared (near-IR) reflectance values are high between 700 nm and 1000 nm. Hence, there is a need to develop a database to store spectral signature data. However, the database adopted from other studies requires an evaluation of dataset applicability for the specific task, such as detecting MATAG variety (*Imanian et al., 2021*). Furthermore, creating a large database of crop spectral signatures is difficult because it requires continuous monitoring of crops from seeding to harvesting.

For example, spectral signature libraries for agricultural research are accessible, such as the SPECCHIO Spectral online database held by the University of Zurich's Remote Sensing Laboratories in the Department of Geography (*SPECCHIO, 2022*). The library can display the spectral signature of significant crops such as wheat and potatoes. The database includes biophysical parameters of yields and soil characteristics. The library has been tested, but several things could be improved, including the lack of a multi-criteria query. A lengthy list containing hundreds of records is visualised for each search. Instead, it should be more systematic to include the crop's plantation date and location. Other agriculture libraries and databases are being developed. However, some are no longer available, such as the Vegetation Spectral Library, created with National Science Foundation funding by the Systems Ecology Laboratory at the University of Texas in El Paso (*Systems Ecology Laboratory, 2017*). Based on the published literature, no suitable library exists to be used for detecting MATAG. Hence, future studies are proposed to fill this limitation by developing a library specifically used to identify MATAG.

MATAG detection necessitates images during different growth stages, making fieldwork problematic in terms of labour and costly when using conventional visual assessment techniques based on the human eye (*Chu et al., 2025*). Conventional crop mapping is time-consuming and needs ongoing field research to validate and classify the images from RGB, multispectral, and hyperspectral sensors (*Zhang et al., 2025*). These problems can be solved by collecting spectral signatures for MATAG at various growth stages and mapping the reflectance of MATAG in the spectral signature library using sensors such as RGB and hyperspectral. Therefore, detecting MATAG using spectral signatures is highly desirable. The spectral signature can precisely map the MATAG variety as a spectral signature graph. Coconut species have specific spectral signatures with unique graph curves based on their characteristics. Then, a spectral library can compare the reflectance of MATAG in a field, estimating the infestation proportion (*Yang and Kong, 2017*). Moreover, it can identify plant locations through mapping coconut varieties. The spectral signature graph is stored in a digital database to prevent loss and provide easy access to researchers worldwide (*Rossel et al., 2016*). To the best of our knowledge, no study used spectral signatures to detect MATAG variety in any growing stages, starting from seeding, sprouting, growing, reaching maturity, and blooming. Only a few studies use the spectral signature analysis for coconut monitoring, and not specific for the detection of different coconut species (Table 1). Therefore, this approach could contribute to new knowledge and guide researchers to apply MATAG in the future.

Table 1

Examples of previous studies related to applying a spectral signature to coconut variety detection

Research focus	Findings	Reference
Select new antagonistic Trichoderma strains capable of protecting wild rocket and baby lettuce from harmful soil-borne pathogens.	Significant changes in the spectral signatures of healthy, infected, and bio-protected plants. OSAVI, SAVI, TSAVI, and TVI were strongly correlated with DSI.	*Manganiello et al. (2021)*
Use a portable spectrometer device for acquiring spectral signatures of various plant classifications.	Scanned spectral signatures of avocado, banana, cacao, coconut, mango, sugar cane, and cotton fruit/santol crops recognised by Mapua-Phil-Lidar-2 crops classification.	*Lazaro et al. (2019)*
Create a mechanism for identifying the spectral signature of tropical plants that	The FFT-processed reflectance demonstrates how the spectral signatures of each plant per location differ from	*Ballado et al. (2017)*

Research focus	Findings	Reference
grow in arid, wet, and near-sea environments.	one another. The peak value of Reflectance – FFT results for coconut is 1.1278 @194Hz (Arid Land).	
Collect field spectral signatures of CSI-affected coconut plants at various stages of infestation.	The spectral signatures of coconuts with varying degrees of infestation are different in the 8-band Worldview-2 satellite imagery, primarily in the NIR-1 and NIR-2 bands, followed by the Red Edge band.	*Parangit et al. (2014)*
Investigate the potential use of high-resolution data for horticultural crop type classification and delineation using a semi-automatic classification method versus traditional visual interpretation techniques.	Plantations that were older and more mature were classified more accurately, whereas young and recently planted plantations (3 years or less) had poor classification accuracy due to a mixed spectral signature, wider spacing, and poor plantation stands.	*Hebbar et al. (2014)*

4. COMPARISON BETWEEN TRADITIONAL METHODS AND SMARTPHONE-SPECTRAL SIGNATURE-BASED APPROACHES FOR DETECTING MATAG HYBRID

Traditional methods of MATAG variety cultivation include visual inspection and laboratory analysis. These methods have both advantages and disadvantages. The collected data are manually recorded in notebooks or logbooks, making them simple to adopt and applicable to different age groups of farmers because they require no digital infrastructure. It uses basic tools such as measuring tapes, poles, and even binoculars to identify the characteristics of crop species. The farmers will also physically evaluate the seedling colour and seedling age using morphological observation, thus allowing for direct assessment and decision-making. Although it is inexpensive, monitoring is subjective and inconsistent. Only surface-level problems can be observed, resulting in a lack of precision and depth (*Mahant and Pal, 2025*). It is also time-consuming and labour-intensive to accurately identify different Matag variety species, as limited to the farmer's knowledge and experience (*Arumugam and Hatta, 2022*). It is unsuitable for large-scale operations due to the need for extensive skills by qualified experts, with significant resources. Data retrieval and aggregation are inefficient, with limited data integration possibilities. Manual data collection and interpretation using items such as magnifying glasses, soil kits, and moisture meters can be prone to errors (*Mihrete and Mihretu, 2025*). Furthermore, laboratory analysis is suitable for less common MATAG samples, is costly, takes a longer time to produce the results, and is not suitable for large-scale MATAG monitoring due to the requirement for laboratory facilities and qualified personnel.

The monitoring of MATAG has improved substantially as technology has become more sophisticated. Farmers can use smartphone devices as an interface to capture the high-resolution images and spectral data of MATAG seedlings collected from unmanned aerial vehicles (UAVs) equipped with cameras and sensors. Images of the trees are then analysed using artificial intelligence and machine learning algorithms by a mobile application (*Singh et al., 2021*). When reflectance data are collected using external devices such as a UAV, the processed reflectance data can be uploaded to a cloud database or server. These processed spectral datasets are then retrieved by the apps and displayed in a user-friendly interface for farmers (*Heim et al., 2024*). In this context, the smartphone serves mostly as the end-user platform, while external devices provide additional spectral information. This approach allows for the early identification of problems in the field, frequently before obvious signs occur. It also provides detailed aerial views, allowing for early detection of pest infestations, disease outbreaks, and nutrient deficits on the trees. Farmers can take a picture of an infected tree and send it to the mobile application, which can figure it out within minutes. It has user-friendly interfaces that include GPS mapping, automated alerts, data analytics, and cloud storage. It offers instructional tools and advice on best practices in the plantation. It can be used to detect diseases in real-time across large areas. It is portable since farmers may receive information directly (*Ibrahim et al., 2025*). However, the accuracy may vary based on the quality of the provided smartphone camera and sensors, as well as the specificity of the algorithms. The initial setup cost is high, and technical skills through training are required to configure, operate, and interpret the data efficiently. It also requires consistent internet connectivity (*Liu et al., 2023*).

