THE OPPORTUNITY OF ADVANCED TECHNOLOGIES UTILIZATION FOR DETECTING BASAL STEM ROT (BSR) IN PALM OIL PLANTATION: A REVIEW

PEMANFAATAN TEKNOLOGI CANGGIH UNTUK MENDETEKSI BUSUK PANGKAL BATANG (BSR) PADA PERKEBUNAN KELAPA SAWIT: REVIEW

Hasbi Mubarak SUUD[1)], Bayu Taruna Widjaja PUTRA[2,3,*)], Nazmi Mat NAWI[4)], Wahyu Nurkholis Hadi SYAHPUTRA[2,3,5)]

[1)] Study Program of Agricultural Science, Faculty of Agriculture, Jember 68121, East Java, Indonesia
[2)] Laboratory of Precision Agriculture and Geo-Informatics, University of Jember, Jember 68121, East Java, Indonesia
[3)] Center of Excellence of Artificial Intelligence on Industrial Agriculture, University of Jember, Jember 68121, East Java, Indonesia
[4)] Universiti Putra Malaysia, Malaysia
[5)] Agrotechnology Study Program, Faculty of Agriculture, University of Jember, Jember 68121, East Java, Indonesia
Tel: +62811350512; E-mail: bayu@unej.ac.id
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ABSTRACT

Basal Stem Rot (BSR) disease attacks in oil palm plantations are still the most significant cause of losses in oil palm plantations. The leading cause of BSR disease in oil palm plants is the Ganoderma Boninense fungus. The spread of BSR in an oil palm area can be massive due to transmission through root contact, airborne, and sporophores spread on the soil and in dead plant debris. The application of advanced technologies to mitigate and prevent the spread of BSR disease can be carried out considering that the nature of the spread and characteristics of this disease infection are well known. Advanced technologies such as the Internet of Things (IoT) are suitable for real-time monitoring of large areas. The key to successfully detecting BSR disease in oil palm plants is the selection of sensor technologies for monitoring and machine learning (ML) models used for segmenting and classifying infected plant characteristics. This paper comprehensively summarizes the spread of BSR disease and then describes various technologies and ML models for monitoring and preventing BSR disease in oil palm plantations. The use of ML can be potentially used for early detection of BSR. Finally, this paper can complement and provide a basis for developing technology to prevent the spread of BSR disease.

ABSTRAK

Penyakit Busuk Pangkal Batang (BSR) pada perkebunan kelapa sawit masih menjadi penyebab utama kerugian di perkebunan tersebut. Penyebab utama penyakit BSR pada tanaman kelapa sawit adalah jamur Ganoderma boninense. Penyebaran BSR pada area kelapa sawit dapat berlangsung masif karena penularannya melalui kontak akar, udara, dan penyebaran sporofor pada tanah serta sisa-sisa tanaman yang mati. Aplikasi teknologi canggih untuk mengurangi dan mencegah penyebaran penyakit BSR dapat dilakukan mengingat sifat penyebaran dan karakteristik infeksi penyakit ini sudah dikenal. Teknologi canggih seperti Internet of Things (IoT) sangat cocok untuk pemantauan secara real-time pada area yang luas. Kunci keberhasilan dalam mendeteksi penyakit BSR pada tanaman kelapa sawit adalah pemilihan teknologi sensor untuk pemantauan dan model pembelajaran mesin yang digunakan untuk segmentasi dan klasifikasi karakteristik tanaman yang terinfeksi. Makalah ini merangkum secara komprehensif penyebaran penyakit BSR, kemudian mendeskripsikan berbagai teknologi dan model pembelajaran mesin untuk pemantauan dan pencegahan penyakit BSR di perkebunan kelapa sawit. Diharapkan, artikel ini dapat melengkapi dan memberikan dasar bagi pengembangan teknologi dalam mencegah penyebaran penyakit BSR.

INTRODUCTION

Palm oil is a competitive and efficient commodity for vegetable oil production, particularly when considering production costs and the ratio of planting area to oil yield *(Destiarni & Jamil, 2021*). Apart from that, palm oil commodities have been proven to improve the welfare of small farmers if they follow the principles of correct cultivation methods *(Thoumazeau et al., 2024).* The economic prospects for palm oil commodities are increasing due to the diversification of derivative products in biomaterials, biofuels, and bioenergy, which can become a powerful new bioeconomic force *(Sakai et al., 2022).* The main derivatives of palm oil products are food ingredients such as margarine, spreads, ice cream, confectionery fats, emulsifiers, and vanaspati

(Ximenes et al., 2022). Apart from that, methyl ester compounds from palm oil can be the primary alternative material for burning diesel engines. Even diesel fuel with a 20% mixture of palm oil (B20) has been proven to produce almost the same axial flame temperature as pure diesel fuel but with lower NO_x and CO_2 emissions *(Pourhoseini et al., 2021).* Palm oil produces oil derivative products; even its leaves, stems, empty bunches, kernel shells, and mesocarp fibers can be used as asphalt hardeners and construction materials *(Al-Sabaeei et al., 2022).* In developing countries like Indonesia, this commodity has proven to be an industrial sector that drives the economy by fostering entrepreneurship, enhancing village development, and supporting household income *(Hariyanti et al., 2024).*

