



**Oil Palm Tree Detection and Counting using  
Backpropagation Neural Network from RGB-based  
Satellite Image**

by

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## LIST OF ABBREVIATIONS

UAV	Unmanned Aerial Vehicles
DEM	Digital Elevation Models
AI	Artificial Intelligence
ANN	Artificial Neural Network
BPNN	Backpropagation Neural Network
BHB	Boustead Holdings Berhad
JPEG	Joint Photographic Experts Group
ASD	Analytical Spectral Devices
CVA	Change Vector Analysis
SVM	Support Vector Machine
OBIA	Object-Based Image Analysis
RGB	Red, Green, and Blue
CNES	Centre National d'Etudes Spatiales
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

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## **Pengesanan dan Pengiraan Pokok Kelapa Sawit menggunakan Perambatan Balik Rangkaian Saraf daripada Imej Satelit Berasaskan RGB**

### **ABSTRAK**

Kelapa sawit adalah salah satu sumber terpenting di Malaysia dan dieksport ke negara lain untuk mengeluarkan produk berasaskan minyak sawit. Bagi menangani permintaan ini, kualiti dan kuantiti pokok kelapa sawit adalah isu utama bagi pengeluar, justeru pemantauan ladang yang betul seperti pengesanan dan pengiraan pokok adalah perlu bagi memastikan pengeluaran yang optimum. Cara tradisional bagi memantau ladang kelapa sawit adalah dengan mengatur pekerja memeriksa setiap kawasan tetapi ini memerlukan masa, tenaga dan kos yang banyak, dan juga kurang efisien. Justeru, penderiaan jauh boleh dimanfaatkan bagi memantau ladang kelapa sawit dengan lebih efektif. Pengimejan jarak jauh adalah tindakan untuk mendapatkan gambar dari jauh. Melalui pengimejan satelit, imej berasaskan RGB dengan resolusi tinggi yang terperinci boleh didapati, kadangkala tanpa sebarang kos, mewakili kawasan liputan yang luas yang mungkin sukar diakses oleh manusia. Walau bagaimanapun, imej ini mempunyai banyak kekurangan, justeru algoritma yang sesuai perlu digunakan. Oleh itu, penyelidikan ini mencadangkan kaedah memantau ladang kelapa sawit menggunakan 'Backpropagation Neural Network' (BPNN) dari imej satelit berasaskan RGB. Di sini, imej kawasan ujian diambil dari platform percuma, Google Earth Pro, dan kemudiannya diproses dengan operasi pemotongan untuk dibahagikan dalam kepingan yang lebih terperinci menggunakan aplikasi 'Photo'. Kesemua pemprosesan imej dilakukan menggunakan MATLAB di mana gambar yang telah dipotong ditapis menggunakan 'median filter' bagi membuang hingar kerana ianya mempunyai prestasi yang lebih baik dalam menyimpan semua perincian yang berguna dalam imej. Kemudian, imej bersih ini ditukar ke 'grayscale' dan disegmentasi berdasarkan nilai ambang daripada 'histogram' dalam mengesan kehadiran pokok kelapa sawit pada imej. Operasi morfologi dibuat merangkumi pengisian lubang, pembukaan, penutupan, dan pengeluaran objek yang tidak diperlukan untuk mendapatkan bentuk pokok dari gambar binari dengan lebih baik. Jelmaan legeh berdasarkan prinsip topologi juga dibuat bagi memisahkan pokok-pokok yang berdekatan. Pada peringkat pengelasan, BPNN dibina dengan struktur jaringan satu lapisan masukan, tiga lapisan tersembunyi, satu lapisan keluaran, bias fungsi pengaktifan 'bipolar sigmoid', dan kadar pembelajaran 0.1. Akhirnya, kejituan pengesanan dikira berdasarkan TP, FN, dan FP dengan membandingkan kepada data dasar. Secara keseluruhan, keputusan akhir menunjukkan kejituan pengesanan dan pengiraan pokok menggunakan algoritma BPNN adalah 95.62%, dengan kepersisan, penarikan balik, dan ukuran-F adalah masing-masing 85.94%, 84.05%, dan 84.92%. Ujian selanjutnya dengan ladang kelapa sawit yang telah disahkan juga memberikan kejituan yang bagus iaitu 82.96%. Penemuan ini menemui potensi penggunaan imej percuma berasaskan RGB dari pelantar satelit untuk pemantauan ladang kelapa sawit, khususnya pengesanan dan pengiraan pokok, berbanding dengan satelit komersial lain, yang sangat bermanfaat terutama bagi pekebun kecil.

