Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2023, 2023:40
https://doi.org/10.28919/cmbn/7911
ISSN: 2052-2541

DETECTING GANODERMA BASAL STEM ROT DISEASE ON OIL PALM USING ARTIFICIAL NEURAL NETWORK METHOD

HERMANTORO[1,*], MUHAMMAD A. KURNIAWAN[1], JOKO P. TRINUGROHO[2], TEDDY SUPARYANTO[1,2], MAHMUD ISNAN[2], DIGDO SUDIGYO[2], BENS PARDAMEAN[2,3]

[1]Faculty of Agricultural Technology, Institute of Agriculture STIPER, Yogyakarta 55282, Indonesia

[2]Bioinformatics and Data Science Research Center, Bina Nusantara University, Jakarta 11480, Indonesia

[3]Computer Science Department, BINUS Graduate Program – Master of Computer Science Program, Bina Nusantara University, Jakarta 11480, Indonesia

Abstract. The oil palm tree is one of the essential plants with a major contribution to the Indonesian economy but is also vulnerable to pathogen infection, such as *Ganoderma*. *Ganoderma boninense* is a group of polyporous fungi which is responsible for Basal Stem Rot disease. The disease is extremely serious and easily spreads, posing a significant threat to the economy, so early detection of the disease becomes vital. However, the current detection techniques for the disease are expensive and time-consuming; hence, they are not ideal for large plantation areas. The development of image processing technology could be utilized to predict *Ganoderma* infection, using the images that are captured by a drone. This research aims to predict the spread of *Ganoderma* infection, in the oil palm tree plantation area in North Sumatra, Indonesia, by utilizing image processing and Artificial Neural Network methods. Our model results showed the prediction accuracy (with Green color) was 73,8%. In addition, we also showed the distribution of *Ganoderma* infection in the area: score 0 was 229 trees, score 1 was 295 trees, score 2 was 112 trees, score 3 was 238 trees, and score 4 was 23 trees. Overall, our research provided a non-destructive method to detect Basal Stem Rot disease in the oil palm plantation sites.

Keywords: *Ganoderma*; basal stem rot; image processing; artificial neural network.

*Corresponding author
E-mail address: herman@instiperjogja.ac.id

Received February 13, 2023

2020 AMS Subject Classification: 93A30, 65D18, 97R40, 68T01.

1. INTRODUCTION

The oil palm (*Elaeis guineensis* Jacq.) plantation sector in Indonesia has grown very rapidly in the last 10 years. In 1998, the area of oil palm plantations was 2.7 million ha, with a production volume of 5.6 million tons of CPO (crude palm oil), and the export volume of palm oil was 852,843 tons with a value of US $ 333,866,000 [1](BPS-Statistics Indonesia, 2020). Meanwhile, in 2003, the area of oil palm plantations reached 5.06 million ha, with a CPO production volume of 9.6 million tons or an average of 1.8 tons per ha/year, and the export volume of palm oil was 6.333 million tons with the value of US$ 2.092 billion [1]. The composition of ownership of the oil palm plantation area consists of smallholder plantations at 29.7%, PT Perkebunan Nusantara (Indonesian state-owned enterprise) at 13.2%, and large private plantations at 57.1% [2].

In 2008, the area of oil palm plantations in Indonesia was almost 7 million ha. Like other crops, oil palm is also susceptible to various diseases [3, 4]. One of the most common diseases that affect oil palm is basal stem rot disease (BSR), which is caused by *Ganoderma* [5, 6, 7, 8]. It is the most serious disease in oil palm, especially in Malaysia and Indonesia, the two largest palm oil-producing countries in the world [5, 7, 9].

BSR was first described in 1915 in the Republic of the Congo, West Africa [10]. In Malaysia, this disease used to infect old oil palms that were more than 25 years old, which would indeed be replanted so that BSR was considered not economically important [11]. However, by the 1960s, when oil palm began to be considered a leading plantation crop, BSR disease continued to increase when even younger oil palms (10-15 years old) were infected [12, 13]. Recently, *Ganoderma* attacked oil palms aged 12-24 years and even plants aged 4-5 years, especially in replanting areas that were originally planted with coconut plants [11].