BSR disease reduces crop yields and destroys the lignin in cell walls. BSR disease symptoms are absent in the early stages and only emerge later. Although the infection develops slowly, it can spread across thousands of hectares of oil palm plantations *(Naher et al., 2013)*. It also spreads very fast through contact with infected roots and basidiospores. This fungus can also spread and live in felled stems and remaining wood fibers in the soil *(Rees et al., 2012).* BSR spreads rapidly, affecting oil palm of all ages but is most severe in plants over 25 years old. It is most prevalent in laterite, coastal, inland, and peat soils *(Ibrahim et al., 2020).*

Currently, BSR detection in oil palm plantations relies on manual observation and laboratory analysis, as the fungi primarily inhabit the trunk and roots. Given its rapid and invasive nature, advanced technologies such as IoT, ML, and remote sensing offer faster detection. IoT integrates sensors, including soil, temperature, and leaf sensors, with single-board microcontrollers, aiding crop monitoring, irrigation, pest control, soil mapping, and disease detection, making it increasingly popular in agriculture *(Rudrakar & Rughani, 2023)*. For large-scale plantations, remote sensing is the most effective method, with data acquired via satellites or UAVs in formats such as RGB images, spectroradiometer, multispectral, and hyperspectral data. Remote sensing has proven reliable for monitoring oil palm health *(Santoso et al., 2019)*, and advancements in imaging sensors with varying spatial, temporal, and spectral resolutions enhance its capabilities. Multispectral and hyperspectral imaging datasets enable detailed analysis of land cover changes, including plant canopy and soil characteristics, with prior studies confirming remote sensing's effectiveness in early plant disease detection *(Abdullah et al., 2023).*

Early BSR detection requires fast, accurate data processing for timely decisions. Machine learning (ML) enhances disease detection accuracy, efficiently handling large datasets for data-driven decision-making. *(Ennaji et al., 2023).* ML explores data by building estimation models and relationships between parameters. It processes structured datasets to predict trends. Supervised learning handles known classifications, while unsupervised learning finds patterns. Model development includes classification, regression, clustering, dimensionality reduction, reinforcement learning, and deep learning *(Sarker, 2021)*. Applying ML in the agricultural sector usually goes through data extraction and classification stages to produce output (*Kipli et al., 2023*). ML is widely used in agriculture for planting, harvesting, and post-harvest stages. It supports disease detection, soil analysis, plant age estimation, population counting, and yield classification (*Meshram et al., 2021*).

This study aims to elucidate the opportunities for advanced technologies to detect BSR disease spreading in oil palm plantations. The presence of *G. Boninense* can be detected by the appearance of basidioma in the planting medium and changes in leaf color on oil palm seedlings under 1 year old. In addition, environmental factors such as temperature, duration, and intensity of rainfall, dew levels, soil temperature and water content, soil fertility, soil organic matter content, wind, herbicide history, and air pollution also influence the spread of pathogens. It also highlights the strengths and limitations of these technologies. By highlighting the strengths and limitations of existing technologies, this article proposes a novel approach that combines advanced sensor fusion with real-time processing to provide more reliable, cost-effective, and scalable solutions for early BSR detection in diverse environmental conditions.

MASSIVE DAMAGE DUE TO THE SPREAD OF BSR DISEASE IN OIL PALM PLANTATIONS

BSR is a severe threat to oil palm plantations and has been proven to cause severe economic losses for palm oil-producing countries. The fungus ganoderma boninsense (*G. Boninense*) is the main cause of BSR disease, which can result in economic losses of up to 43% over 6 months due to reduced oil palm yields (Assis et al., 2016). BSR infection in oil palm plantations can reduce plant yields between 50% and 80% (*Corley & Tinker, 2015)*. BSR disease is the biggest threat to oil palm plantations caused by the Ganoderma Boninense (*G. Boninense*) fungus which attacks the roots to the base of the plant stem. Without early detection or control, infected plants die within 6–12 months of symptom onset, with an 80% mortality rate in productive-age plants.

In Johor, Malaysia, the BSR infection rate rose from 1.51% in 1994 to 3.71% in 2009, averaging a 10.3% annual increase (*Roslan & Idris, 2012*).

Studies using the Bayesian Model Averaging (BMA) model approach show that the level of economic loss is estimated to reach 68% of the yield of all infected plants (*Assis et al., 2020)*. In 2009, BSR disease spread across 151,208 hectares in Malaysia, causing an estimated loss of US$ 351 million *(Parthiban et al., 2016*). By 2040, if uncontrolled, it could destroy 860,610 ha of productive oil palm plantations, leading to job losses and rising palm oil prices (*Olaniyi & Szulczyk, 2020*). Indonesia is also estimated to experience losses of US$ 38 million for every 1% of oil palm plantation areas that experience BSR attacks based on calculations using commodity prices in 1996. It Is estimated that losses due to oil palm plantations attacked by BSR in Southeast Asia could reach 500 million US$ per year (*Ahmadi et al., 2017*). The first convincing discovery of *G. Boninense* infection was in gardens owned by private corporations in North Sumatra, with an attack rate of 22% of the plant population per hectare in 2017 *(Haryadi et al., 2019*). Losses due to the spread of BSR disease have not only hit Malaysia and Indonesia; in fact it was recently discovered that several oil palm plantations in Papua New Guinea experienced BSR infection rates of up to 50% (*Murphy et al., 2021)*. Statistics of losses due to BSR can be seen in Table 1.