# Oil Palm Tree Detection and Counting using Backpropagation Neural Network from RGB-based Satellite Image

## ABSTRACT

Oil palm is known as one of the most important resources in Malaysia and is exported to other countries which can be used to produce many palm oil products. To handle this demand, the quality and quantity of oil palm tree plantations are the main issue for the producers, thus proper plantation monitoring like tree detection and counting are required to ensure optimum production. The traditional way to monitor oil palm plantation is by arranging human labour to check every area accordingly but this is known to be time, energy and cost consuming, plus less efficient. Therefore, remote sensing can be utilised to monitor the oil palm plantation effectively. Remote sensing imaging is the action of getting images from a distance. Through satellite imaging, RGB-based image with a detailed, high-resolution information can be obtained, sometimes at no cost, representing a wide coverage area which can be difficult to be reached by humans. However, RGB-based satellite image has its limitations, thus a proper algorithm has to be used to process these images. Hence, this research proposes a method to monitor oil palm tree plantation using Backpropagation Neural Network (BPNN) from RGB-based satellite image. Here, RGB-based satellite image on the selected oil palm plantation area is obtained from a free access platform, Google Earth Pro, and then processed with cropping operation to divide into detailed parts using “Photo” application. All image processing is performed in MATLAB where first, the cropped image undergoes noise removal using median filter as it has better performance to keep all the useful detail in the image. Then, the clean image is converted into grayscale image and region-based segmentation based on the threshold value obtained from the histogram is performed so that it can detect the presence of all oil palm trees from the image. Morphological operation is conducted after that which includes hole filling, opening, closing, and removal of unnecessary object to get better trees detection from the binary image. Watershed transform based on topological principle is also conducted to separate neighbouring trees. In the classification stage, the BPNN is built with the network structure of one input layer, three hidden layers, one output layer, bias of bipolar sigmoid activation function, and learning rate of 0.1. Finally, a validation accuracy is calculated which deals with TP, FN, and FP to compare with the ground truth data. Overall, the final results demonstrate that the accuracy of the tree detection and counting using BPNN algorithm is 95.62%, with precision, recall, and F-measure are 85.94%, 84.05%, and 84.92% respectively. Further testing with other validated oil palm plantation also gives a good accuracy of 82.96%. These findings discover the potential usage of free RGB images from satellite imagery platform to perform oil palm plantation monitoring, specifically tree detection and counting, compared to other commercial satellites, which is very beneficial especially for smallholders.

## CHAPTER 1 : INTRODUCTION

### 1.1 Research Background

Oil palm trees, which scientific name in biological science is "*Elaeis guineensis*", are commercial crops commonly transplanted in the South-Eastern Asia countries such as Thailand, Malaysia and Indonesia. Oil palm tree is one of the famous tropical plants which adapt to the high precipitation level that generally has rainy, sunny and warm temperature environment. It consists of crown-shaped top feature characteristics and an upright stem. The stalk top emerges eight fronds which extending and growing outward. It has a significant shape similar to an eight-pointed star from an aerial perspective. It is also interesting that the oil palm tree is a conscious plant, which is categorised alike as a forest tree than agricultural plants (Chong, Kanniah, Pohl, & Tan, 2017). Figure 1.1 shows a sample of an oil palm tree in a farm.



Figure 1.1: Oil palm tree or "*Elaeis guineensis*" (Kirkpatrick, 2015)

In general, the oil palm is mostly planted for vegetable oil production, as the oil palm kernel and crude oils are the most consumed vegetable oil worldwide when compared with other types of vegetable oil (Chong et al., 2017). Also, it can be used to produce food and other products such as plastics, detergents and biodiesel. Oil palm has become one of the most important crops in Indonesia because of the highest vegetable production in the whole world (Yuliar, 2019). Malaysia is proposed as the second-largest palm oil producer after Indonesia in the world and has brought a large number of benefits and high financial returns to the country (Paterson, 2019). Malaysia handles 39% of world palm oil production and 44% of world exports (Khairunniza-Bejo, Yusoff, Nik Yusoff, Abu Seman, & Anuar, 2015). It has also been reported that the monthly export of oil palm products in 2015 is 25,370,294 tonnes which have valued at about RM60 million (Hashim, Shariff, Bejo, Muharam, & Ahmad, 2018). Figure 1.2 shows the consumption of vegetable oil throughout the world.