The attack of BSR in Indonesia was initially low in oil palm plants aged 7 years, then it increased by 40% when oil palm plants reached 12 years of age [14]. In the fourth generation of crops, the attack of BSR occurred earlier, namely on the older plants 1 to 2 years [14]. BSR could also attack oil palm seedlings, presumably because the pathogens that cause the disease are increasingly spreading on land that is often rejuvenated [15].

BSR disease causes low palm oil production and a decrease in fresh fruit weight. The damage caused by the disease can reach 80% to 100%, and it can even cause death in the affected plants [16, 17]. BSR is a threat to various oil palm plantations in Indonesia, especially in plantations that have undergone repeated rejuvenation [15]. A previous study reported that the more often oil palm plantations are replanted or in oil palm plantation areas previously planted with coffee, rubber, or other plantation crops, the lower the diversity, abundance, and distribution of bio-control agents found [18]. The decrease in the presence, diversity, and abundance of antagonist agents could increase the incidence of BSR.

Given the effect of BSR disease on oil palm trees, detecting the infected trees is crucial. Until now, several methods of BSR detection have been developed, which include the use of *Ganoderma* selective medium [19], screening with ELISA (Enzyme-linked immunosorbent assay) and PCR (Polymerase Chain Reaction) [20], integrating of headspace solid-phase microextraction (HS-SPME) technique with gas chromatography-mass spectrometry (GC–MS) [21], and the use of the electronic device that analyzed odor [22]. However, these techniques possess several drawbacks, such as being expensive and time-consuming, which are not ideal for implementation on the large scale [23]. Therefore, developing an efficient and more economical method will be beneficial for detecting BSR infection in large plantation areas.

The development of a Geographic Information System (GIS) together with Remote Sensing (RS) has enabled an effective and efficient way to obtain and analyze geographic information on large surfaces, including oil palm plantation areas [24, 25]. Further, machine learning approach, such as Artificial Neural Network (ANN) has been used to classify the ripeness of oil palm fresh fruit [26, 27, 28], weed identification [29], plant counting [30, 31], and oil palm leaves deficiency detection [32]. One of the ANN algorithms is Self-Organizing Maps (SOM), which have the capabilities of clustering, visualization, and classification to produce low dimensional representation data called feature map [33]. The SOM has been used to analyze soil physical properties and the distribution of toxic elements in polluted mining soils [34, 35]. Therefore, the SOM has great potential to be implemented for the detection of BSR disease on oil palm trees.

Based on these reasons, we captured images of oil palm trees with drones and further analyzed them using the Artificial Neural Network method. The purpose of this study is to predict BSR disease in healthy oil palm trees and map the distribution of oil palm trees affected by the disease.

2. Data and Method

2.1. Study Area. The study was carried out at Perkebunan Dolok Village, Limapuluh Regency, Batubara County, North Sumatera Province, Indonesia. It is geographically located at 99°25'49.18" East Longitude and 3°9'53.68" North Latitude. The area of this study block was 8.39 ha; the number of trees in this block was as many as 755 oil palm trees, with a spacing of 9 m x 8 m.