MATAG variety identification can be monitored using spectral signature libraries, which analyse the specific wavelengths of light reflected by various plant tissues. These libraries store data on the spectral signatures of healthy and unhealthy coconut leaves, which can be utilised for determining disease transmission across large areas (*Roslin et al., 2021*). Mobile applications can be created to display the spectral signature of MATAG leaves through smartphones while also providing farmers with control measures of the disease. Smartphones can detect plant species using processed images from RGB, multispectral, or hyperspectral sensors, as well as an algorithm (*Che'Ya et al., 2022*). By connecting mobile devices with UAVs, images of coconut tree crowns can be captured, and it is used to estimate total leaf area, number of bunches and fruits, and other phenotypic traits (*Arumugam and Md Hatta, 2022*). Such a connection can help to minimise data collection time and costs while also improving phenotyping data accuracy. Most smartphones are equipped only with RGB cameras. Hence, spectral signature analysis on smartphones is either limited to RGB-based indices or supported by add-on accessories (i.e., clip-on portable spectrometers) that increase the spectral range (*Schlemitz and Mezhuyev, 2024*). As an alternative, smartphones can be connected to external databases of pre-collected spectral libraries, which enables the phone to be utilised as the interface for spectral data visualisation and decision support.

While traditional methods for recognising MATAG diseases remain acceptable, smartphones with built-in cameras or that connect to external spectral sensors to evaluate the light reflected from coconut trees provide a more efficient, accurate, and cost-effective alternative. Smartphones can give precise data, detecting diseases that are invisible to the naked eye in real-time. Furthermore, smartphones are highly scalable, making them appropriate for large-scale plantations. Traditional approaches, on the other hand, have limited scalability due to labour constraints. Smartphones allow for seamless data integration, analysis, and storage, usually set up with cloud-based systems, whereas traditional methods rely on manual records that are difficult to analyse and prone to loss or damage. Traditional methods are less expensive initially. Despite the higher initial costs of smartphones, they provide better long-term cost reductions and benefits through optimised resource usage and increased yields, making them a good investment. Smartphones are designed to be user-friendly, but they need a certain amount of digital literacy, whereas traditional methods do not require technological proficiency but can be time-consuming and inconsistent (*Padhiary et al., 2025*). The combination of traditional and modern approaches might leverage the strengths of each to provide an efficient system for MATAG variety identification and farm management. The comparison between the advantages and disadvantages of traditional methods with smartphone-spectral signature-based approaches is presented in Fig. 3.

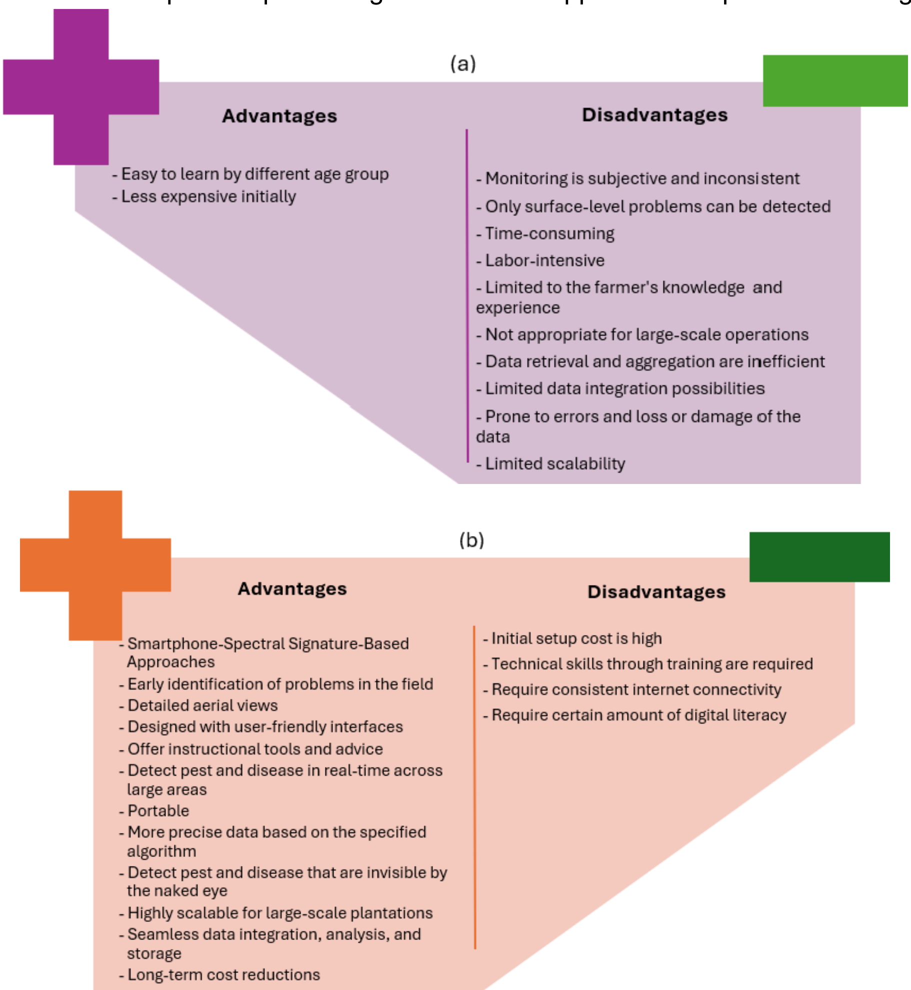

Fig. 3 - Advantages and Disadvantages between Traditional Methods (a) and Smartphone-Spectral Signature-Based Approaches (b) for Detecting MATAG Hybrid

5. MECHANISM OF MATAG VARIETY DETECTION BASED ON SPECTRAL SIGNATURE ANALYSIS USING A SMARTPHONE

5.1. Collection of Reflectance Data and Spectral Signatures

At first, the farmers need to ensure that the GPS in the smartphone is turned on to tag the location of the MATAG trees. After collecting the on-leaf surface of the seedlings, the reflectance of the spectral data is collected using a Handheld Spectroradiometer, under clear sky field conditions. It has a highly sensitive detector array with a low stray light grating, a built-in shutter, DriftLock dark current compensation, and second-order filtering, which produces a high signal-to-noise spectrum with second. Spectral data collection involves two primary steps, which include spectral sampling (Fig. 4) and spectral library compilation. During calibration, the white panel diffuses around 99% of incident light across its spectral range. Specifically, the reflectance value of the white reference panel is almost one for each wavelength (*Buddenbaum et al., 2019*). The MATAG trees should be chosen at random for 10 samples, with a spacing of 5 cm between the optical sensor and the sample. Accordingly, this method works to record data without inaccuracy or noise (*Che'Ya, 2016*). Reflectance data and spectral signature images for identifying MATAG species should be captured through RGB or hyperspectral sensors (*Strauss et al., 2021*).

The images are then divided into digital segments, and objects within the images are analysed using computer vision techniques such as machine learning and support vector machines. Hence, the spectral signature of a crop cannot be accurately assessed by parametric approaches such as regression or functional statistics. Non-parametric methods for hyperspectral spectroscopy include PCA, Fuzzy logic, SVM, CA, PLS, and NNs. Fisher's Linear Discriminant Analysis (LDA) classifies imaging and non-imaging hyperspectral data into two or more classes (*Golhani et al., 2018*). The generated images are examined for spectral signature differences among several MATAG types.