Table 1

The summary on BSR-related losses

Metric	Value	Source
Yield losses	Can reduce yield by 50% to 80%	(*Murphy et al., 2021; Zakaria, 2022*)
Annual economic losses	Estimated between US$ 38 million to US$ 351 million.	(*Parthiban et al., 2016; Paterson, 2023*)
Environment Impact	CO_2 and CH_4 emissions from decomposition; soil pollution from chemical treatments.	(*Jazuli et al., 2022*)
Agricultural Implication	Increased replanting costs; challenges in disease management.	(*Paterson, 2023*)

SPREAD OF BSR IN OIL PALM PLANTATIONS

The disease triangle concept highlights the interaction between the host, pathogen, and environment, all of which influence disease spread. Infectious diseases emerge when susceptible hosts, virulent pathogens, and favorable environmental conditions align (*Mead et al., 2022*). Several types of ganoderma, such as *G. Boninense, G. Miniotacinctum, G. Chalceum, G. Tornatum, G. Zonatum*, and *G. Xylonoides*, can be the cause of the spread of BSR disease. However, G. Boninense is the main cause of BSR infection in oil palm plants (*Zakaria, 2022*). Several types of seeds are claimed to be more susceptible and more resistant to disease. Progenies from palm oil seeds PK 2724 and PK 2567 were detected as seeds that were susceptible to infection. AVROS oil palm seeds are also more vigorous than the Ekona and Calabar varieties (*Chong et al., 2012*). In the latest study, 31 oil palm progenies had partial resistance to Ganoderma attacks in peatlands, but further confirmation and testing in the nursery were needed to ensure their performance (*Amiruddin, 2022*). Environmental factors can also influence pathogen behavior, such as germination speed, spread of inoculum, ability to survive and penetrate pathogens, and the potential for infection.

Stages Development of Ganoderma Boninense

The development phases of *G. Boninense* are the same as fungi in general as seen in Fig. 1(a). The mature fruiting body will produce basidiospores. Basidiospores can spread through the air or with the help of insects and then germinate into monokaryotic mycelia. This mycelium is not yet pathogenic to oil palm plants (*Khoo & Chong, 2023*). Pathogenic properties for oil palm plants only appear in dikaryotic mycelia after fusion or mating occurs. Dikaryotic mycelia are more commonly found on the surface of stems and roots than on the interior of oil palm stems (*Pilotti et al., 2018)*. The dikaryotic mycelia grows into mycelium, which eventually develops into an infectious inoculum. Mycelium will continue to develop into a fruiting body if it is infected with the suitable medium. The base of the stem of an oil palm plant that is injured or has been pruned is the medium most easily infected by mycelium *G. Boninense* (*Jazuli et al., 2022*). This *G. Boninense* fungus colony has a characteristic white color on the surface and a dark color on the reverse side. On infected stems, fruiting bodies often appear to contain spores with layers varying in color from yellow to brown *(Khoo & Chong, 2023*).

Dikaryotic mycelia form rapidly in favorable conditions. *In vitro* studies show *G. boninense* spores germinate within 1–2 days in darkness. Monokaryotic mycelia grow 4–5 days after transfer to potato dextrose agar (PDA), with clamp cell formation observed 5–7 days post-mating, indicating successful fusion (*Pilotti et al., 2003*). The development of dikaryotic mycelia, which infects the base of the oil palm stem, is characterized by the appearance of a slightly raised white button which changes shape into a dome structure within 2 days. This structure develops into a slender white column with a length of 1.1 cm and a width of 1.1 cm. Within 14 days, the structure of the column becomes harder and starts to turn brown, except for the apical tissue, which remains white. The apical tissue eventually stops growing and forms a growth cap. The longer it grows, the color of the cap becomes browner, and the size also increases. Its size can reach a length of 17.8 cm and a width of 14.6 cm at 14 weeks after infection (*Ho & Nawawi, 1986a*).

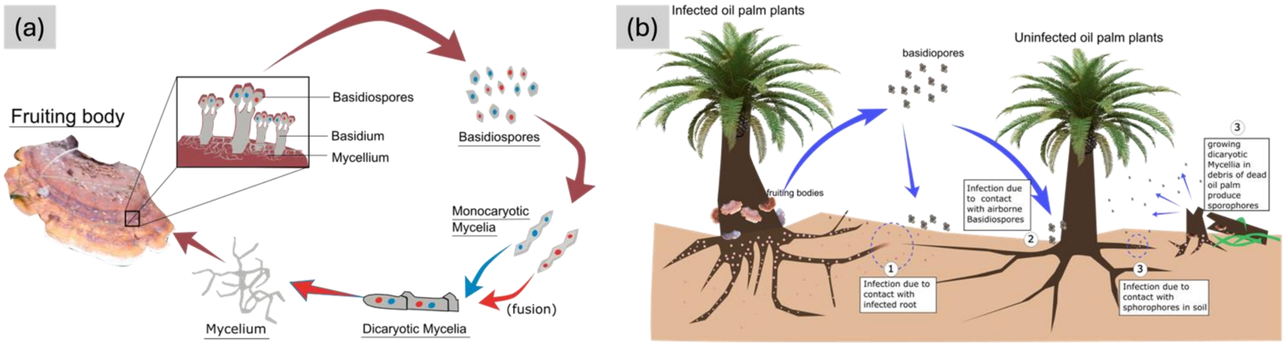

Fig. 1 - *G. boninense* and BSR transmission: (a) Life cycle of *G. boninense*. (b) Transmission via root-to-root contact, basidiospores, and free sporophores in debris and soil.