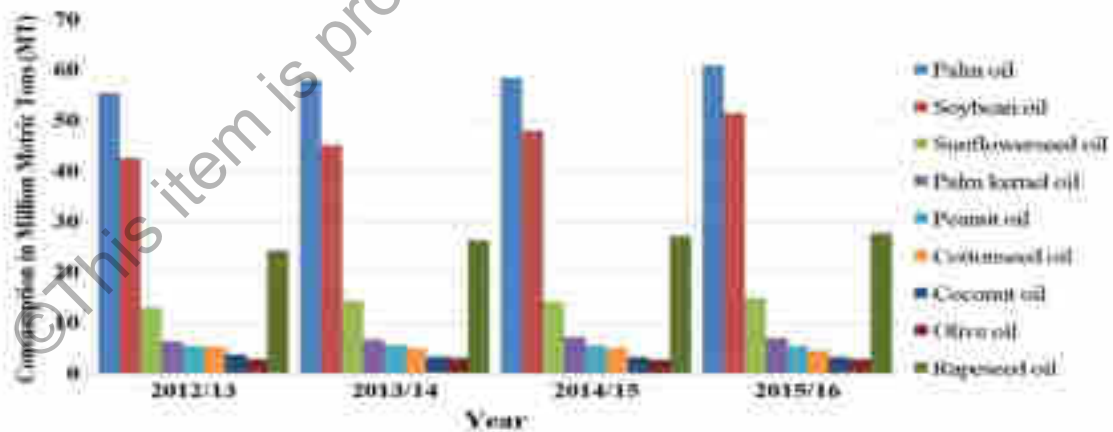


Figure 1.2: Consumption of vegetable oil throughout the world (Chong et al., 2017)

Because of that, oil palm plan production is one of the important businesses in Malaysia which can be beneficial to the national economy. To support the high demand of this vegetable oil from the market, the quantity and the quality of the oil palm trees

must be sufficient for the industry use for production (Tugi et al., 2015). Researches have come out with various approaches to perform effective plantation monitoring. One of the technologies that can be utilised is remote sensing imaging. Remote sensing is a technology that has been used in agricultural areas for decades, as it can capture images that can provide a large area coverage and coarse spatial resolution from a distance, depending on the sensor (Maris, 2018).

After the remote sensing imagery of oil palm plantation has been obtained, it will undergo digital image processing sequences to extract some of the important information or feature for the classification stage. Classification of information from the image is the most important step and can be performed using Artificial Intelligence (AI). AI is defined as the artwork of making a computer do things that require human intelligence; for example, AI can solve complex problems that require reasoning processes and knowledge like a human expert. To extract classification of information from remote sensing images, a suitable Artificial Neural Network (ANN) method can be adapted. ANN is defined as a data interpreting system that has developed as a generalization of the mathematical models of human intelligence with the design of input layer, hidden layer and output layer. Oil palm counting is classified under supervised training where it can be conducted by inserting a template image of an oil palm tree into the ANN in order for it to memorize feature characteristics (Majumdar, Majumder, Kole, & Chakraborty, 2015).

## **1.2 Problem Statement**

Reports show that the number of palm oil industries is increasing year by year especially in South-East Asia regions such as Malaysia and Indonesia, due to the high demand for palm oil products worldwide (Khairunniza-Bejo et al., 2015). Thus, it is

important to ensure sufficient quality and quantity from time to time, making plantation monitoring a critical issue that needs to be handled properly. However, the traditional way for plantation monitoring is time-consuming, high costing and less efficient (Shanmugam, Agasta Adline, Aishwarya, & Krithika, 2017). One of the approaches that are beneficial for plantation monitoring is the usage of remote sensing. With the arrival of new technology for mapping, the use of remote sensing imaging can assist the monitoring of oil palm tree either the plantation area is large or small (Tugi et al., 2015).