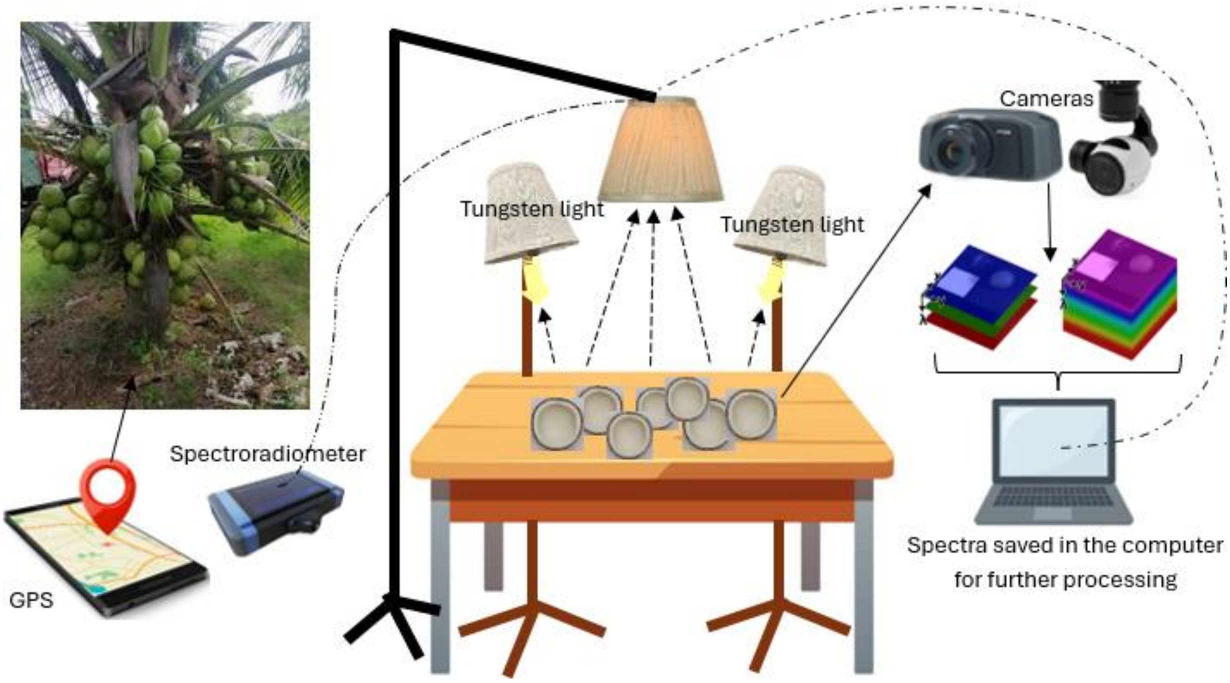

Fig. 4 - Configuration of spectral sampling in MATAG variety detection

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

Image preparation uses an algorithm incorporated into the system (*Miao et al., 2018*). The preprocessing phase ensures that the image collects only the analyses of hybrid components and excludes the other coconut species, also known as the separation technique. The colour of the images will be restored using colour constancy and uniformity (*Mendes et al., 2020*). The plant's various characteristics will next be retrieved and compared to the MATAG hybrid model to verify their uniqueness. The user receives findings that include the type of MATAG, the causing agent, a technique to control the infection, and prevention guidelines for overcoming the infection (*Ouhami et al., 2021*).

MATAG variety detection could be accomplished by capturing images of crops with seedlings using a camera. Under certain conditions, the camera may capture the image and detect the status of the plant harbouring the different MATAG species based on light reflectance (*Areni, 2020*). Implementing hyperspectral sensors in smartphone devices is one way to improve the limits. A hyperspectral sensor can measure hundreds of electromagnetic spectrum bands within its range. The hyperspectral sensor's spectral bands monitor only a few nanometres of the electromagnetic spectrum, generating a wavelength with great spectral resolution (*Ko, 2019*). As a result, each pixel in a hyperspectral image acquires a specific set of data about the reflectance (or transmittance) of each spectral band (*Che'Ya, 2013*).

The total amount of these data is known as a spectral signature (or spectral profile), and it is captured by a non-imaging hyperspectral sensor (i.e., point spectroscopy) without the need for additional spatial information (*Park et al., 2020*). Hyperspectral sensors detect the spectral bands of each pixel in an image and merge the spectrum and spatial resolutions. As a result, each pixel in the image has a unique spectral signature, which comprises reflectance values for all spectrum bands detected by the hyperspectral sensor (*Hassanzadeh, 2020*). From another perspective, the final image is a hyperspectral data cube with two dimensions of spatial information and a single size for spectral information. In general, hyperspectral sensors can measure the NIR (700-1000 nm) and SWIR (1000-2500 nm) wavelengths of the electromagnetic spectrum (400-700 nm) (*Contreras, 2020*).

The interaction between spectral signature information and ground data demonstrated that the rate of MATAG variety detection in the crop may be predicted. Spectral reflectance can reveal species variances at specific wavelengths. *Roslin et al. (2021)* discovered that in the visible spectrum (450 nm to 700 nm), numerous weed spectral signatures were quite comparable, and several overlapped. Undoubtedly, not all MATAG have the same spectral signature on the coconut species, hence calibration and validation are still needed to identify MATAG. At the same time, in the infrared region (700 nm to 990 nm), different species' spectra are recognised by their wavelengths. Because each coconut has its own unique features, the significant bands for each species can be discovered in a specific region (710 nm to 750 nm), including MATAG. The damaged area could serve as an indicator for identifying MATAG species using spectral signatures. As a result, information on the spectral signature of the MATAG, as well as other sorts of pests and diseases, must be stored in a user-friendly manner.

The image data can be collected in red, green, and blue (RGB), and the MATAG will be identified based on its shape and colour using image processing. Thus, utilising a smartphone, the user can identify MATAG using apps connected to a cloud-based data processing machine. The spectroradiometer will capture spectral signatures (hyperspectral data) that can be used to classify MATAG. Thus, RGB, spectral, and hyperspectral information can be utilised to identify and refer to hyperspectral data. Certain smartphones only record RGB images. They can, however, process the RGB information and generate the results using artificial intelligence (AI) on the cloud server. The spectral signature of plants is already stored in the spectral library, which may be accessed if the user has a hyperspectral sensor and compares it to the spectral library in smartphone devices.

5.3. Generation of Spectral Signature Graph

The following subsection illustrates how spectral reflectance profiles can be analysed for MATAG and related coconut varieties. Applications for MATAG variety detection should rely on the ability to obtain a spectral signature that is related to tree features and plant health. Hence, a spectral signature graph could be associated with a variety of tree features, including age category, varietal difference, density, and shade composition (*Che'Ya et al., 2022a*). Other factors include healthy and unhealthy trees, with spectral signature values varying according to the types of MATAG hybrid. For data analysis, all raw data were sent to a computer. The data was saved in a Microsoft Excel file. In addition, the data should be arranged into 10 nm spectral bands, rather than its original 1 nm value (Fig. 5). The spectral signature may be seen in the spectral reflectance graph for each MATAG species. To further analyse subtle differences among coconut varieties, the first derivative of spectral reflectance is often used, as reported in a previous study (*Che'Ya et al., 2022c*). The general formula for calculating the first derivative between two adjacent reflectance values is given in Equation 1:

i. Visualising Spectral Reflectance. Construct a graphic illustration that shows spectral reflectance for MATAG.
ii. First Derivative Analysis. Use Equation (1) to calculate the first derivatives and then generate the spectral signature and first derivative graphs.

(1)

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

where:

FD = First Derivative.

Ry_1, Ry_2= Reflectance of the first and second reflectance pairs n1 and n2.

λx_1, λx_2= Wavelength of first and second reflectance pairs n1 and n2.

n = Position of reflectance.