The spread of BSR in oil palm plants can be seen in Fig. 1(b). The spread of BSR is mainly due to the invasion of the *G. Boninense* pathogen in the roots. *G. Boninense* has the ability to spread through soil (soil-borne) and basidiospores in massive numbers with the help of wind or insects. The spread of G. Boninense basidiospores is not only influenced by one environmental factor but a combination of several factors *(Ho & Nawawi, 1986b*). Airborne basidiospores will develop on the surface of oil palm stems that are injured or have been pruned. Basidiospores that fall to the soil surface can be carried by water or insects, moving to the root area and colonizing oil palm roots. In addition, dikaryotic mycelia in the remaining roots and stems of dead oil palms can continue to grow and produce sporophores which can infect healthy plants *(Pilotti et al., 2018*).

Symptoms of Infection in Oil Palm Plants

In the initial phase of the inoculum infecting oil palm plants, no symptoms can be observed directly with the naked eye (*Siddiqui et al., 2021*). Based on recent observations, morphological symptoms on leaves only appear if the development of BSR disease on plants is severe or reaches 60-70% (*Chong et al., 2017*). The initial characteristics of infected plant roots include changes in metabolism, characterized by the discovery of fatty acid compounds and steroidal compounds in large quantities in roots infected with G. Boninense *(Isha et al., 2020*) The first morphological symptom that appears is chlorosis on oil palm leaves. This phase shows that G. *Boninense* has colonized the roots. Then, there is characteristic necrosis in the roots at the beginning of the infection, which then spreads to the base of the stem. Apart from that, stunted growth and curled leaves are symptoms in infected oil palm plants. This stage of infection indicates that the infection has reached the base of the oil palm plant stem.

Other symptoms that often appear on infected plants include the appearance symptoms of drought stress on the plant, spots appearing on the plant canopy on one side, a flat crown, many buds that should have opened but have not yet opened, the appearance of basidiocarp at the base of the lower stem, leaves unopened spears, and palm stems breaking and falling in cases of severe infection (*Parthiban et al., 2016*). If fruiting bodies appear on oil palm plants, this indicates that the infection stage is severe. There has been massive degradation of plant stems. Old oil palm plants will die in 6 to 24 months, while young plants will die 2 to 3 years after the first symptoms of infection are detected (*Siddiqui et al., 2021*).

Environmental Factors Support the Spread of BSR Disease

BSR disease can spread in various conditions and types of soil, even in oil palm plantations on peatlands, cases of BSR infection have been found (*Midot et al., 2019*). Based on a survey conducted in

Malaysia, the most cases of BSR infection were found in lateritic soils and the least in peatlands. Lateritic soil is soil that has high aluminum and iron content. Usually, lateritic soils are formed in wet and hot tropical areas and are characterized by a red color *(A. R. Mareddy, 2017*). Land use history can also influence the spread of BSR infection. BSR disease can develop more massively in oil palm plantations located in coastal areas where the oil palm land was previously coconut plantation land. The spread of BSR disease has been shown to be more severe in areas with higher plant densities *(Jazuli et al., 2024*).

The chance of plants being infected with *G. Boninense* is greater in oil palm plantations that have undergone more than three replantings. Also, old plants have a greater chance of being infected than plants that have not yet produced fresh fruit bunches *(Priwiratama et al., 2020*). BSR infection can occur in various life cycles of oil palm plants. In cases found in Indonesia, the infection attack rate in 4 years old oil palm plants was between 1.42% and 4.28%. The attack rate on 17 years old oil palm plants is 50%. Meanwhile, in plantations with 33 year old oil palm plants, the infection rate was 0.71% *(Lisnawita et al., 2016*).

Tabel 2

The behavior of Ganoderma Boninense in each environmental parameter

No.	Parameter	Remarks
1.	Temperature	• Optimal growth at 27–30°C; inhibited below 15°C and above 35°C; o growth at 45°C *(Chong et al., 2017; Nawawi & Ho, 1990*).
2.	Relative Humidity (RH)	• Optimal at 50–60%; reduced growth above 60%.
3.	Soil pH	• Best growth at pH 3–5.5 (*Chong et al., 2017*) • pH 6 reduces BSR growth and supports seedlings (*Rahman & Othman, 2020*).
4.	Sunlight	• Higher infection risk in shaded seedlings (*Rees et al., 2007*).

Molecular Testing Methods for BSR Disease

BSR infection can be detected by direct observation and molecular detection. The molecular detection approach is the fastest way to detect BSR infection (*Bahari et al., 2024*). Detection can also be done simpler, namely by observing pathogenic fungi directly at both macro and microscopic levels. However, this method takes a long time and has low resolution and sensitivity. Several molecular approaches to detect *G. Boninense* infection are real-time polymerase chain reaction (PCR) testing on fungal samples obtained in the field. The fruiting bodies or basidiomata part of the fungus is the most sensitive part for detecting the presence of pathogen DNA compared to the stem and root tissue of the fungus *G. Boninense* (*Hilmi et al., 2022*). Another commonly used early detection method for spreading BSR is a multiplex PCR-DNA kit using oil palm plants' root and stem tissue samples *(Idris et al., 2010*).