Although remote sensing is useful in the agricultural field nowadays, it is still facing many challenges. Currently, remote sensing is impartially an expensive method of analysis, especially when measuring or analysing smaller areas (Gunzenhauser & Shanahan, 2013). Special measuring systems or sensors might be required to collect respective data. Besides, remote sensing information requires specialized training and experts in processing them, thus making the whole process to be prohibitive to some (Wang et al., 2010). Therefore, it is very important to select the best method in remote sensing for oil palm plantation monitoring, as affordable approach can be valuable for smallholders as well (Yang, 2005, p. 120-145). Free satellite images can be utilised and with proper image processing techniques, oil palm trees can be detected and counted within the plantation (Zhong, Zhu, & Soon, 2016).

There are three major theoretical and conceptual satellite imageries that have been used in agricultural research which are panchromatic, multispectral, and hyperspectral. A panchromatic image consists of only one band and it is usually displaying grayscale image which shows the light intensity reflection from the ground with limited information such as for tree detection (Seifried, 2014). For multispectral image, it consists of several

bands of data of red, green, blue, or RGB whereas the hyperspectral image consists of hundreds of spectral bands or continuous spectrums (Santoso, Tani, & Wang, 2016). Thus, multispectral imagery with RGB is suitable in this research as it able to provide great number of spectral bands, freely accessible with small resolution size. Although hyperspectral imagery is able to provide more number of spectral bands, it is difficult to get access to the images as mostly are only available for commercial usage (Zhao, Mu, Zhao, & Yang, 2019).

Thus, there is a need to have a suitable remote sensing imagery for oil palm plantation. As the freely accessible data are in the form of RGB-based / multispectral imagery, suitable image processing methods are required to process them for monitoring the oil palm plantation, specifically in detecting and counting the trees. In general, to extract essential information and necessary data from any image, it needs to undergo digital image interpreting procedures: image acquisition, segmentation, and classification. Most of the time, the target object categorization is the final step of all the digital processing operations. Therefore, the aid of an appropriate ANN algorithm will be able to perform the classification process with shorter processing time and hence, faster performance (Kaur & Singla, 2016).

### **1.3 Objectives**

The aim of this research is to adapt suitable ANN-based algorithm, which is Backpropagation Neural Network (BPNN) for oil palm trees detection and counting from RGB-based satellite images. To obtain this, several objectives are needed:

- To propose suitable image processing techniques in detecting the background (vegetation area) and the foreground (oil palm tree estimation) from the RGB-based satellite image
- To adapt a BPNN-based algorithm in identifying and counting the oil palm trees from the foreground
- To validate the performance of the overall method in detecting and counting oil palm trees

#### **1.4 Scope**

The scope of this research is to utilise Google Earth Pro to get free satellite data and high-resolution images of the targeted oil palm plantation. Some other systems such as QuickBird satellite imagery can only be accessed with a fee, thus making it prohibitive to some.

The second scope is to identify oil palm tree by applying suitable image processing algorithm to the satellite image. It is expected that after the application of image processing, the oil palm tree can be detected and counted which can aid plantation owners for immediate monitoring. Due to the nature of the images captured and used in this research, the oil palm detection is determined from the crown tree itself. This operation is performed on the green pigment of the tree which is chlorophyll and is suitable for all sizes and ages of oil palm tree.

## CHAPTER 2 : LITERATURE REVIEW

### 2.1 Introduction

Oil palm trees is known as one of the most important agricultural crops in Malaysia which is exported to other countries. To maintain the productivity of palm oil products, the plantation area needs to be monitored systematically to forecast maximum output. This chapter is going to discuss present methods other researchers have utilised in agricultural applications in general, specifically towards monitoring oil palm trees. This review will summarise these methods to highlight the gap that will be covered by this project's methodology.

### 2.2 Remote Sensing

Among all of the methods that have been proposed, remote sensing has become one of the most useful techniques in agricultural field to be used by most of the researchers. Remote sensing defines as the action of acquiring data about the earth's land and water surfaces using information acquired from an overhead perspective by using electromagnetic radiation from the electromagnetic spectrum, whether emitted or reflected from the earth's surface (Wang et al., 2010). Remote sensing is also a platform to let farmers use aerial data to get more detailed information and able to take appropriate action during the growing season (The MathWorks, 2018) (Gunzenhauser & Shanahan, 2013).

