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# Discovering the *Ganoderma Boninense* Detection Methods Using Machine Learning: A Review of Manual, Laboratory, and Remote Approaches

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**ABSTRACT** *Ganoderma* disease is a kind of infection that actuates oil palm death. Early detection of *Ganoderma* disease is the most recommended strategy for proper treatment and disease control plan to be taken promptly. In this paper, the detection methods for *Ganoderma* disease were reviewed and categorized accordingly. It was found that the combination of remote sensors and machine learning techniques could identify the disease up to four severity levels, including the early stage of infection. It also significantly reduced the labor and time costs compared to the traditional visual inspection and lab-based approaches. In terms of machine learning, support vector machine (SVM) using the idea of finding a hyperplane was suggested as the best classifier in several studies. Despite only one research was done on ANN and no research evaluating CNN and GAN in *Ganoderma* disease detection; ANN, CNN and GAN were recognized as the potential machine learning techniques that could enhance the detection system.

**INDEX TERMS** Basal stem rot, *Ganoderma*, machine learning, oil palm, remote sensors.

## I. INTRODUCTION

Oil palm, *Elaeis guineensis* Jacq., is a key commercial crop in food, cosmetics, plastics, detergent, lubricant, and biofuel industries [1], [2]. Palm oil and palm kernel oil make up 40% of vegetable oil in the world [3]. About 85% of total oil palm production is from Indonesia and Malaysia, where Indonesia contributes to the larger portion [2]. However, the crop in both countries is prone to *Ganoderma* disease [2], [4], [5].

*Ganoderma* disease is caused by basidiomycete fungus called *Ganoderma boninense* that spreads from the palm roots [6]. It will destroy the internal palm tissues, causing basal stem rot (BSR), which affects the delivery of water and other nutrients to treetop. Eventually, it leads to the death of the entire oil palm [1], [7].

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*Ganoderma* disease will induce certain symptoms on fruits, leaves, roots, and stems of the oil palm trees. In order to grade the infection severity, the *Ganoderma* disease severity index (GDSI) was introduced by Izzuddin *et al.* [8] based on visual symptoms. Initially, three categories were proposed and defined accordingly. The first category is healthy (T0), where the oil palm visually looks healthy without showing any foliar symptom, as well as the absence of white mycelium and fruiting bodies at the palm base. The second category is mild (T1), where the oil palm visually looks healthy but showing foliar symptom and the presence of white mycelium, small white button or fruiting bodies at the palm base that has no stem and bole botting. The third category is severe (T2), where the *Ganoderma* fruiting bodies, stem, and bole rotting are visible at the palm base, meanwhile the oil palm has more than one unopened spear leaves, drooping and yellowing of leaves, and old fronds snapping at the petiole. Izzuddin *et al.* [9] then expanded the GDSI into four categories: healthy (T0), early (T1), moderate (T2), and severe (T3), by including the test result from *Ganoderma* selective medium (GSM) and PCR-DNA. In addition, the definition for moderate and severe *Ganoderma* infections was refined. A moderately infected oil palm tree is characterized by the existence of less than 30% of both foliar symptoms and rotting at the base of the stem, whereas a severely infected oil palm tree is characterized by the existence of more than 30% of both foliar symptoms and rotting at the base of the stem. However, based on the BSR classification by Ibrahim [5], the mildly infected palm is associated with the presence of white mycelium or fruiting body without foliar symptoms or less than 10% of stem rotting at the base; the moderately infected palm is associated with the presence of white mycelium, less than 50% of foliar symptoms, and less than 30% of stem rotting at the base; severely infected palm is associated with the presence of white mycelium, more than 50% of foliar symptoms, and more than 30% of stem rotting at the base.

*Ganoderma* disease leads to the yield reduction of fresh fruit bunches between 1000 kg (0.04 t) and 0.434 kg/$m^2$ (4.34 t/ha) on ten years to twenty years of planting, respectively [10]. Up to the present, there is no cure for this particular disease. Paterson [2] predicted that the BSR incidents would continue to increase to very high levels on most parts of the island of Sumatra due to the dramatic increase of unsuitability of the climate for oil palm after 2050.

Hitherto, appropriate disease control and management is the only strategy to overcome the realized issue. It was reported that oil palm trees with below 20% of infection could still be saved by applying proper treatment [11], [12]. Early detection of *Ganoderma* disease is crucial to enable quick action to be taken at the beginning of BSR infection in order to minimize the economic losses [13]. In this review paper, we present the currently available *Ganoderma* disease detection methods and highlighted the values of machine learning to reach the purpose of early detection. We aim to contribute in terms of pointing out relevant research gaps to researchers who plan to establish a novel *Ganoderma* detection tool.

## II. METHODS OF DETECTING GANODERMA DISEASE

Methods of detecting *Ganoderma* disease can be divided into three types based on manual, lab-based and remote settings as illustrated in Figure 1.