The enzyme-linked immunosorbent assay (ELISA) application can detect *G. Boninense* infection. This technique uses polyclonal antibodies to detect the presence of *G. Boninense* serologically. Detection can also be done by detecting the presence of typical ergosterol produced by the fungus *G. Boninense*. This method is carried out by making an extraction solution from samples suspected of being exposed to G. Boninense spores or mycelia. Ergosterol is detected if there is thin layer chromatography (TLC) in the extract solution and can then be quantified using high-performance liquid chromatography *(Muniroh et al., 2014*). However, this molecular method is quite complicated and expensive, so it is not appropriate to carry out in large areas with lots of samples (*Siddiqui et al., 2021)*.

Many detection procedures can be done, but there is no truly effective way to stop the spread of BSR unless the biomarkers of *G. Boninense* have been detected *(Mohd Hilmi Tan et al., 2023*). Biomarkers are changes in cells, biochemistry, or molecules that can objectively measure normal biological processes, pathogenic processes, and pharmacological responses to treatment to control the development of infection. Biomarkers are technological tools that can help understand the causes, distribution status, diagnosis, and treatment response to a disease. The search for appropriate biomarkers to detect *G. Boninense* is currently being developed, but none are ready to be applied in the field. One of the biomarker developments being developed is the Oil palm extract medium (OPEM) model. This model is still being developed to produce a faster and non-invasive method for diagnosing Ganoderma in oil palm plantations *(Santiago et al., 2023*). The mRNA marker *EgPIN5* is a promising biomarker for early *G. Boninense* detection, identifying infection as early as 11 days post-inoculation before symptoms appear. LFA strips with ssDNA aptamers targeting *EgPIN5* RNA fragments offer a low-cost, visual detection method. While this approach shows potential, its sensitivity remains limited due to the low RNA copy numbers in field samples (*Bahari et al., 2024*).

Management of the Current Spread of BSR Disease

Management of the spread of *G. Boninense* can currently be done physically, chemically, and by biocontrol. Cleaning infected plantation areas must be done in detail. Clean clearing and windrowing procedures can be carried out to minimize the spread of inoculum. Infected oil palm plants must be chopped, crushed, and stacked between planting rows, although it cannot be guaranteed that the pathogen will not spread and infect healthy plants if this is done. Using fungicides to control the spread of *G. Boninense* is not very effective because this fungus is soil-borne. Fungicides will first be degraded in the soil before reaching their target. Injection of 90 ml of hexaconazole with 10 liters of water into the stems of infected oil palm plants can increase the survival rate by up to 70% and the ability to produce for several years to come (*Mohammed et al., 2014*). The use of biocontrol agents to control the spread of infection has been widely developed and shows reasonable success rates. Use of fungi *Trichoderma* spp., Aspergillus spp., and Penicillium spp. They were proven antagonistic to *G. Boninense* through in vitro experiments (*Naher et al., 2013*).

A mixture of Trichoderma spp, namely Trichoderma aspergillum, Trichoderma harzianum, and Trichoderma virens, as a biocontrol agent, can reduce symptoms of disease infection between 83% and 89%. The Trichoderma spp mixture can be applied in the nursery three months before planting the seeds *(Musa et al., 2018*). Application of Trichoderma aspergillum strain T76-14 is known to be able to respond to oil palm seedlings to control and limit pathogen colonization in host tissue and inhibit the distribution of *G. Boninense* in the soil (*Samlikamnoed et al., 2023)*. Three bacterial strains, namely, Pseudomonas aeruginosa strain JQ-41, Serratia marcescens strain S16, and Stenotrophomonas rhizophila strain CASMBAUDAL2, together with one fungal strain, Trichoderma sp., and one actinomycetes strain, Streptomyces sp., have been proven to be able to prevent the growth of *G. Boninense* with inhibition levels between 70% - 88.5% (*Rupaedah et al., 2024*). Currently further studies are being carried out to formulate integrated control through a deeper understanding of the influence of physical, chemical and biological factors on the spread of *G. Boninense* infection. Temperature treatment, administration of boron and potassium, and application of the fungicide Manzoceb are known to reduce the specific metabolic rate of *G. Boninense* and have no effect on the development and metabolism of *Trichoderma virens* (*Anothai et al., 2023*).

THE POTENTIAL OF IoT UTILIZATION TO DETECT THE SPREAD OF BASAL STEM ROT DISEASE

Molecular infection testing can provide accurate confirmation of whether a plant has been infected with G. Boninense and how severe the infection is because it directly tests DNA sequences. However, this method requires complex lab tests, high expertise, is costly, and challenging for large-scale application. Therefore, advanced technologies like sensors and IoT have been developed for faster early detection of *G. Boninense* in oil palm fields. Imaging sensors, including RGB, multispectral, hyperspectral, thermal, fluorescence, and 3D, are widely used in precision agriculture. They can be applied in microscopes for cellular analysis, mounted on vehicles for plant imaging, deployed on UAVs for aerial monitoring, or placed on satellites for large-scale ecosystem assessment *(Mahlein, 2016*). High-resolution aerial images from UAVs can classify oil palm conditions based on tree crowns using image processing, ML, and deep learning. Hyperspectral imaging detects infection characteristics by combining absorption, reflectance, and fluorescence data into a hypercube (*Vasefi et al., 2016*). Non-imaging sensors like portable GC-MS, electronic noses, biosensors, and nuclear magnetic resonance (*Wei et al., 2021*). Table 3 summarizes sensor technologies tested for BSR detection in oil palms.