Generally, remote sensing imaging in agriculture is a technology to observe the synoptic view of the large plantation area and to monitor the state of vigorousness and

stress due to disease, pest and nutrient deficiency (Noor, 2016). Furthermore, earth observation remote sensing involves many types of instruments and platforms to get information or data onboard satellites tens of thousands of kilometres above the earth. Then, the data obtained need to be stored in a proper format based on many considerations to prevent error (Yang, 2005). In summary, remote sensing imaging provides complete and accurate information about our Earth's surface that can ease the researchers to access some area without visiting there personally (Sum & Shukor, 2019). Particular research has collected the present remote sensing image processing using soft computing to let other researchers understand and identify interesting challenges and opportunities of soft computing in remote sensing image processing (Zhong et al., 2016). Figure 2.1 shows one of the current satellite systems, the Landsat-8 satellite, that can be used to obtain image representing Earth's surface. Figure 2.2 shows an example of remote sensing imagery from a satellite.

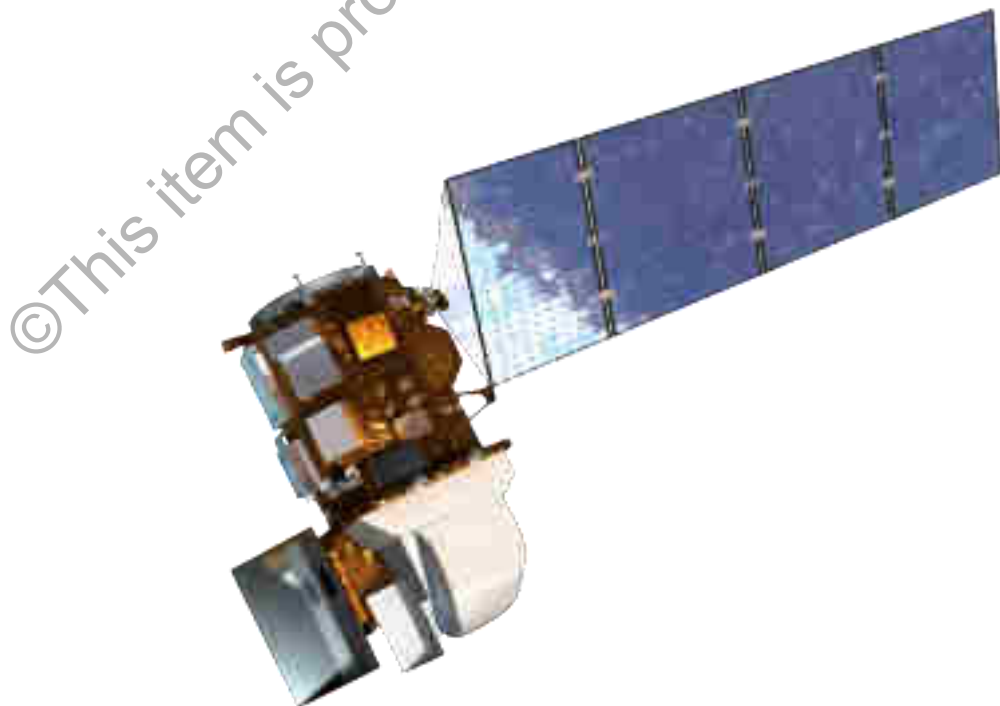


Figure 2.1: Landsat-8 satellite (“Landsat 8 Landsat Science,” 2019)



Figure 2.2: An example of remote sensing imagery (“Remote sensing application used for agricultural studies | UN-SPIDER Knowledge Portal,” 2019)

Due to its advantages, remote sensing imaging has been utilised for various agricultural applications. One of the applications is for pest and disease detection. Researchers able to find out plants with diseases in the early stage by using Canny edge detection and histogram matching (Shanmugam et al., 2017). In other research, remote sensing data is applied in visible and near-infrared regions for rice disease detection (Z. Qin, Zhang, Christensen, Li, & Tang, 2003). Others examine the potential of multispectral remote sensing for multi-temporal analysis of crop diseases (Franke & Menz, 2007). Furthermore, remote sensing data is used to detect chestnut ink disease (Martins, Castro, Macedo, Marques, & Abreu, 2007), early detection of plant disease (Chew, Hashim, Lau, Battay, & Kang, 2014), detection of diseased rubber plantations (Ranganath et al., 2004), citrus gummosis disease severity classification (Mohite, Jagyasi, Kulkarni, & Pappula, 2016) and multisensory fusion for crop disease detection (Moshou et al., 2011).