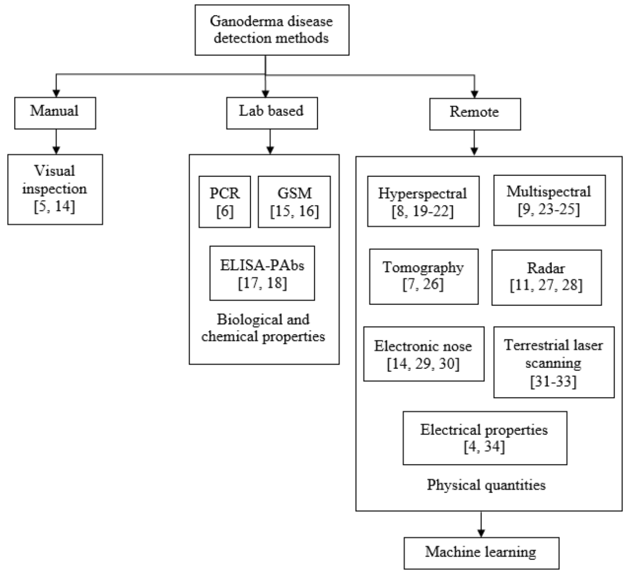



**FIGURE 1.** Classification of *Ganoderma* disease detection methods.

### A. MANUAL GANODERMA DISEASE DETECTION

Workers in the oil palm plantation area perform a visual inspection to manually detect the BSR infected oil palm trees based on the visible external symptoms at fruits, leaves, stems and roots [5].

In general, *Ganoderma* disease has a four-level disease typology, in which 0 labelling healthy trees, 1 labelling a mild attack, 2 labelling a medium attack, and 3 labelling a severe attack or near-fatal infestation. The infection levels 1, 2, and 3 are described in Table 1, whereas the oil palm appearance in all categories is illustrated in Table 2 [14].

**TABLE 1.** *Ganoderma*-specific visual symptoms. Adapted from [14].

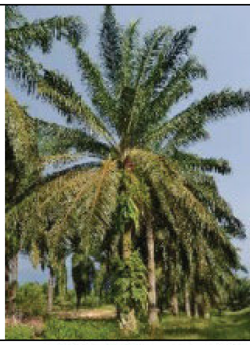
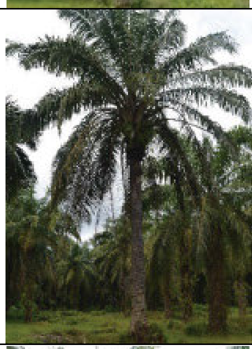
| Infection level | Change in stem conditions | Change in canopy structure |
|---|---|---|
| 1 | Existence of mycelium in the stem bark. | Drying or yellowing of several leaves. Existence of one or two unopened spear leaves. |
| 2 | Existence of fruiting bodies at the stem base. | Presence of leaf necrosis. Existence of three to five unopened spear leaves. Declination of older leaves. |
| 3 | Existence of rotten stem. | Existence of widely spread leaf necrosis. Absence of new leaf and new bunch. "Skirt-like" shape of crown caused by full leaf declination. |

This detection method is mainly based on the observers' experience and knowledge. Hence, it is subjected to both inter- and intra-observer variabilities. Most of the time, hundreds of oil palm trees are to be looked into, which make the visual screening overloaded. Unlike the significant symptoms which could be perceived easily, the insignificant symptoms of *Ganoderma* disease, particular at the early stage of infection, can be missed out, thus exhibiting a disease detection challenge.

### B. LAB-BASED GANODERMA DISEASE DETECTION

Due to the advancement in the field of biochemistry, immunology, and molecular science, the protein and molecular structures of specific fungi are well studied and

**TABLE 2.** Digital images of oil palm tree in different *Ganoderma* disease level. Adapted from [5].

| Infection degree | Infection status | Image |
|---|---|---|
| 0 | Healthy |  |
| 1 | Mildly infected |  |
| 2 | Moderately infected |  |
| 3 | Severely infected |  |

determined. This leads to the development of lab-based *Ganoderma* disease detection that usually involves specific standard operating procedures and laboratory materials.

### 1) GANODERMA SELECTIVE MEDIUM (GSM)

*Ganoderma* selective medium (GSM) was developed by Ariffin and Idris [15] for the isolation of *Ganoderma*. GSM consists of two parts, as shown in Table 3.

**TABLE 3.** Composition of GSM.

| Part A | | Part B | |
|---|---|---|---|
| Bacto-peptone | 5.0 g | Streptomycin sulphate | 300 mg |
| Agar | 20.0 g | Chloramphenicol | 100 mg |
| $MgSO_4, 7H_2O$ | 0.25 g | PCNB, pure | 285 mg |
| $K_2HPO_4$ | 0.50 g | Ridomil (25% WP) | 130 mg |
| Distilled water, pH 5.5 | 900 ml | Benlate - T20 | 150 mg |
| | | Ethanol, 95% | 20 ml |
| | | Lactic acid, 50% | 2 ml |
| | | Tannic acid | 1.25 g |
| | | Distilled water, pH 5.5 | 80 ml |

Firstly, part A was homogenized by being stirred on a hot plate at 100 °C until the ingredients were completely dissolved. It was then followed by a fifteen-minute autoclaving process. Meanwhile, part B was stirred at room temperature for two hours. Next, it was aseptically poured into the container with part A when the temperature of the autoclaved medium has dropped to the range between 45 °C to 50 °C.

It should be noted that tannic acid, which possesses antibacterial properties, worked as an inhibited growth compound for the contaminant in GSM. This ingredient also induced the formation of brown halo around the colony as illustrated in Figure 2. Another ingredient in part B, namely pentachloronitrobenzene (PCNB), was believed acting as a carbon source in the medium to allow the growth of *Ganoderma* [16].

Unfortunately, GSM could not be used in Indonesia due to the restriction of the use of PCNB according to Indonesia's government regulation No. 85/1999 on Toxic and Hazardous Waste Management, which stated that PCNB is considered as a hazardous and toxic chemical [16]. United States Environmental Protection Agency (EPA) also labelled PNCB as a carcinogenic element. In addition, another GSM's ingredient, namely Ridomil, was not distributed in Indonesia anymore [16]. Taken together, it implied that the application of GSM was easily dragged by the unavailability of its ingredients. Moreover, the accuracy concern of GSM is questionable because other basidiomycete fungi could also grow on these media. Hence the application of GSM for large scale monitoring purpose is not recommended.