Table 3

Sensor Technology for BSR Detection in Oil Palm

Technology	Sensor	Measurement Technique	Pros	Cons	Ref.
Imaging	High-resolution RGB	UAV with 12.1 MP RGB camera	Low cost, easy to use	Sun bias, low infection correlation	(*Izzuddin et al., 2019*)
	Multispectral Imaging	UAV with multispectral camera	Full spectrum for classification, NIR effective for BSR	Accuracy depends on segmentation and sample size	(*Ahmadi et al., 2022*)
	Hyperspectral Imaging	Hyperspectral sensors on canopy	Detailed spectral-spatial models, low cost	Expensive instruments, complex data processing	(*Kurihara et al., 2022*)

Technology	Sensor	Measurement Technique	Pros	Cons	Ref.
	FLIR Thermal Imaging	FLIR cameras placed around trees	Easy to use, clear thermal stats	Narrow measurement spectrum, difficult infection suspicion	(*Hashim et al., 2021*)
Spectroscopy	Mid-infrared Spectroscopy	FTIR spectrometer in lab	High accuracy, detects biochemical compounds	Complicated sampling and analysis, expensive tools	(*Liaghat et al., 2014*)
	NIR Spectroscopy	NIRscan Nano spectrometer on leaves	Simple, rapid, non-destructive	Low sensitivity, complex calibration	(*Mohd Hilmi Tan et al., 2023*)
	Dielectric Spectroscopy	Measures dielectric properties of leaves	Rapid, detects health levels	Hard to pinpoint disease cause	(*Khaled et al., 2022*)
Satellite	WorldView-3 Satellite	Pixel value analysis of palm crown reflectance	Can classify infection symptoms	Requires expertise, accuracy depends on model selection	(*Santoso et al., 2019*)
	Sentinel-2 Satellite	Vegetation indices from multispectral data	Comprehensive data, low cost	No thermal band, influenced by cloud cover	(*Handrian et al., 2022*)
Sensor	Intelligent Electronic Nose	32 sensor elements detect compounds in soil, stem, and leaves	Classifies healthy and infected plants, estimates infection area	Reduced sensitivity in humid conditions, calibration challenges	(*Markom et al., 2009*)
	E-Nose MOS Gas Sensor	MOS sensors in the lab detect chemical properties	Quick detection, affordable	Sensitive to temperature/humidity	(*Marhaenanto et al., 2025*)
	Terrestrial Laser Scanning	3D laser scanning around oil palm trees	Effective at detecting unopened spears in infected plants	Time-consuming setup, requires trained staff for data extraction	(*Husin et al., 2020*)
	Electrical Resistance Sensor	Measures electrical resistance in stems/soil	Rapid, easy, and low-cost	Data highly influenced by temperature, humidity, and other factors	(Aziz et al., 2019)
Imaging with consumer-grade camera	Camera Canon 600D	Mounted to DJI phantom 3 to capture area	Low-cost, easy to use, large area	Data highly influenced by light intensity	(*Hermantoro et al., 2023*)
	Canon SX240 HS	Mounted to Turnigy 9XR Octocopter UAV	Low-cost, large area	Light-sensitive	(*Bejo et al., 2018*)

The IoT extends beyond sensor technology for data acquisition and can be developed into an integrated system for managing plant pests and diseases. This includes data traffic management, big data processing, sensor-CPU interfaces, and machine-user interaction design (*Nayagam et al., 2023*). Architectures integrating all components of an IoT system continue to evolve to simplify the integration of diverse systems and hardware. Lysis, a cloud-based architecture platform, has four key functions: integrating IoT with social networks, enabling virtual objects and device communication, storing sensor data while controlling sensor behavior, and allowing data requests from the same sensor across different IoT systems (*Girau et al., 2016*). The Lysis platform integrates sensors for real-time plant detection, classifies data using the Model Builder Micro Engine, and displays results via a smartphone app. The basic framework of the IoT layer architecture should have sensors and actuators, connectivity and communication paths, edge devices and gateways, Cloud Platform, Data Analytics (machine and deep learning), mobile and web applications, decision support systems, and finally security and privacy (*Dhaka et al., 2023*). The IoT is not only limited to sensor technology for data acquisition but can also be developed into an integrated system for managing plant pests and diseases. This can include data traffic management, big data processing, sensor and CPU interfaces, and machine-user interaction design (*Nayagam et al., 2023*). Architectures that integrate all parts of an IoT system continue to evolve to bridge the complexity of integrating dissimilar systems and hardware. Lysis is an example of a cloud-based architecture platform that has 4 essential functions, namely social network integration with IoT, creating virtual objects and communication between devices, features for storing data from sensors and controlling sensor behavior, and the ability to request data from the same sensor but from different IoT systems. The Lysis platform can be developed into a plant detection system capable of connecting various collocated sensors and sending the data in real-time to a dataset management platform. The collected dataset is classified and modeled in the Model Builder Micro Engine, the results of which are displayed in the app on the user's smartphone (*Delnevo et al., 2022*). The basic framework of the IoT layer architecture should have sensors and actuators, connectivity and communication paths, edge devices and gateways, Cloud Platform, Data Analytics, mobile and web applications, decision support systems, and finally security and privacy.