Another application of remote sensing imaging in agriculture is for land monitoring. An example of this is for wheat monitoring (Xue, Jianwen, Hongbo, & Fangyan, 2008). Apart from that, remote sensing imaging is also used for land cover study for tree detection and delineation (Syed Hanapi, Shukor, & Johari, 2019).

Tree detection and counting is also one of the applications commonly applied in oil palm monitoring. From here, productivity can be estimated to meet the demand. One of the studies is to build a robust and user-friendly method to let oil palm managers using remote sensing imagery to count oil palm trees (Santoso et al., 2016). There is an approach to detect oil palm trees from QuickBird imagery by computing the local peak detection which each peak represents the apex of each tree referred to the interpretation of the discriminating power of a vegetation index (Srestasathiern & Rakwatin, 2014). Automatic detection and counting of oil palm trees from airborne imagery by applying blob analysis is also performed (Shafri, Hamdan, & Saripan, 2011). Previous research also shows that different image processing techniques and watershed transform can be applied to true colour and multispectral imagery for oil palm tree detection and counting (Ya Wern, 2019). Another method employs for oil palm trees counting from the satellite imagery using Support Vector Machine (SVM) algorithm of Object-Based Image Analysis (OBIA) (Rizeei, Shafri, Mohamoud, Pradhan, & Kalantar, 2018) (Kalantar, Idrees, Mansor, & Halins, 2017). It has reported that digital image processing is feasible to perform counting oil palm tree from multispectral image using the Speed up Robust Feature with small sample (Rajput, Hannan, Sagar, & Jeve, 2017). Apart from that, tree counting using labelled boundary in dense and sparse vegetative regions can also be performed by applying image processing techniques, watershed transform, and result graph by deep learning model (Khan & Gupta, 2018).

Normally, remote sensing imagery is classified into three basic types which are panchromatic, multispectral, and hyperspectral (Seifried, 2014). Hyperspectral and multispectral work by detecting specific chemical and material bonds from sensors without physical contact. Here, multimodal and temporal data from the Earth's ground are collected. With multisensory and advance image fusion techniques cooperate to each other, it will create better possibilities to compute and take out essential information. For example, optical and microwave remote sensing image combination is a powerful tool to enhance multi-sensor image extraction (Pohl, Chong, & John, 2011). Due to the wide coverage and accuracy that can be obtained from remote sensing, this technology is frequently adopted in the agriculture field.

### **2.2.1 Panchromatic**

Panchromatic is a satellite imagery that fundamentally black-and-white in colour. The first satellite imagery patterns are captured using a binary camera inserted into a spacecraft. The United States National Reconnaissance Office has launched the CORONA satellite in the 1960s. The aim of the CORONA satellite is to discover their interested areas of Earth; surface and suspected military movement is conducted for low risk. Moreover, the U.S. government has declassified plenty CORONA images in 1995, the globalisation action has caused them to become one of the affordable and most reliable sources of the past satellite imagery. As the photos are obtained in audio pairs, it is also utilised as Digital Elevation Models (DEMs). Nowadays, the CORONA imagery uses to process the black-and-white photographic negatives (Seifried, 2014). Figure 2.3 shows the panchromatic satellite image sample from CORONA.



Figure 2.3: Panchromatic satellite image from CORONA (Seifried, 2014)

### 2.2.2 Multispectral

Multispectral defines as a type of image having “red, green, blue”, also known as RGB image that records colours beyond the RGB spectrum which is near-infrared. GeoEye-1 is one of the examples for multispectral imagery having 4-band which includes red, green, blue and near-infrared while Landsat satellite consists of 8 bands. It is important to take note the non-visible wavelengths while using multispectral imageries, because they can be applied to detect different vegetation growth levels. The chlorophyll pigment that exist in all plants reflected a certain level of light which cannot be observe by the human’s vision, and only can be detected by professional cameras (Seifried, 2014). Figure 2.4 shows a sample of the 7-band multispectral satellite image.