### 2) POLYMERASE CHAIN REACTION (PCR)

Polymerase chain reaction (PCR) is a laboratory technique used to amplify the DNA target from a DNA mixture. Interestingly, the internal transcribed spacers (ITS) of nuclear ribosomal DNA (nrDNA) is generally recognized as the official barcode for identifying the fungi species at the molecular level due to the multi-copy number per genome of the conserved feature within species.

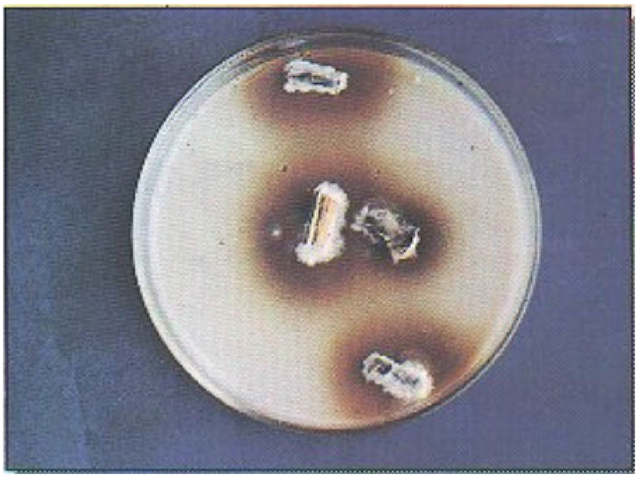


**FIGURE 2.** Isolation of Ganoderma on complete GSM through the formation of brown halo around the colony. Adapted from [15].

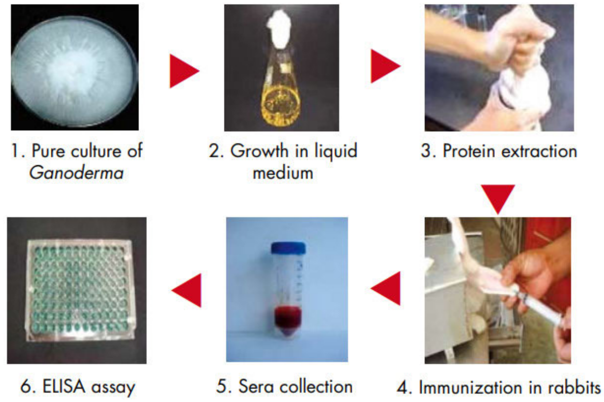



**FIGURE 3.** Flow of ELISA-PAbs. Adapted from [17].

Midot *et al.* [6] amplified the ITS region using two universal primer pairs, namely ITS1 and ITS4, as well as ITS1F and ITS4B, in a PCR reaction. The template DNA was amplified through thermal cycling that involved initial denaturation, annealing and extension at different temperature settings. The PCR products were then separated through electrophoresis on an agarose gel stained with ethidium bromide and visualized under ultraviolet (UV) light. Lastly, the PCR products were subjected to purification. Their results showed that a major haplotype, designated GbHap1 (81.2%), was detected in samples collected from all sampling locations in Sarawak. This finding suggests that the PCR method could be used for the systematic detection of *Ganoderma* fungal pathogen.

Yet, the routine analysis of this application involved the protocol complexities, reagent cost, sensitivity to contamination, and the requirement of highly skilled laboratory personnel, which might not be favorable to intensive monitoring.

#### 3) ENZYME-LINKED IMMUNOSORBENT ASSAY POLYCLONAL ANTIBODIES (ELISA-PABS)

Enzyme-linked immunosorbent assay polyclonal antibodies (ELISA-PAbs) is an immunology assay designed to rapidly quantify a particular protein molecule in a protein mixture using certain highly specific antibodies [17].

Firstly, the oil palm tissue sample extracted from leaf, stem or root was finely grounded, followed by dilution with extraction buffer and lastly, centrifugation. The total protein concentration was evaluated with bovine serum albumin (BSA) as the standard. Next, the indirect ELISA was carried out using the procedures as presented in Figure 3.

This approach offered greater simplicity and required less equipment as compared to PCR using DNA probes. It also showed better detection as compared to GSM [18]. Despite those advantages, the protocol of ELISA-PABS is still sophisticated and time-consuming, making it less favorable to large scale screening.

### C. REMOTE GANODERMA DISEASE DETECTION

Lately, remote sensing techniques arise to allow the collection of massive input data from the oil palm plantation area. Khosrokhani *et al.* [19] described remote sensing as a sort of art and science of information collection with respect to the targeted object without direct physical contact. Remote sensing technology involves the usage of passive or active sensors, which are responsible for capturing the desired signals, and an interface such as a computer to display the raw data to the user. Further analysis can be done either by the user input or thru certain pre-defined computer functions to diagnose the *Ganoderma* disease. Remote *Ganoderma* disease detection methods can be categorized into several groups depending on the input data forms.

#### 1) HYPERSPECTRAL SENSOR

The hyperspectral sensor collects the data consisting of hundreds or thousands of continuous spectral bands to track the spectral responses of the targeted object over a specific continuous wavelength [19]. As a result, the detailed spectral signatures are obtained to enable the identification of the object. In terms of oil palm trees, healthy trees usually present lower visible (VIS) reflectance and higher near infrared (NIR) reflectance, whereas unhealthy trees demonstrate different spectral patterns regulated by the physiology and morphology of the leaves [20]. Hyperspectral imaging can be divided into ground-based, airborne and space-borne according to the data collection approaches. Ground-based hyperspectral imaging requires the experimental setup on the ground. Airborne hyperspectral imaging requires the use of an unmanned aerial vehicle. Space-borne hyperspectral imaging involves satellites in space.