Fig. 5 presents an example of spectral reflectance profiles for MATAG seedlings. These curves can be further analysed using the derivative approach shown in Equation 1, which enhances the detection of small variations between overlapping spectra. The spectral reflectance profile of the three different coconut seedlings shows a similar trend. According to the graph, the spectral reflectance showed a low reflectance in the visible region with a small peak in the green region, and an increase begins at 680 nm. However, it is observed that numerous noises are clearer at certain points in the near-infrared region. The spectral data of the three coconut seedlings were similar in the visible region, and many overlapped each other. In the near-infrared region, the spectra of different seedlings also showed quite similar patterns, but they can be observed between 733 nm and 1000 nm. The reflectance of MRD coconut seedlings showed the highest NIR reflectance, and the lowest belongs to the reflectance of MATAG coconut seedlings. However, this study only detects and classifies MATAG coconut seedlings based on spectral data using a machine learning algorithm, without any integration with the mobile application. Future studies are needed to develop an intelligent identification system for the MATAG variety based on spectral signature analysis using a smartphone device.

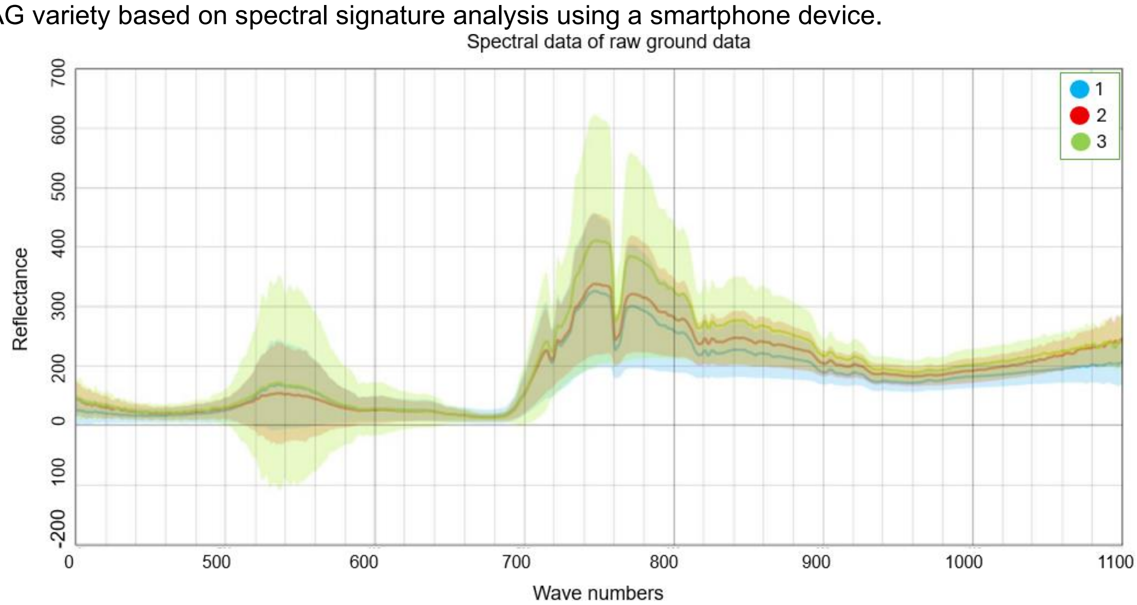

Fig. 5 - Spectral data of coconut seedlings of MATAG, MYD and MRD

5.4. Proposed Framework for Incorporating Spectral Libraries into Mobile Application

While no mobile applications currently exist for MATAG variety detection using spectral signatures, this section presents a conceptual application framework for how such applications could be developed and implemented. Farmers should choose a smartphone with a high-resolution camera capable of taking good pictures. Some smartphones have multi-spectral sensors, but basic smartphones can also be used using apps developed for MATAG variety identification and spectral analysis. The apps use algorithms to evaluate spectral data and associate it with several MATAG species. Plantix and Cropio are two applications for crop monitoring that can be connected with MATAG variety detection. To ensure accurate spectral analysis, images must be captured under consistent lighting conditions. The smartphone will improve the image quality by adjusting brightness, contrast, and reducing noise. It will also extract spectral information from the images, then transmit the results to a server for further assessment. This outcome includes examining the light reflected by the MATAG trees in various electromagnetic spectrum wavelengths, including red, green, blue, and near-infrared. The server detects the unique MATAG variety via spectral signature analysis. The selected variety is then reported back to the farmer via mobile apps, giving them correct information about the trees.

Creating an online database via smartphone from the processed images of spectral signatures for MATAG requires continuous monitoring of the plantation. The database should have a list of MATAG varieties that can be used to identify specific characteristics as either the true-to-type or off-type seedlings, on an image. Therefore, MATAG classification demands images from various seedling ages to harvesting stages, as well as dates that coincide with crop growth stages. Aerial images should adjust the spectral resolution to fit the spectral signatures in the database. Other metadata, such as instrument characteristics, date of acquisition, vegetation biophysical parameters, soil characteristics, and other significant data, can also be displayed in this database.

The camera attached to a smartphone can be used to obtain imagery data for MATAG trees collected on the ground and varying levels of canopy decline, and stored in the database. With that, developers have created a smartphone attachment and application for simple spectroscopy. It uses a camera and a small spectrometer to collect the spectral data in MATAG trees. Farmers can identify with the MATAG variety using all the processing links to the server, including image preprocessing, transformation, and clustering (*Nesarajan et al., 2020*). The additional information includes the specific date and time, percentage of cloud cover, temperature, humidity, species homogeneity, the health of MATAG, size of the surveyed area, illumination and viewing setting, device calibration, and instrument settings that can be inserted into the smartphone.

Therefore, a spectrum library must be created to store MATAG variety data, identify different disease severity levels across a large area, and provide users with an action plan for crop management. The spectral library also contains normatively measured and processed background situation parameters for the specified MATAG species. The five components of the spectral library system include a knowledge database, a measured spectral library, an auxiliary library, spectral analysis, and an end-user application demonstration. 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 spectral analysis could be pre-analysed to verify the accuracy of the library before end-users use it in practical tasks. Fig. 6 presents an example of the data model of the spectral library system of MATAG.

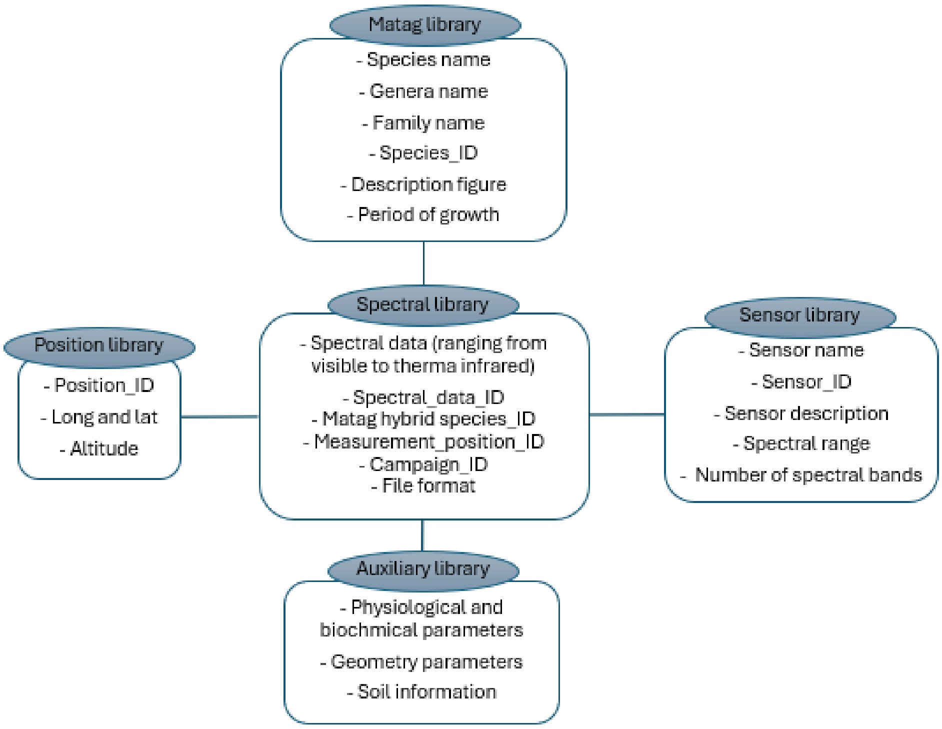

Fig. 6 - The data model of the Spectral Library System of MATAG variety detection

The spectral signature graph can be stored in a multifunctional database, such as mobile applications, enabling easy access by consumers and researchers (*Rossel et al., 2016*). The spectral signature was displayed as a reflectance graph for each MATAG variety identification. Creating a spectral library for MATAG in crop fields using the proposed mobile apps is an excellent technique to record spectral signatures for future reference.