2.2. Data Collection.

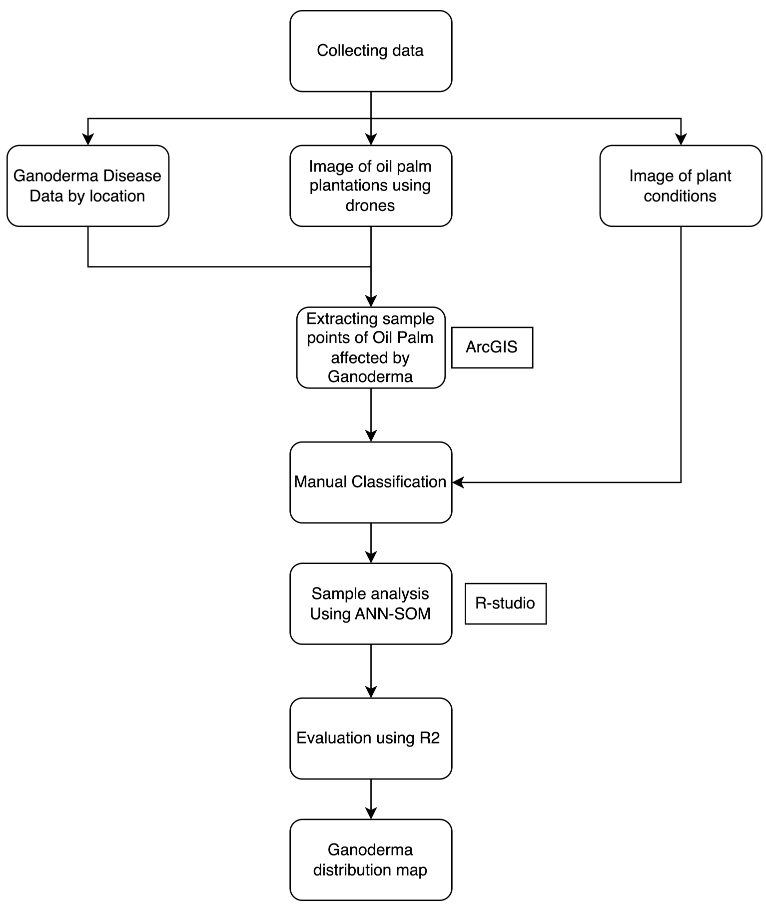

FIGURE 1. Flowchart of proposed methodology

There are three different data types used in this study, including: 1) *Ganoderma* disease data by location. This data was obtained based on the results of a survey conducted by the company several months prior to the study, which acted a reference in determining the oil palm infected with *Ganoderma*. 2) The image of oil palm plantations captured using drones. Drone DJI Phantom 3 Standard was used for taking photos of oil palms in the air. The Pix4D application was used to set the drone flight routes. Then, Garmin GPS 64s was used to create coordinates for oil palm trees that were affected. 3) The image of plant condition. The Camera Canon 600D was used to obtain images of oil palm trees on the land.

TABLE 1. The scoring of the *Ganoderma* attack.

No.	Scoring	Percentage of Plant Damage	Physical Characteristics
1	Score 0	0%−5%	Healthy plant
2	Score 1	6%−25%	The leaf midrib withers, breaks and hangs
3	Score 2	26%−50%	There are more than three spear leaves (the youngest, unexpanded leaf)
4	Score 3	51%−75%	Ganoderma mushroom bodies appear on plant stems
5	Score 4	76%−100%	Nearly the whole tree dries out, falls over, and dies

2.3. Proposed of Methodology. The flowchart in Figure 1 depicts the overall stages of research. First and foremost, three types of data were collected: *Ganoderma* disease data by location, aerial images of oil palm fields, and image of plant condition. Following that, we collected samples from oil palm points infected with *Ganoderma* disease. The coordinates of the *Ganoderma*-affected oil palm were inserted into the Arcgis 10.3 application and integrated with study maps based on Garmin GPS 64s locations. The oil palm sample points were then processed with the Arcgis 10.3 application, which attempts to determine the RGB value of each existing sample point.

Manual classification was carried out using pictures of plant conditions in order to obtain a *Ganoderma* disease class, which was divided into 5 different scores. The labeling of *Ganoderma* attack intensity referred to the classification based on the severity of the oil palm plant in the study by Nasution et al. [36]. The five-class scoring of *Ganoderma* attack severity is categorized in Table 1. The results of the manual classification were then analyzed using the Self Organizing Maps (SOM) method, one type of ANN, using the Rstudio application. The goal was to obtain a match between the manual classification results and the SOM analysis results. R2 was used to evaluate the analysis outcomes. Better results were achieved by increasing R2 value. Finally, the *Ganoderma* distribution map was generated using the highest scoring feature.