A portable handheld spectroradiometer GER model 1500 (Geophysical and Environmental Research Corporation, Millbrook, NY) with 571 available spectral bands was used by Ahmadi *et al.* [21] to study the spectral analysis at leaf level. They found that the majority of the satisfactory results happened in the visible range, particularly in the green wavelength. The result further revealed that the frond number 9 was the sensitive frond number for the proposed ANN model as it managed to provide the highest accuracy of 100.0% as compared with frond number 17 [21].

Perkin Elmer 2000 Series Fourier Transform Infrared (FTIR) spectrometer with selected scanning range from 650 to 4000 $cm^{-1}$ was employed by Alexander *et al.* [22] to investigate the *Ganoderma boninense* cells detection in the oil palm tissues. Result reported that the FTIR technique was capable of detecting the presence of *Ganoderma boninense* when the percentage of the content of *Ganoderma boninense* cells in oil palm tissues was only 5%. Noteworthily, this approach attempted to detect the spectroscopic fingerprints of *Ganoderma* at the cellular level.

In another study, the airborne imaging spectrometer for applications (AISA) dual hyperspectral imaging system was fixed on the aircraft type Short SC-7 Skyvan, a twin-engine turboprop cargo aircraft to acquire the airborne hyperspectral images [8]. As a result, continuum removal (CR) analysis was recommended. Although the added airborne feature increased the efficiency of data acquisition in large plantation area, however, the process of analyzing the collected data was challenging due to the noise problem caused by environmental factors.

In order to examine the hyperspectral reflectance of five-month-old oil palm seedlings, FireflEYE S185 (Cubert GmbH, Ulm, Germany) snapshot camera was fixed horizontally on a custom tripod stand which was located 2.6 m above the ground level [20]. The hyperspectral reflectance of the first four leaflets of frond number 1 and frond number 2 was extracted manually and randomly. It should be noted that this method also required careful consideration when dealing with sun angle, shadow, and weather conditions to minimize the environmental interferences.

#### 2) MULTISPECTRAL SENSOR

A multispectral sensor captures the reflected or emitted energy from a specific object or area in multiple discrete bands of the electromagnetic spectrum, generally involves three to ten bands. As compared to hyperspectral data, less information would be obtained from multispectral data. Multispectral imaging can be divided into ground-based, airborne and space-borne.

Each spectral band has a specific response to plants biophysical changes, where the green (G) band is sensitive to the plant or leaf nitrogen and pigment, the red (R) band is sensitive to chlorophyll a and b content, the red edge (RE) band is sensitive to plant stress and chlorophyll content, and NIR is sensitive to water content, moisture, and biomass of plant [9].

Izzuddin *et al.* [9] demonstrated the use of Parrot Sequoia multispectral camera system that was mounted on a DJI Phantom Matrice, a lightweight quadcopter-type unmanned aerial vehicle (UAV) to capture the multispectral images. Based on their findings, analysis of multispectral band combinations provided higher accuracy as compared to individual band analysis.

Quickbird satellite sensor owned by DigitalGlobe, United States, provides multispectral imagery at 2.5 m resolution, and it can be used to identify individual oil palms with fronds of 6 to 8 m [23]. Santoso *et al.* [24] implemented three selected classifier models: support vector machine, random forest, and classification and regression tree models on the Quickbird imagery that was archived on 4 August 2008. Among the testing classifiers, the random forest model offered the best performance in the prediction, classification, and mapping of BSR infected oil palm as reflected in its good overall accuracy, producer accuracy, user accuracy, and kappa value [24].

DigitalGlobe's another satellite, namely Worldview-3, also provides multispectral imagery at 1.24 m resolution, which is a bit higher than that of the Quickbird satellite. Worldview-3 imagery with the following nine bands: coastal (400 to 450 nm), blue (450 to 510 nm), green (510 to 580 nm), yellow (585 to 625 nm), red (630 to 690 nm), red edge (705 to 745 nm), NIR 1 (770 to 895 nm), NIR 2 (860 to 1040 nm), and panchromatic (450 to 800 nm) was archived by Santoso *et al.* [25] on 6 August 2016 for BSR studies. A poor result was obtained due to the possibly inappropriate selection of BSR disease criteria. Hence, considerable refinement is needed.

#### 3) TOMOGRAPHY

Tomography is an imaging technique using ray transmission measurement to illustrate a 2D cross-sectional view of an object's interior [26].

A portable gamma-ray computed tomography system for early detection of oil palm BSR was locally built at the Malaysian Nuclear Agency, Kajang, Malaysia, based on GammaScorpion [26]. Although the authors stated that this mobile CT system could detect BSR infected oil palm in situ, the statistical result was not provided. The use of this system remains a challenge as the radiation emitted from the system might affect human health.

Ishaq *et al.* [7] conducted a study to detect the internal lesion of BSR using PiCUS Sonic Tomograph by strategically placing a set of sensors around a tree trunk. As a result, the tomogram accuracy was 96% in detecting the BSR and 82% in determining the BSR severity level. Although it gave a promising result, the setup protocol was time-consuming due to the location of sensor placement. Different sensor placement patterns may produce different results.

#### 4) RADAR

Radar stands for 'radio detection and ranging'. It is a system that works by transmitting energy in the form of microwave signals into space and then monitoring the reflected signals from the object. This system does not face image distortion problem as it is less influenced by weather conditions, such as cloud cover, haze, and solar illumination.