5.5. Proposed System Architecture of IoT-Enhanced Smartphone Platform for MATAG Detection

The proposed platform describes IoT sensors as the primary spectral data collectors, with smartphones functioning as user interfaces and local processing units. Such an approach will integrate the smartphone accessibility with the precision of dedicated spectral sensors. The proposed mobile app design consists of two parts: system architecture (back-end) and menu design (graphical user interface), as illustrated in Table 2. The system architecture consists of three layers: presentation, logic, and data. The presentation layer allows users to view and interact with the app. The flow should be intuitive, with every menu having a specific objective. The logic layer serves as an API for farmers to obtain data from the database layer and send requests to the presentation layer. The data are then transmitted to the presentation layer. The data layer is the core of the proposed mobile application, where all data will be stored and retrieved. Each request for information in the presentation layer passes through the logic layer and then to the data layer before being displayed to the user in the presentation layer. Fig. 7 demonstrates the theoretical basis for creating a spectral signature graph to detect the MATAG variety that uses smartphones.

Table 2

List of main menus of the proposed mobile applications

Menu	Details Information
Location	Research site, crop-field area, and total number of plots used in the study
Planting schedule	Schedule of planting activities
UAV images	Spectral images
Field problems	Images showing field conditions and observed problems
Pest and disease	MATAG pest and disease categories, their spectral-signature graphs, and recommended control measures
Weather forecast	Weather conditions and forecasts for the field site
Yield	Quantity of harvested produce
Report	A function that allows farmers to prepare and submit reports on various MATAG characteristics

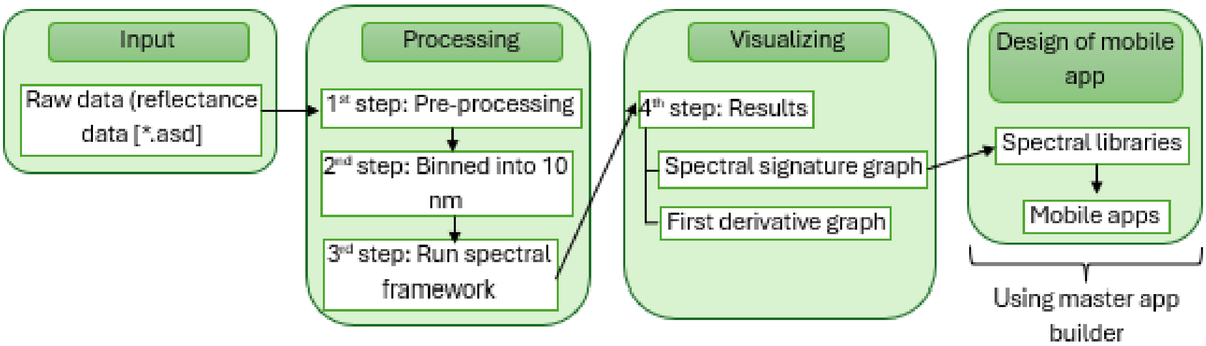

Fig. 7 - Theoretical framework for generating the spectral signature graph for detecting the MATAG variety using a smartphone

The spectral imaging module can be placed either on an aerial platform like a UAV or a stationary platform like a high pole, which keeps collecting data at regular intervals, which are determined by the type of MATAG and its characteristics. In the spectral imaging module, the data is sent directly to the cloud (*Inamdar et al., 2021*). Following the use of image-to-map geometric rectification techniques to coincide the image data with the actual map coordinates, the image is preprocessed before the spectral response is extracted from it. The processing involves applying suitable smoothing filters to the image to remove any outliers or incorrect data.

The next step involves the use of the Internet of Things (IoT), which enables the storage of farm data over the cloud to be utilised for data analytics and pattern recognition. Fig. 8 shows the overall system. The data that were obtained from the seedlings is collected and transmitted by the sensor nodes. These data are given to the Sink node, which transforms them into IP packets that can be transmitted to the cloud. The spectral Image Module captures the spectral image and sends it to the cloud on its own. The cloud then processes the data before being sent to the user. The cloud platform is accessible to farmers, who can access the dataset and its output (*Esther et al., 2019*).

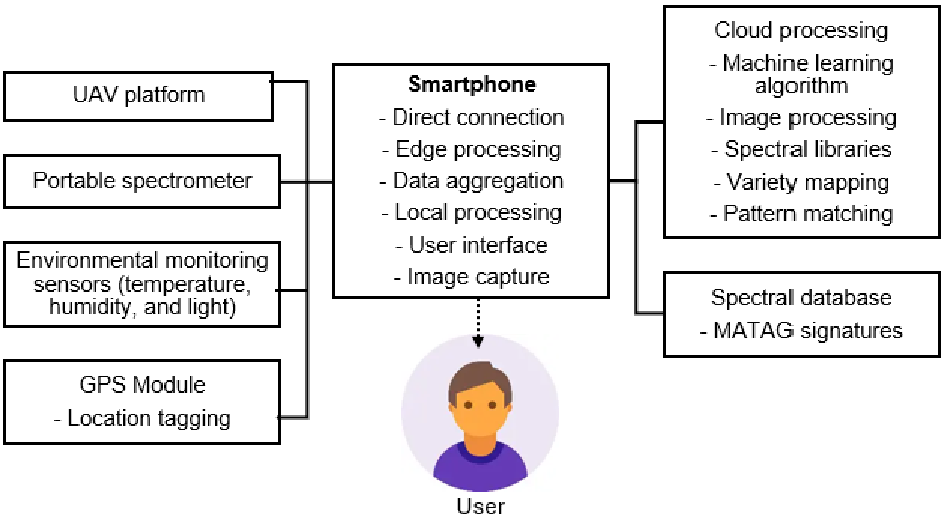

Fig. 8 - IoT-Enhanced Smartphone Platform

The spectral response of an image is then extracted. The sensor module's sensitivity to various wavelengths of optical radiation is determined by its spectral response. Therefore, the farmer can obtain information about the MATAG variety based on the number of different wavelengths. For example, the necessary parameters are estimated using the NDVI value as a standard. Data collected from the sensor node will be buried in the ground through the sink node stored in the cloud alongside the processed data. The data from these two sources are compared and processed per the MATAG's needs and the parameters estimated from the data collected (*Mohanty et al., 2022*). A proposed procedure for the development of intelligent MATAG coconut seedling identification using spectral signature analysis is presented in Fig. 9.