Figure 2.4: 7-band multispectral image from Landsat 5 (Seifried, 2014)

Multispectral images have been used by researchers for land management using participatory sensing, remote sensing and weather data (Mohite et al., 2016), land use or land cover (Apan, Castillo, Narayan Maraseni, & Salmo, 2018), land-use and land-cover mapping and analysis (Alhassan, Henry, Ramanna, & Storie, 2019), multi-sensor using data fusion and GIS to oil palm plantation monitoring (Pohl et al., 2011), as well as detection and counting of oil palm trees (Santoso et al., 2016) (Srestasathiern & Rakwatin, 2014) (Rajput et al., 2017).

### 2.2.3 Hyperspectral

Hyperspectral imagery records hundred light rays of very narrow bands. The purpose is to discover the consecutive spectrum of light from the surrounding environment, more willingly than capture it in discrete bands. Most of the time, hyperspectral imageries are used in areas which are unreachable by humans. Figure 2.5 shows a sample of the hyperspectral imaging in agriculture.

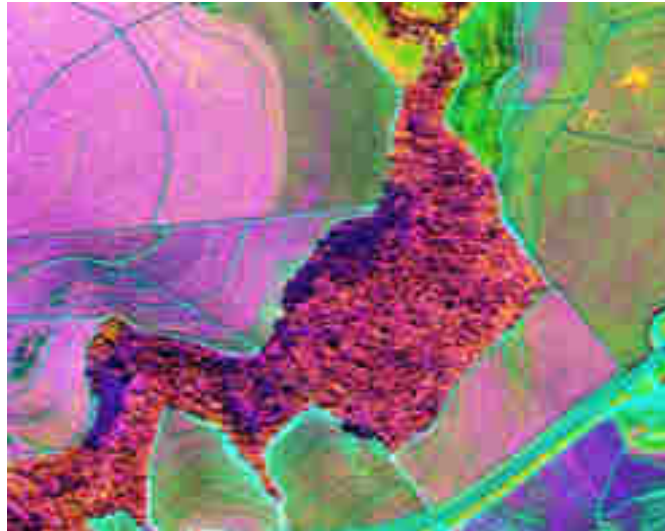


Figure 2.5: Hyperspectral imaging in agriculture (Igor, 2016)

Many researchers have applied hyperspectral remote sensing, one of them is to undergo spectral recognition techniques to extract building materials (Ye, Cui, Pirasteh, Li, & Li, 2017). In addition, hyperspectral remote sensing is generally used for crop growth and nutrition monitoring in the agricultural field (Feng, Xu, He, Zhao, & Yang, 2020). Moreover, by applying remote sensing imagery, the greenness area from the Earth's surface can be detected (Deriggi, n.d.).

### 2.3 Image Processing Methods in Processing Remote Sensing Images

Image processing is a skill to perform some action on an image data, which is to obtain better quality image or to take out some essential information from the image. It is also known as a type of signal processing method by giving input data in an image and hence the output can be target object's characteristics or features associated with the image. Image processing fundamentally comprises of importing photos or images by using image acquisition tools, interpreting the image and in the end, obtain the results which can be modified image or datasheet report based on image analysis. All the necessary steps will be explained comprehensively in the coming subsections.

### 2.3.1 Image Acquisition

Image acquisition is an essential step in image processing; it is also the first step in the overall process. Usually, the input image obtains in many ways or tools in different type of formats, for example in JPEG format. Satellite images can be obtained from various sources such as Google Earth Pro or USGS. Figure 2.6 shows the sample of Google Earth Pro layout. A satellite image obtained about the earth's geographical data from the multisensory instrument which is remote sensing that able to be used for image processing.



Figure 2.6: Google Earth Pro layout (“Google Earth Pro 7.3.1 update brings 64-bit support, performance improvements - Neowin,” 2018)

To detect a tree, researchers need to know the important green pigment in the plant which is the chlorophyll. Chlorophyll is the main carrier of photosynthesis in plants (Li et al., 2018); thus to test crop status using remote sensing, the chlorophyll content is the most important biological substance. It can be used to check crop growths and physiological condition with the present of chlorophyll cells in floras' leaves (Nandibewoor, Muddebihal, & Hegadi, 2017). Chlorophyll in leaves functions to absorb