The Synthetic Aperture Radar (SAR) system can provide complementary information for optical remote sensing through the backscattering signals from SAR. Those signals are sensitive to the architecture as well as the dielectric properties of land surfaces, including plant canopy, soils, and built-up [11]. Mohd Najib *et al.* [27] managed to detect the water bodies and oil palm trees through manipulation of the horizontal-horizontal (HH) (Horizontal-transmit, Horizontal-receive) and horizontal-vertical (HV) (Horizontal-transmit, Vertical-receive) polarizations of ALOS PALSAR SAR data.

Hashim *et al.* [11] extracted the ALOS PALSAR 2 images with dual polarization, HH and HV, from the developer, Japan Aerospace Exploration Agency (JAXA), to study the detection of *Ganoderma* disease. However, it failed to provide satisfactory results in identifying the healthy and infected oil palms. The poor performance could be due to ignorance of key parameters and variables, such as biomass and moisture content.

Toh *et al.* [28] examined the relationship between the biophysical parameters of *Ganoderma* infected oil palm with the L band backscatter coefficient. The number of fronds, number of pinnae, frond length, and petiole width were found to be greatly correlated with the occurrence of high *Ganoderma* disease severity index. It should be noted that this study was limited to oil palm trees aged 8 years old and 16 years old.

#### 5) ELECTRONIC NOSE

Electronic nose is a technology that mimics the mammalian sense of smell by creating a composite response that is unique and specific to each odorant [13].

Volatile organic compounds (VOCs) released from *Ganoderma boninense* cultures and infected oil palm wood were analyzed using the headspace solid-phase micro-extraction (HS-SPME) method coupled with gas chromatography-mass spectrometry (GC-MS) [29]. Most of the VOCs were determined.

Rahmat *et al.* [30] developed a modified carbon electrode with reduced graphene oxide (rGO) and zinc oxide nanoparticles (ZnO-NPs) as surface modifiers. Meanwhile, the disposable modified screen-printed carbon electrode (SPCE) was built to be used as a sensing material to detect the stress in oil palms leaves induced by *Ganoderma* infection. The results showed that the ZnO-NPs/rGO/SPCE modified electrode could exhibit good sensitivity towards stress oil palm leaves crude extracts. It also presented good stability and reproducibility, indicating that the ZnO-NPs/rGO/SPCE modified electrode could be utilized as a potential candidate for the stress monitoring in oil palm leaves caused by *Ganoderma* infection.

#### 6) TERRESTRIAL LASER SCANNING (TLS)

Terrestrial laser scanning (TLS), also known as ground-based LiDAR, is an active remote sensing imaging method that employs laser light to measure the range or distance to a targeted object. It operates by releasing a pulsed laser light to illuminate the target. The reflected pulses are then measured with a sensor to directly represent the external structures, meanwhile, carry out profiling for the targeted objects [31].

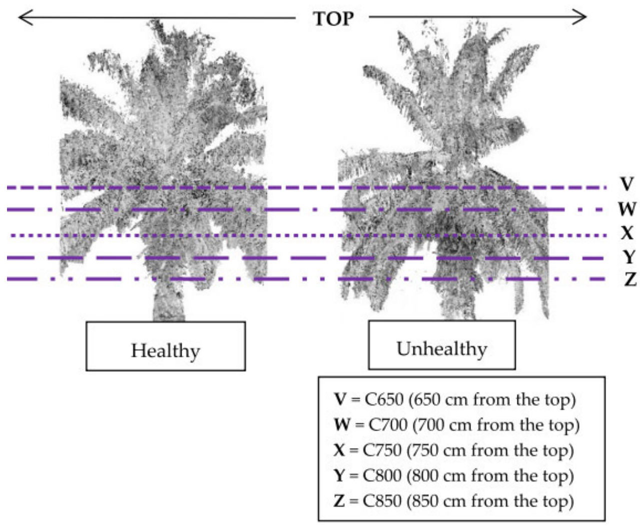



**FIGURE 4. Point cloud images illustrate the positions of C650, C700, C750, C800, and C850. Adapted from [33].**

Khairunniza-Bejo and Vong [32] was the first that proposed the use of TLS application for the study of BSR detection. The scanning of oil palm trunks and canopies was done by using Faro Laser Scanner 3D data. The results pointed that in the case of oil palm at 150 cm height, the trunk area and its respective perimeter were associated with the oil palm BSR severity level up to four infection levels with the coefficient of determination, R2 at 0.8814 and 0.7312, respectively. In short, the higher the BSR infection level, the smaller the trunk area as well as the perimeter.

Husin *et al.* [31] analyzed oil palm canopy architecture using the point clouds data through TLS technology. They selected five parameters: S200 (canopy strata at the level of 200 cm from the top), S850 (canopy strata at the level of 850 cm from the top), crown pixel (pixel amount inside the crown), angle of frond (angle degree between fronds) and the number of fronds. Based on the outcomes from statistical analysis, the number of fronds was considered as the best single parameter for the BSR detection as early as mild infection.

Husin *et al.* [33] also investigated the impact of BSR on the oil palm crown profile. The crown strata profiles indicated that the healthy oil palm trees have higher crown densities as compared to the unhealthy oil palm trees starting from 250 cm from top to bottom. Additionally, five crown strata (C650, C700, C750, C800 and C850) at the bottom area, as illustrated in Figure 4, were found to have significant differences with p-values smaller than 0.0001 based on the *t*-test.