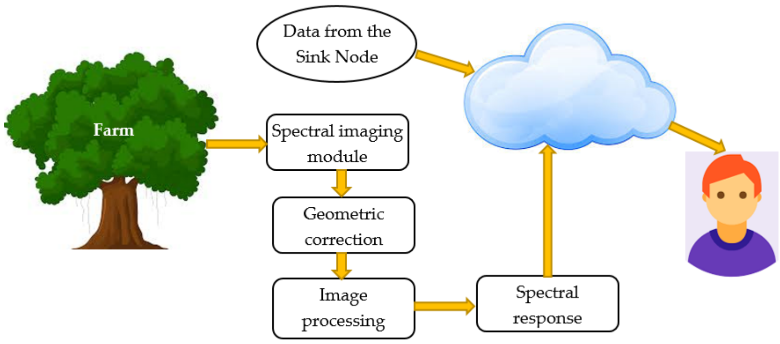

Fig. 9 - Spectral imaging with IoT

Finally, the future MATAG detection apps can provide a health assessment based on the spectral signature analysis based on healthy, stressed, or diseased categories that can improve interpretation and decision making. The app may provide recommendations for interventions, such as fertiliser application, pest control measures, or watering schedules. Regular monitoring and data collection are essential. The app can be used periodically to capture new data and update the health status of the MATAG trees. In short, tools will be involved in developing apps that involve the smartphone with a camera and GPS (to capture images and geotagging), mobile applications (software that performs spectral analysis), cloud services (to store data and perform complex computations), and machine learning models (to analyse spectral data and predict health conditions).

As a summary, the integrated workflow begins with UAV-mounted sensors collecting canopy-scale reflectance data, complemented by IoT devices monitoring soil and environmental parameters. In the meantime, smartphones are used by farmers to capture close-up seedling images. All data streams are integrated via a centralised platform, where analysis is performed, and the processed results are then returned to the farmer's smartphone for decision-making. Each technology complements the others to ensure continuous monitoring from planting to maturity.

6. CASE STUDIES AND TESTIMONIALS FROM FARMERS ON HOW SMARTPHONE HAVE REVOLUTIONISED CROP MONITORING PRACTICES

Three case studies reported the application of spectral signature analysis for coconut variety detection and monitoring using smartphones, which could be applied to MATAG studies in the future. First, an article published in the Journal of Agricultural Technology monitors health and detects diseases in coconut palms using spectral signature analysis. The researchers built a mobile app that uses a smartphone camera to capture images of coconut leaves. The app processes the images to extract spectral signatures, mainly focusing on specific wavelengths that relate to chlorophyll content and other indicators of plant health. Data collected by the app is analysed to determine stress indicators, including nutrient deficiencies or the presence of pests and diseases (*Singh et al., 2021*).

Second, an article published in the International Journal of Remote Sensing predicts the yield of coconut trees using spectral data collected. The researchers developed a mobile app to capture images of the coconut canopy. The app used machine learning algorithms to analyse the spectral data and predict crop production. Normalised Difference Vegetation Index (NDVI) was used to assess the health and productivity of the trees. The mobile app provided accurate yield predictions with a high association between predicted and actual yields (*Hebbar et al., 2022*).

Third, an article published in the Plantation Management Journal improves plantation management practices by monitoring coconut tree growth and health using spectral data. The app collected spectral data from the leaves and processed it to provide insights into the overall health of the plantation. Parameters such as leaf area index (LAI) and chlorophyll content were generated from the spectral signatures. Farmers reported improved management practices, such as optimised irrigation and fertilisation, based on the data provided from the app (*Samarakoon et al., 2025*).

However, none of the above studies detect the MATAG variety or even crop species based on the spectral signature analysis using a smartphone. Hence, this review mentions an app that found the weed species, which could be adopted for the identification of MATAG species in the future. For example, *Roslin et al. (2021)* generated a spectral signature graph of weeds and created a mobile app for spectral signature analysis of weeds. Using Master AppsBuilder, all spectral signatures were saved in a spectral database and illustrated on smartphones. Fig. 10 displays the website's main menu, which includes a list of applications, while Fig. 11 provides the content of menus, images, description, the control technique, and a spectral signature graph of MATAG. The main menu consists of information, spectral signatures, and recommendations for weed control. Users can download the mobile app on their devices. Besides the case study, this study also identified the testimonials from farmers on crop monitoring practices that were extracted from Google search, as shown in Fig. 12.

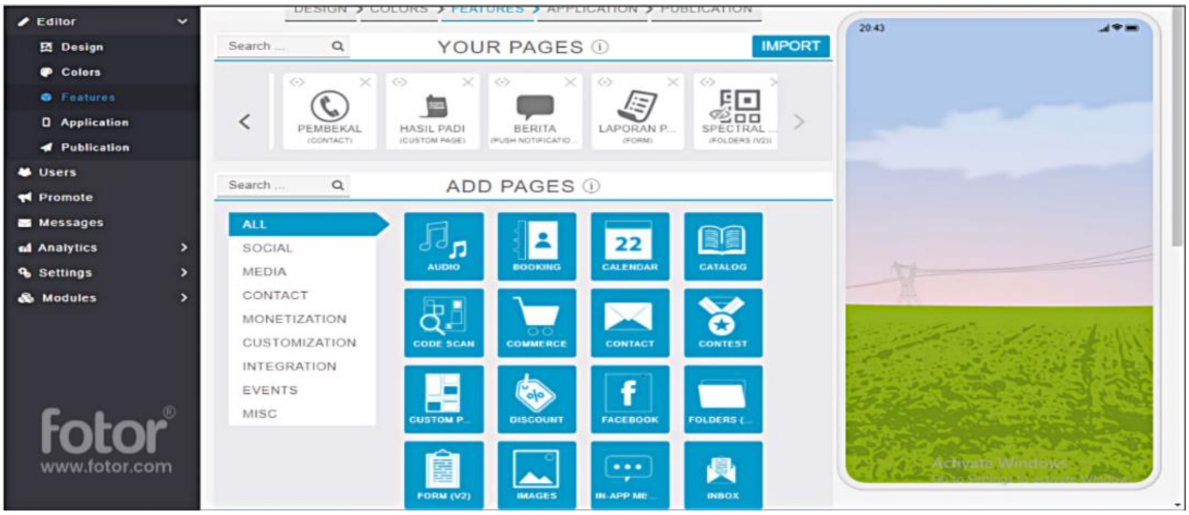

Fig. 10 - The application Editor tool and Feature menu in the MasterAppBuilder Application. (PEMBEKAL: SUPPLIER, HASIL PADI: RICE YIELD, BERITA: NEWS, LAPORAN: FORM)