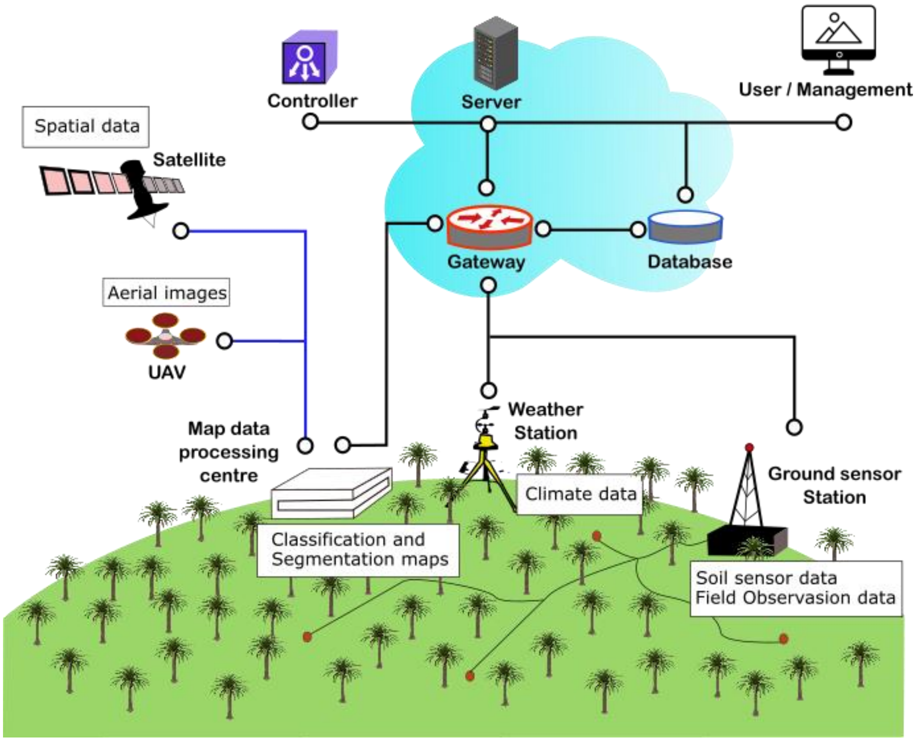

Fig. 2 - Concept of applying IoT for developing a BSR outbreak warning system

IoT technology makes it possible to apply it in building an early warning system for the spread of BSR disease in oil palm plantations. An initial overview of the concept of early warning for BSR disease using IoT can be seen in Fig. 2. Detection via imagery from UAVs and satellites can detect the characteristics of BSR infection, especially through monitoring the condition of the oil palm plant canopy. Satellite data containing multispectral information such as Sentinel-2, Landsat, and WorldView-3 are possible to use because they have many spectra to be analyzed either through modeling the spectral values or through converting the spectral values to obtain vegetative indices or surface temperature (*Handrian et al., 2022*). A UAV can capture aerial images for clearer analysis. Hyperspectral cameras offer high accuracy in segmenting and classifying BSR-infected oil palms but are costly. Monitoring often includes high-resolution aerial maps to enhance segmentation and classification. Hyperspectral data detects early BSR infection as mycelium develops on bark or fragile wood (*Kurihara et al., 2022*).

However, the characteristics of the plant canopy cannot wholly describe the spread of infection due to G. Boninense attacks the roots and base of oil palm plant stems. It has been proven with prior reports that the average accuracy of remote sensing in classifying the severity is around 80%, and in classifying healthy and unhealthy trees is around 86.67% (*Siddiqui et al., 2021*). So, field observations are still necessary to provide information about the presence of infected plants and confirm the monitoring result from remote sensing and sensors. These field observations can be carried out simultaneously with plant maintenance work. G. Boninense is also a fungus that can spread through airborne and direct contact, so it is also necessary to monitor environmental conditions by acquiring weather and climate data and soil conditions. Weather and climate data can be taken from weather stations, and soil condition data can be monitored using soil sensors or manual measurements. Meanwhile, data on soil electroconductivity distribution on land can be used to monitor soil conditions. Apart from carrying out analysis to predict disease outbreaks, steps to verify the results of predictions also need to be taken to control the spread of disease infections. Manual verification approaches and molecular detection can be carried out as further steps to verify the BSR outbreak warning system results.(*Wang et al., 2023*). Manual verification approaches and molecular detection can be carried out as further steps to verify the BSR outbreak warning system results.

MODEL DEVELOPMENT FOR DETECTING BSR

Detection models are crucial factors other than data acquisition techniques and methods determining detection success. ML applications in precision agricultural systems can be used to detect plant pests and diseases. ML integrated into IoT is very powerful for real-time detection systems. ML has a role in predicting and detecting the spread of epidemics by studying datasets containing information about pathogen behavior, demographics, population, information about biology and biodiversity. Many models can be used to predict and detect the spread of disease infections, ranging from regression models neural networks to deep learning. Apart from that, the types of datasets used also vary, starting from spatial, epidemiological, meteorological, and remotely sensed data (*Alfred & Obit, 2021*). ML construction can be divided into several parts: dataset preparation, data preprocessing, data correlation analysis, determining the suitable model, and testing and verifying the selected model. The final stage is implementation (*An et al., 2024*). Many statistical models and ML models can be used to prepare an early detection system for evaluating the spread of a disease. The model choice depends on the dataset type and the purpose of data processing. For example, if the goal is to obtain the relationship between spatial and temporal data in the spread of disease, spatio-temporal models can be used. If the goal is to detect climate data indicating what disease outbreak will occur, you can use Bayesian ML *(Haque et al., 2024*). Several ML models that can be used to detect BSR disease in oil palm plantations are presented in Table 4.