#### 7) ELECTRICAL PROPERTIES

The electrical properties of a material depend on the water content inside the material as water has a permanent electric dipole moment, allowing polarization when an external electric field is applied. Since *Ganoderma* disease restricts the water consumption and delivery to the leaves, leading to

**TABLE 4.** Comparison of *ganoderma* detection methods.

| Methods | Sub category | Type of analysis | Features | Pros | Cons |
|---|---|---|---|---|---|
| Manual | Visual inspection | Qualitative | • Canopy<br>• Trunk<br>• Root | • Simple operation by skilled personnel.<br>• Low apparatus cost. | • Diagnosis is subjected to human visual processing bias.<br>• Input variables cannot be recorded for further study.<br>• Limited processing capacity. |
| Lab-based | GSM | Qualitative | • Root tissue | • Isolation of *Ganoderma* allows opportunities for pathogen-based further study. | • PCNB is hazardous and restricted in Indonesia.<br>• Limited processing capacity. |
| | PCR | Qualitative | • Trunk tissue | • High reliability. | • Lengthy protocols.<br>• Limited processing capacity. |
| | ELISA-PAbs | Qualitative | • Leaf tissue<br>• Stem tissue<br>• Root tissue | • High sensitivity. | • High false positive rate (potentially caused by reaction of antibodies with antigens from other fungi species).<br>• Limited processing capacity. |
| Remote | Hyperspectral sensor | Quantitative | • Leaf spectral | • Able to record spatial features. | • Easily influenced by sunlight condition. |
| | Multispectral sensor | Quantitative | • Leaf spectral | • Large coverage area with satellite. | • Easily influenced by sunlight condition. |
| | Tomography | Quantitative | • Trunk area | • In situ trunk interior inspection.<br>• Able to detect air voids inside trunk. | • Limited to transverse plane.<br>• Risk of radiation. |
| | Radar | Quantitative | • Canopy<br>• Soil | • Large coverage area.<br>• Monitoring of biophysical parameters.<br>• Unaffected by weather conditions. | • Results influenced by multiple variables. |
| | Electronic nose | Quantitative | • Leaf ordour | • Detection of *Ganoderma*-specific smell via volatile organic compounds. | • Not all organic compounds in *Ganoderma* are well studied. |
| | TLS | Quantitative | • Canopy | • Point clouds data enabling visualization of 3D tree architecture. | • Complicated setup for individual tree. |
| | Electrical properties | Quantitative | • Leaf properties<br>• Soil properties | • Monitoring of water status in plant or soil. | • Different measurement points may give different results. |

a decreased water content in all plant organs, detecting the electrical properties of leaves or soil can be used for BSR detection.

Khaled *et al.* [4] was the first research team to use dielectric spectroscopy to detect BSR. Electrical properties, including impedance, capacitance, dielectric constant, and dissipation factor of oil palm leaves, were measured with a precision solid dielectric test fixture (16451B, Keysight Technologies, Japan) that was connected to an impedance analyzer (4294A, Agilent Technologies, Japan) and a computer that was responsible for controlling and data logging. Based on the study, impedance provided a more accurate estimation of BSR severity.

Aziz *et al.* [34] presented another approach of BSR detection by utilizing a soil moisture sensor to measure the soil resistivity in a unit of an ohm (Ω) at a distance of 15 cm surrounding the basal stem of oil palm trees. The results indicated that healthy oil palm trees significantly possessed a higher mean ($ER_{MEAN} \geq 400$) of electrical resistance readings as compared to infected oil palm trees ($ER_{MEAN} < 400$). A new index, called K-index, was introduced and used together with $ER_{MEAN}$ to develop a model that has provided accuracy rates at 82% and gained a 100% successful rate during validation.

### D. COMPARISON OF GANODERMA DISEASE DETECTION METHODS

The three *Ganoderma* disease detection methods possess pros and cons as described in Table 4. Although manual detection is the simplest yet traditional method without the need of data storage and experimental setup, however its reliability is greatly dependent on the knowledge and experience of workers. The process of transferring knowledge and experience from worker to worker is slow and difficult, making the manpower expansion rate lags behind the oil palm field expansion rate. Furthermore, human error could be made easily due to fatigue and working mood. Nevertheless, this method is appreciated in terms of discovering knowledge regarding disease external symptoms as well as establishing a disease severity index from scratch. Lab-based detection is generally recognized as highly reliable method as it is *Ganoderma*-specific. Most studies employed GSM and PCR to validate the results of proposed methods [9], [20], [31]. Despite insufficiency of this method for large scale disease detection task, yet it is meaningful in the projects of formulating biological control agent and fungicide. Despite high capital investment, considerable attention is still paid to remote sensing techniques for *Ganoderma* detection. The key advantage of remote sensor is the data could be stored for further study, facilitating the expansion of knowledge boundaries systematically.

## III. MACHINE LEARNING FOR GANODERMA DISEASE DETECTION

Manpower and time constraints, which are usually viewed as the limitations of most *Ganoderma* disease detection methods, are also recognized as the development opportunities which should be worked through innovative approaches. In the previous plant disease studies, people started to investigate information technology as well as deep learning artificial intelligence tools. Researchers were further motivated by the significant improvement in human healthcare system as contributed by machine learning and internet of things (IoT) [35]–[39]. Hence, the concept of an automated plant disease detection system was proposed [40]. Machine learning has been utilized to analyze and classify the input data for automatically detecting plant disease [41]–[43]. In terms of *Ganoderma* disease of oil palm, remote sensors with quantifiable input data are utilized and paired with machine learning approaches. This method offers several advantages, such as simple operation, low cost, and rapid detection, making it a powerful agricultural technology tool. Several machine learning approaches have been identified and listed in Figure 5. All of them would be discussed explicitly in the following section.