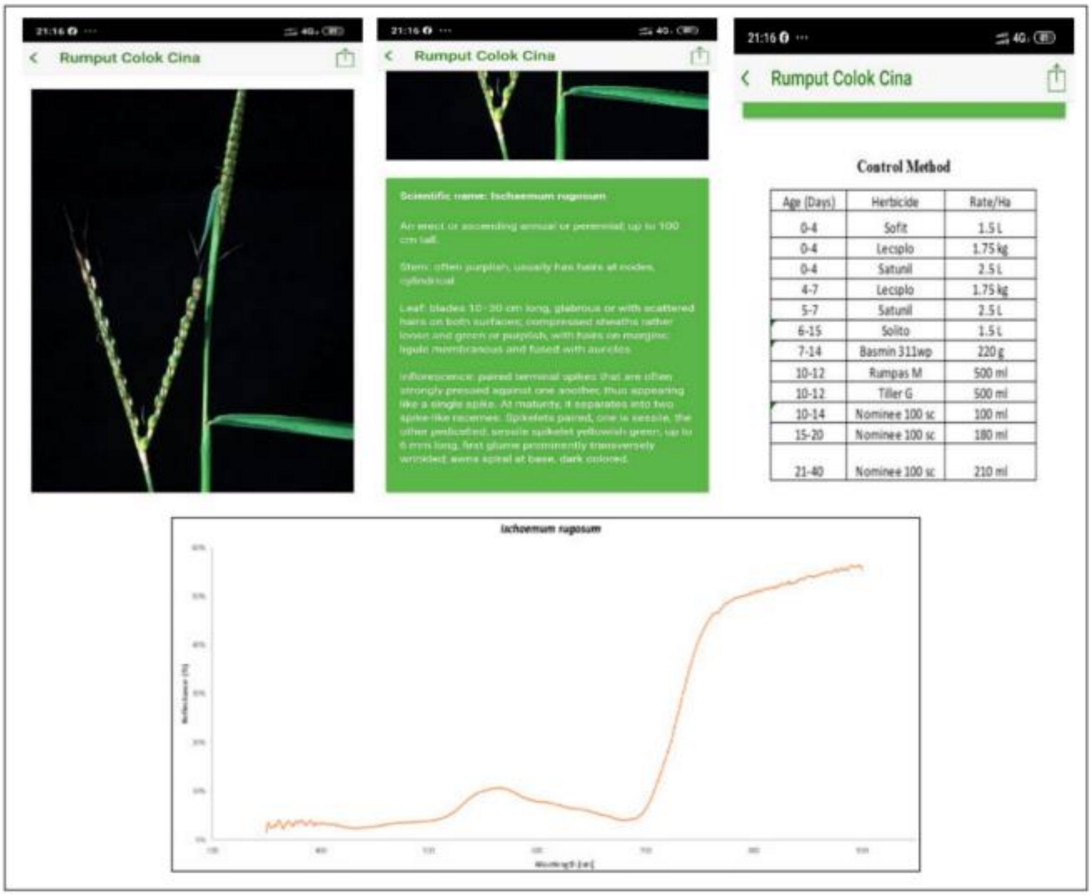

Fig. 11 - The content of menus, pictures, description, control method, and spectral signature graph of MATAG

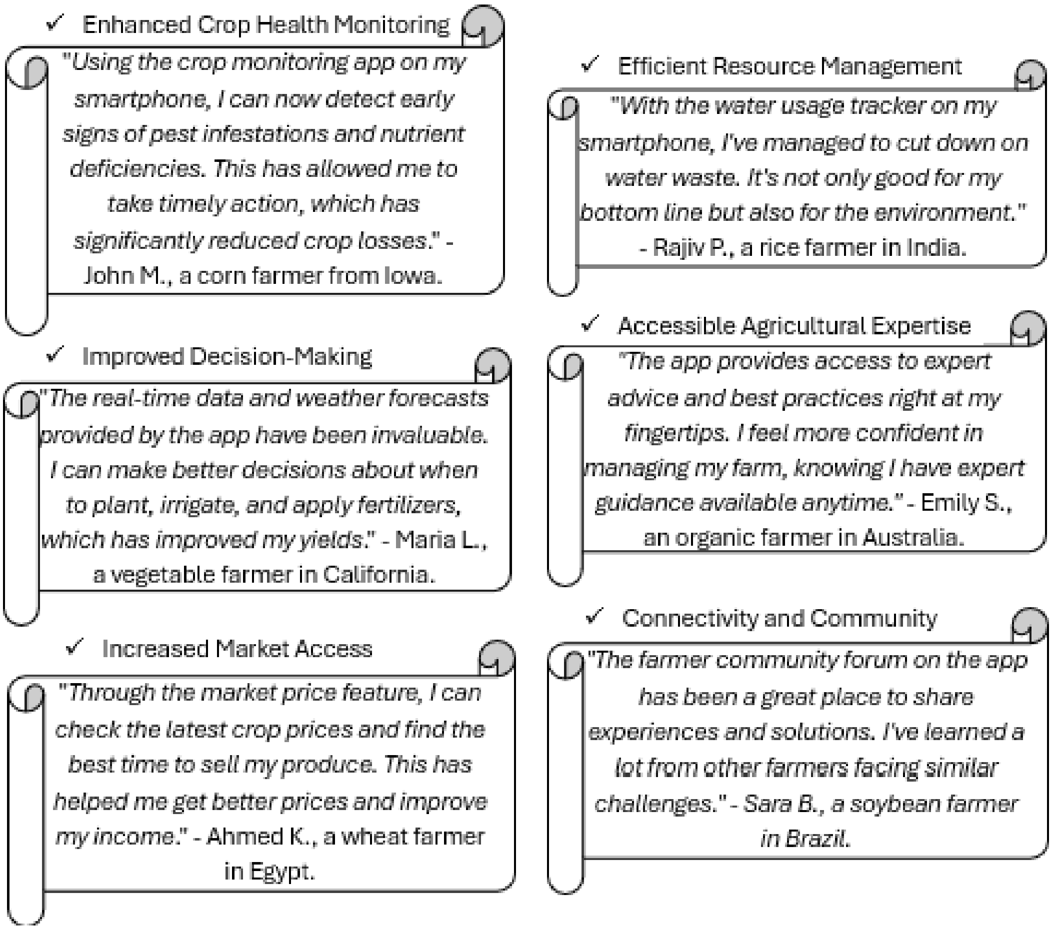

Fig. 12 - Testimonials from Farmers

7. POTENTIAL BENEFIT OF USING SMARTPHONE DEVICES TO THE AGRICULTURAL INDUSTRY

This section presents potential benefits and future perspectives for integrating smartphone-based spectral signatures into MATAG detection rather than established conclusions. While smartphones and spectral technologies show promise for MATAG identification, further field validation and multi-location trials are required before widespread adoption. Studies suggest that using smartphones for crop monitoring may have potential advantages for farm management. First, farmers can use a smartphone to identify early signs of crop stress, nutrient deficiencies, and disease outbreaks through real-time image-based monitoring, enabling timely and site-specific interventions (*Nyakuri et al., 2025*). This feature enables earlier mitigation measures to be implemented, lowering the chance of crop loss while increasing yield. Early intervention also saves resources through preventing expensive chemical treatments. Second, smartphones could help farmers to effectively monitor soil moisture levels, allowing them to change irrigation schedules based on crop needs. This feature assures that crops get enough moisture without wasting water, lowering water costs. Previous research demonstrates that images captured by smartphone sensors (under controlled lighting) can predict soil moisture with moderate accuracy (i.e., MAE = 0.35, RMSE = 0.15, $R^2 \approx 0.60$), confirming the feasibility of image-based soil moisture estimation (Riaz Hasib Hossain and Ashad Kabir, 2023). Third, farmers who have access to precise data on soil moisture, meteorological, and crop growth patterns can maximise resource allocation, including water, fertilisers, and pesticides (*Mansoor et al., 2025*). It ends up with a minimised environmental impact.

Fourth, farmers can use data-driven insights and practical alternatives to reduce risks, increase productivity, and improve overall farm management. This informed decision-making aspect eliminates the need for expensive trial-and-error procedures (*Mishra and Mishra, 2024*). Fifth, smartphones automate data gathering and analysis, reducing the need for human record-keeping and data entry. This characteristic not only saves time but also reduces the possibility of errors or anomalies in the handling of data (*Payero et al., 2021*). Farmers can concentrate more on their main farming tasks, leading to improved operational efficiency. Sixth, online monitoring using sensors might decrease agricultural maintenance expenditures. Such monitoring is crucial for small and medium-sized farms, where resources are limited. It can cut maintenance costs by up to 30% by enabling online monitoring via sensors. Real-time data on crop status improves production efficiency and resource utilisation (*Aarif et al., 2025*). Seventh, a smartphone should be compatible with existing farm management systems and interface with other farm-related devices. This compatibility implies seamless exchange of data while reducing the need for extra hardware or software investments (*Choudhary et al., 2025*).