Tabel 4

Several ML models for classifying the level of BSR disease infection in oil palm plants.

Models	Dataset Type	Purpose	Pros	Cons	Ref.
Kernel Naïve Bayes	3D plot data from laser scans	Detect unopened spears, classify infection	Can classify with small datasets	Biased by poor data, not for continuous features	(*Husin et al., 2020*)
ANN Backpropagation	VIS-NIR spectral data	Identify best wavelength for BSR	No parameter tuning, versatile	Sensitive to noise, slow training	(*Ahmadi et al., 2017*)
PLS Discriminant Analysis	Hyperspectral images	Classify plant disease infection levels	Handles high variable-to-sample ratios	Requires deep statistical understanding	(*Lelong et al., 2010*)
Support Vector Machine	Hyperspectral crown images	Classify infection using top fronds	Good for high-dimensional data	Needs large memory, struggles with large datasets	(Khaled et al., 2018)
K-Nearest Neighbor	Hyperspectral frond samples	Classify BSR infection levels	Simple, no need for training model	Needs data smoothing, K-value affects accuracy	(*Liaghat et al., 2014*)
Random Forest	Multispectral data from Sentinel 2A	Map plant infection distribution	Robust, handles imbalanced data	Complex interpretation, long prediction time	(*Handrian et al., 2022*)
Multilayer-Perception NN	Hyperspectral drone images	Separate healthy/diseased plants	Handles non-linear problems	Slow computation, reliant on training data quality	(*Lee et al., 2022*)

Models	Dataset Type	Purpose	Pros	Cons	Ref.
M-CR U-Net	Aerial RGB images	Classify infection severity via image segmentation	Robust for pixel-level segmentation	Downsampling reduces spatial accuracy, overfits on small datasets	(*Win Kent et al., 2023*)

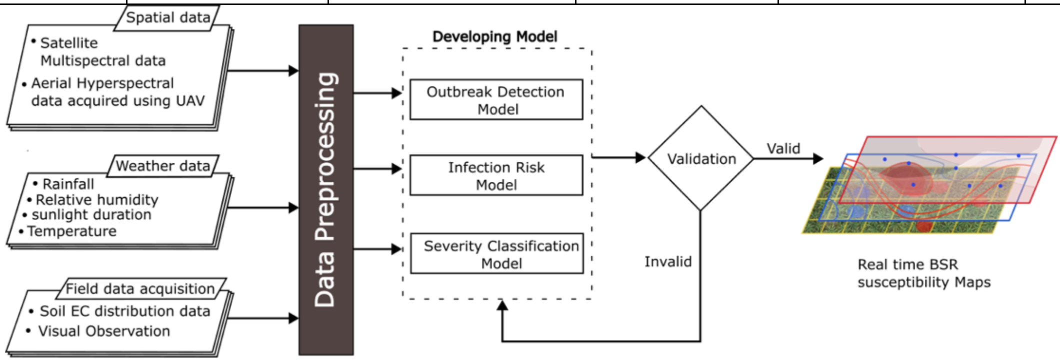

Fig. 3 - **Proposed dataset and ML model development for real-time BSR susceptibility mapping**

Models for segmentation and classification are not limited to those shown in Table 3, there are many more advanced models, especially deep learning models, which can be used for segmentation and classification but have not been widely used to detect the spread of BSR disease. For example, ML systems such as the YOLO (You Only Look Once) series can be used for image recognition and recognizing pest habitat environments. There are 3 models that can be developed to create a BSR outbreak warning system, namely the outbreak detection model, infection risk model, and severity classification model. The severity classification model aims to detect the presence of BSR infection in an oil palm plantation, which can classify infected and healthy plants and the level of infection. Meanwhile, the outbreak detection model is used to detect distribution patterns that may occur and need to be anticipated in the future. The resulting output is an integrated map that can show the existing and potential distribution of BSR infection, as shown in Fig.3. (*Chen et al., 2020*). There are 3 models that can be developed to create a BSR outbreak warning system, namely the outbreak detection model, infection risk model, and severity classification model. The severity classification model aims to detect the presence of BSR infection in an oil palm plantation, which can classify infected and healthy plants and the level of infection. Meanwhile, the outbreak detection model is used to detect distribution patterns that may occur and need to be anticipated in the future. The resulting output is an integrated map that can show the existing and potential distribution of BSR infection, as shown in Fig. 3.

CONCLUSIONS

The Basal Stem Rot disease that attacks oil palm plantations is mainly caused by Ganoderma Boninense, a fungus that can spread via airborne spores, through root contact, or spread by its sporophores in the soil and plant debris. The ability of very fast and massive spread and transmission must be overcome quickly to reduce losses from the loss of potential fresh fruit bunch (FFB) harvests than they should. Advanced technologies can be a solution because of their ability to detect in real time through a precise classification and segmentation system and are able to cover large areas through geospatial data acquisition techniques either via satellite or drone. With the current advances in sensors, IoT, AI technologies, it is very possible to build a monitoring system and early warning system that integrates the results of data acquisition through direct observation, sensors, and dynamic and real-time geospatial data for the next future studies. The key to the success of this system lies in selecting a classification and segmentation model that can detect and assess the level of infection of *G. Boninense* on oil palm plants in oil palm plantations.

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