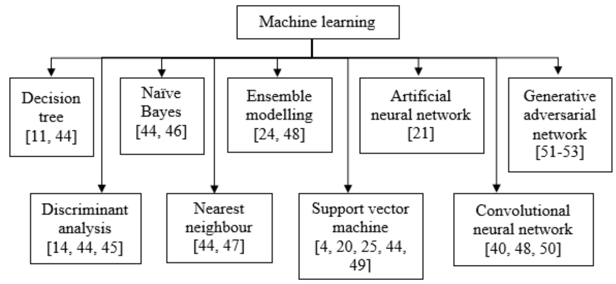



**FIGURE 5.** Machine learning approaches for *Ganoderma* disease detection.

### A. DECISION TREE (DT)

Decision tree (DT) algorithm is a supervised regression machine learning approach that splits the dataset into several tree-like models, which consist of a number of nodes for testing attributes, a number of edges for branching by the value of selected attributes, and a number of leaves for labelling classes [44].

Hashim *et al.* [11] illustrated the application of the DT classifier on the ALOS PALSAR 2 backscatter coefficients to differentiate between *Ganoderma* infected and healthy oil palm trees. HH and HV backscatter classifications achieved the overall accuracy at 45.65% and 56.52%, respectively. The study also reported that the radar backscatter coefficients were affected by complex interactions among plant scattering and soil, and not simply by means of a correlation to a single variable.

DT was used as one of the classifiers by Husin *et al.* [44] and achieved 80% accuracy in the four BSR level classification using the TLS data. From the result, 90% accuracy was achieved in the healthy level classification.

### B. DISCRIMINANT ANALYSIS (DA)

Discriminant analysis (DA) is a supervised classification machine learning approach that assigns observations to pre-defined groups by evaluating the differences between two or more groups of objects with regards to a few variables simultaneously [44].

Partial least square discriminant analysis (PLS-DA) was adopted by Lelong *et al.* [14] in classifying the oil palm into a four-level typology based on the hyperspectral reflectance data. At the end of the study, global performance of close to 94% was achieved.

Quadratic discriminant analysis (QDA) was used as one of the classifiers in a study carried out by Khaled *et al.* [45] to classify four classes of *Ganoderma* infection based on the data of dielectric properties. The mean accuracy of QDA classification in the study was 80.79%. Husin *et al.* [44] also used QDA on TLS data and achieved 75% accuracy in classifying four BSR infection.

Linear discriminant was applied on TLS data and 80% of accuracy was achieved in classifying multiple levels of BSR infection [44].

### C. NAÏVE BAYES (NB)

Naïve Bayes (NB) is a supervised classification machine learning approach that allocates each object to the class with the highest conditional probability, using a strong assumption of independence between the parameters [44].

Husin *et al.* [44] used kernel Naïve Bayes (kNB) to analyze the TLS data for the four BSR level classification. About 85% accuracy was recorded for four level classification, whereas, 100% accuracy was achieved for healthy level classification. The authors suggested that kNB could be used to perform classification.

Nababan *et al.* [46] employed NB in an intelligence-based application to diagnose the type of oil palm plant disease. Bayes method was conducted based on the formulation of the recognized symptoms. Thru the selected symptoms, the bayes value was 80%, with the type of disease was a rotten bunch.

### D. NEAREST NEIGHBOUR

Nearest neighbour is a supervised classification machine learning approach that stores the existing cases and classifies new cases based on similarity measures, such as distance functions [44]. K-nearest neighbour (kNN) algorithm is commonly used for multivariate analysis.

kNN based model managed to predict the *Ganoderma* disease with a high average overall classification accuracy at 97% using the second derivative of hyperspectral reflectance dataset [47].

Husin *et al.* [44] used fine kNN to classify multiple BSR infections based on TLS data. This method obtained the highest accuracy at 82.50%.

### E. ESEMBLE MODELING (EM)

Ensemble modelling (EM) is a supervised regression machine learning approach that builds a set of classifiers, followed by the categorization of new data by taking a weighted vote of those classifiers' combined predictions.

Random forest (RF) is one of the examples of EM in which the classification of data is based on the weighted vote from multiple decision trees [48]. RF classifier model was suggested as the best classifier by Santoso, *et al.* [24] as it achieved 91% overall accuracy on the Quickbird imagery data in classifying the healthy and mildly BSR infected oil palm tree.

### F. SUPPORT VECTOR MACHINE (SVM)

Support vector machine (SVM) is defined as a supervised classification machine learning approach that forms a hyperplane or line in dimensional space to distinctly separate the data into classes [44].

Santoso *et al.* [25] applied SVM on Worldview-3 multispectral imagery data to perform the classification of four BSR classes. However, the overall accuracy was only 54%. It revealed that different canopy conditions caused by

*Ganoderma* disease also affected the characteristics of Worldview-3 spectra.

Khaled *et al.* [4] integrated feature selection (FS) preprocessing technique into SVM in analyzing the electrical properties of oil palm leaves. As a result, SVM-FS achieved an overall accuracy of 88.64%.

Montero *et al.* [49] developed a classification model based on binary SVM to detect bud rot (BR). Bootstrapping was applied to balance the classes. The model successively achieved a performance greater than 96.0%.