Eighth, a smartphone may automate tasks including data collection and processing, freeing up staff for other important farming tasks. This automation lessens labour expenses and improves overall efficiency (*Mumuni and Mumuni, 2025*). Ninth, smartphone use imagines recognition technology to detect pests and diseases that potentially impact crops. Farmers can immediately identify and solve these problems, avoiding the need for costly chemical treatments and related expenditures. Tenth, smartphones allow farmers to precisely monitor soil moisture levels, ensuring that crops receive enough moisture without wasting water resources. IoT-based soil moisture monitoring systems integrated with smartphone alerts enabled real-time irrigation decisions, resulting in up to 30% water savings compared to conventional methods (*Dong et al., 2024*). Eleventh, a smartphone can help farmers optimise their energy consumption by providing real-time data. This optimisation facilitates them to regulate their energy use patterns, lowering energy expenses and environmental impact (*Ahmed and Shakoor, 2025*).

Twelfth, smartphones automate collection and analysis, reducing the need for human record-keeping and data entry. Such automation lowers labour expenses involved with data management, allowing farmers to concentrate on primary farming activities (*Resti et al., 2024*). Thirteenth, smartphones automate data administration, which reduces the probability of errors or discrepancies. This feature indicates that the data is correct and reliable, which reduces the need for costly adjustments (*Kumar, 2024*). Fourteenth, smartphones offer farmers data-driven insights and useful guidance, allowing them to improve their operations. Such a feature leads to increased agricultural yields and greater farm profitability. The global market for smart agriculture is predicted to expand from $12.4 billion in 2020 to $34.1 billion by 2026, indicating the enormous economic potential of implementing these technologies (*Techspian, 2024*). Farmers can use these economic benefits to reduce crop monitoring and management costs, resulting in enhanced efficiency and profitability. Overall, smartphones offer an effective and accessible platform for integrating spectral data into MATAG identification. However, successful adoption will depend on addressing technological limitations, farmer training, and validation in diverse environments.

8. CHALLENGES IN DETECTING THE MATAG VARIETY USING A SMARTPHONE

There are a few challenges in developing future MATAG detection apps for detecting MATAG using spectral signature analysis. The processing capacity, i.e., the operating time of mobile apps, is one of the main challenges. There is also a need to transfer the data to be processed to a remote server. Besides, some locations may not have an Internet connection, which loses its ability the operation time and could cause a delay because it can only be used when there is access to the Internet. When facing a weak Internet connection, the user needs to bring the apps to other nearby locations to ensure that the device is connected to the Internet, which is inefficient in practice (*Mendes et al., 2020*).

Another limitation is the size of the smartphone's screen. The small size of smartphones could result in changing geometric relationships between the user's face and the phone screen and low-resolution frontal cameras. Instead of purchasing a computer that has a bigger screen size, farmers should be able to use their smartphone simply. Although almost all smartphones today have sizable screens, there are some with smaller screens; hence features of the applications must be designed to be user-friendly across screen sizes.

Smartphone keyboards have much smaller buttons or touch spaces than standard desktop or PC keyboards. Therefore, incorrect touches could frequently happen. In addition, when using a capacitive touchscreen interface, there is a problem with dirt on the screen that is caused by fingerprints and finger sweat. Therefore, touch interfaces cannot be used as smartphone interfaces are not disabled-friendly or it is less functional when both hands are carrying something or doing some activities. Moreover, such mobile devices have an integrated camera as the default configuration.

There is also another issue that needs to be considered when developing apps for smartphones. The problem is the skill of the manpower to use the device, such as farmers. They primarily work in the field, are elderly, and do not particularly adapt to such technology. As a result, the future MATAG detection apps must be as simple, intuitive, and handy to use in their daily farming activities (*Abdullahi et al., 2021*). Consequently, user behaviour in using smartphones differs across community backgrounds. For instance, rural farmers in low-income countries may be restricted by low literacy and a lack of exposure to device interfaces. Therefore, they require highly intuitive interfaces, in which using too much text as an interface may be incomprehensible or difficult to use.

Other constraints were the high cost of buying smartphones, maintenance, lack of encouragement, and usage awareness. As a result, some farmers prefer to use the conventional method, which results in low participation of farmers. Moreover, it is not that easy to insert and update the information into the apps (*Abdullahi et al., 2021*). Therefore, smartphone application developers must solve this limitation by creating an interface design that is handy for multiple users.

9. FUTURE RESEARCH OPPORTUNITIES OF MATAG VARIETY DETECTION USING A SMARTPHONE

Many apps are being used in the public domain in the agricultural field, and not just by licensed users. However, most farmers who use these applications have little or no knowledge of the device attributes. Therefore, the future MATAG detection apps need to be designed in a simple way and be efficient to use promptly. However, as a new generation of farmers gains proficiency in using these apps, this issue will be addressed over time.

More apps that involve IoT in their farming practices are being developed, but users will only need a little IT knowledge to use the device. In addition, the developer will design criteria and usability standards so that the apps must consider work tools rather than just applications for enthusiasts or entertainment. It is also projected that software that currently operates on smartphones will progressively shift to larger devices such as tablets, tab, and iPads.

To increase smartphone processing capabilities, apps are likely to use deep learning, machine learning, or artificial intelligence techniques on the smartphone. This approach avoids the inability to use apps in remote areas where Internet access may be unavailable or limited. Instead, the apps are expected to be able to be used offline and then transfer data to a remote server that will be accessible via various devices.

Future developments in smartphone spectral signature technology are anticipated to focus on both hardware and software advancements. Developing equipment with image sensors capable of acquiring wavelengths outside of the visible spectrum is also anticipated to open up new alternatives for this type of application. Smartphones equipped with cameras capable of capturing the spectrum in the near-infrared and infrared zones will allow the implementation of vegetative vigour determination applications, such as creating spectral signature graphs of the MATAG variety in coconut nurseries.

More precise detection of physiological and varietal variations will be made possible by developments in smartphone cameras, such as the incorporation of multispectral and hyperspectral sensors or the use of affordable clip-on spectrometers. Smartphones with powerful processors will be able to conduct on-device spectral analysis without exclusively depending on desktop or lab computers.

The combination of cloud computing and artificial intelligence will be equally significant. Real-time data analysis is feasible with AI algorithms implemented through mobile applications, providing farmers with fast decision support. It will also be essential to create open, standardised spectral libraries for coconut varieties so that farmers and researchers may access reliable reference data. Participatory collection of data, in which farmers help create extensive spectral repositories, could be used to develop these databases.

Smartphones will probably serve as hubs in larger digital agriculture ecosystems in the future, connecting cloud platforms, IoT field sensors, and UAV-based imaging. This integration will facilitate yield forecast, crop health monitoring, and MATAG hybrid identification. Future studies must focus on user accessibility, cost, and training in addition to policy assistance to promote digital agriculture solutions in coconut-producing countries to ensure successful adoption.

10. CONCLUSIONS

This article reviewed the potential of integrating smartphones with spectral signature analysis for detecting the MATAG hybrid. Key topics discussed consist of the morphological challenges of identifying MATAG varieties, the utilisation of spectral reflectance data and derivative analysis, the role of spectral signature libraries, and the comparison of smartphone-based methods with traditional approaches. The spectral signature graph was displayed as a reference to detect various species of MATAG more efficiently. The review emphasises that spectral libraries generated in mobile applications, when combined with external sensors and spectral databases attached to the smartphone, could provide a promising and affordable platform for intelligent MATAG seedling identification. Future research should focus on field validation, farmer adoption strategies, and the development of user-friendly applications tailored to plantation conditions.

11. ACKNOWLEDGEMENT

The authors delegate our thanks to the Department of Agriculture, Jorak (Johor) and Lekir (Perak) for providing the sample of MATAG species in this project and the Ministry of Higher Education, Malaysia under the Long-term Research Grant Scheme (LRGS) for the program titled “Precision Management of Coconut Nursery for Production of High Quality Seedlings”- LRGS/1/2020/UPM/01/2 (Vote No: 5545202) for the funding.

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