Noor Azmi *et al.* [20] applied SVM on the hyperspectral images of oil palm seedlings' front number 1 (F1) and frond number 2 (F2). Five types of kernels, including linear, quadratic, cubic, fine Gaussian, median Gaussian and course Gaussian, were used and compared. All classifiers resulted in 100% accuracy using 35 bands and 18 bands of F1 data. A similar result was obtained through the combination of F1 and F2, indicating that the separation of F1 and F2 data was not necessary.

### G. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network (ANN) consists of multilayer and back-propagation to enable the learning ability of computer in determining the nonlinear combinations [21].

By applying ANN on the first derivative visible-infrared (VIS-NIR) hyperspectral reflectance data, the healthy oil palm trees and those mildly infected by *Ganoderma* disease were classified satisfactorily with an accuracy of 83.3%, and 100.0% in 540 to 550 nm, respectively [21].

### H. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional neural network (CNN) is generally recognized as the upgraded version of ANN called deep learning neural network. This approach utilizes a system much like a multilayer perceptron that has been designed for reduced processing requirements. CNN consists of an output layer, a hidden layer, multiple convolutional layers, pooling layers, fully connected layers, and normalization layers to automatically extract abstracted shallow and deep features of the input [50].

Nguyen *et al.* [48] used 2D-CNN and 3D-CNN to extract spatial-spectral representations of hyperspectral images. Results showed that the concurrent 3D-CNN transformation allowed the model to learn features better from the hyperspectral cubes. However, it also possessed more trainable parameters in each block, making the whole model more complex, more time-consuming, and requiring more computational resources compared to the 2D-CNN. This study was limited to the detection of grapevine viral diseases.

Xiao *et al.* [40] proposed a CNN model to detect strawberry diseases thru digital images. The proposed model managed to get a satisfactory classification accuracy rate at 100% for leaf blight cases affecting the crown, leaf, and fruit; 98% for gray mold cases; and 98% for powdery mildew cases.

It was noteworthy that the CNN model needed a large training dataset, which was ordinarily not the case for plant disease detection. In the case where the number of model parameters exceeded the number of data samples, a small training dataset would easily suffer the overfitting problem, which was resulted from a model that responded too closely to a training dataset and failed to fit additional data or predict future observations reliably [51].

### *I. GENERATIVE ADVERSARIAL NETWORK (GAN)*

Generative adversarial network (GAN) is an unsupervised machine learning that uses a supervised loss as part of training thru two sub-models, which are discriminator and generator models [52]. The discriminator model involves automatically discovering and learning the patterns in input data so that the generator model can be utilized to generate new examples that plausibly could have been drawn from the original dataset. GAN was designed using game theory to create additional samples with the same statistics as the training set. This is also known as data augmentation. Compared with the other methods as mentioned in the existing literature, GAN is the only machine learning method that is capable of generating full synthetic images to increase the dataset's diversity [51].

Wasserstein Generative Adversarial Network (WGAN) was introduced to improve the stability during the training of the model by providing a loss function that correlates with the quality of generated images.

Another variant of the GAN network, called auxiliary classifier GANs (AC-GAN), includes a c classification task into the GAN model. In a project conducted by Wang *et al.* [52] studying the early detection of tomato spotted wilt virus, AC-GAN was modified into outlier removal auxiliary classifier generative adversarial network (OR-AC-GAN) with the allocation of an additional label c+1 in training the discriminator model meanwhile, all fake data was classified into additional class. The proposed OR-AC-GAN model was used to analyze the hyperspectral data. The plant level classification accuracy reached 96.25% before the occurrence of visible symptoms. In addition, the performance of the model was significantly improved with the band selection algorithms.

Li and Chao [53] combined GAN and CNN in formulating an ANN-based continual classification approach. The results showed that the regular CNN could deal with a single task well but having a serious forgetting problem when it dealt with continuous tasks. This issue was solved by including the memory storage and retrieval mechanism provided by the GAN model. Interestingly, the modified continual model managed to distinguish all the categories from both old and new tasks. Hence, it successfully proved that the GAN model could extract key information from old tasks while generating abstracted images as a memory for future task.

## IV. CONCLUSION

Based on the systematic review, it was found that the combination of remote sensors and machine learning techniques were capable of classifying the four severity levels of *Ganoderma* disease, including the early infection stage. Remote sensors could collect the raw data from the oil palm trees through direct or indirect contact, whereas the machine learning techniques are rapid in data processing and analysis.

The high labor and time costs of the traditional visual inspection and lab-based approaches could be solved by employing remote sensing techniques. Nevertheless, those remote sensors still possessed certain limitations. Hyperspectral and multispectral imaging can be influenced by sunlight conditions. Tomography involves the emission of radiation that might affect human health. Although the radar system is not affected by weather condition, it requires energy emission from the satellite, which is under the management of other agencies. The development of the electronic nose is not mature enough as the information regarding the chemical properties of the *Ganoderma* sample has not been fully discovered. TLS and electrical properties measurements involve a complicated setup for each tree which might not be practical to large scale plantation area. More research is still required to explore a more user-friendly and cost-effective data acquisition system.

Many researchers have used traditional machine learning methods, such as DT, DA, NB, kNN, EM and SVM, to detect *Ganoderma* disease severity. SVM was recommended as the best classifier in several studies. Only one related research was done using ANN, whereas no research evaluated CNN and GAN in the detection of *Ganoderma* disease. However, the computing power of ANN and CNN and the generative power of GAN are still considered highly potential in contributing to this kind of research.

## CONFLICT OF INTEREST

There is no conflict of interest reported.

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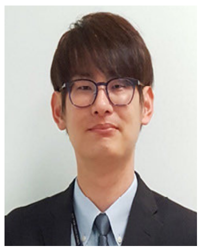

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