3. RESULTS & DISCUSSION

3.1. Plotting Sample Points. We first plotted a map with the supervised classification (Figure 2). In the supervised classification, the training area is selected based on the knowledge of the user. The user can define a limit to find out how close the result with the desired result. This limit is often determined based on the spectral characteristics of the existing training region. The designer can also design the output.

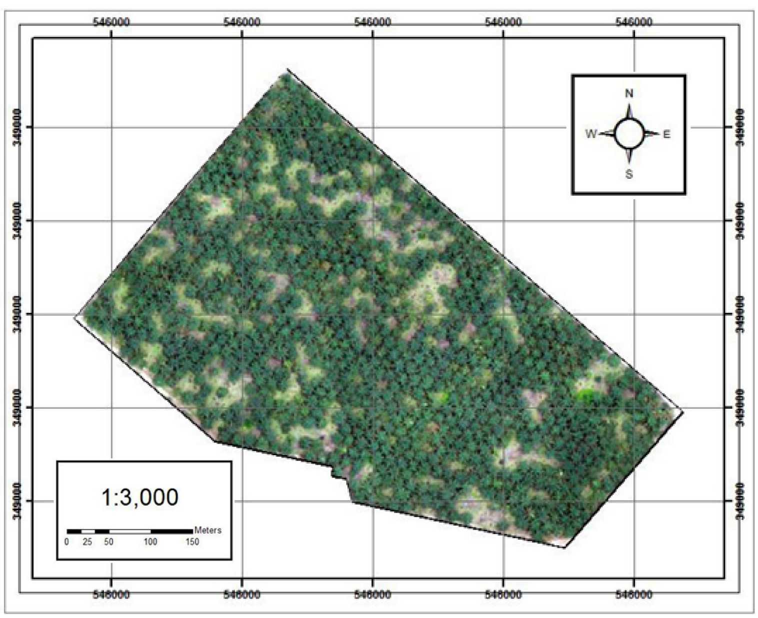

FIGURE 2. The oil palm plantation map was captured with an imaging satellite as a dataset

At the research site, various types of vegetation could be distinguished using supervised commands, which aimed to distinguish the types of colors that existed in the research location. On the map plotted using a supervised command, the expected results were not in accordance with what was expected because there was no color difference that could distinguish between oil palm trees that had a *Ganoderma* score of 0-4.

3.2. Classification of Sample Points. Next, we analyzed 42 sample points using the Arcgis 10.3 application to obtain the RGB value of each sample point. The Buffer command was used to form a circle as wide as the oil palm tree canopy from the width of the palm leaf, and the intersect command calculated the RGB value of the existing palm sample points. Then, the scoring of the oil palm tree samples was determined (Table 2). The result showed that half of the sample points had a score of 0 and 1, which were 10 and 11 sample points respectively. Meanwhile, the other half of the sample points scored between 2-4.

TABLE 2. The analysis of sample points using Arcgis 10.3.

Scoring	**Number of sample points**
0	10
1	11
2	7
3	8
4	6

3.3. Model Analysis and Correlation Test. We then performed a test on the actual/manual classification to find out the correlation between the RGB value to the *Ganoderma* score. The correlation test of the Red (R) color of actual classification showed that the Red value had a positive correlation with the *Ganoderma* score, suggesting that the lower the R-value, the lower the *Ganoderma* score (Figure 3A). This result contradicted the test of Blue (B) color (Figure 3B), which indicated a negative correlation between Blue value and *Ganoderma* score. Meanwhile, the correlation test of the Green (G) color indicated that the Green value in each sample was random (Figure 3C). This may be because the Green value in the palm canopy was extremely dominant compared to the other color values.

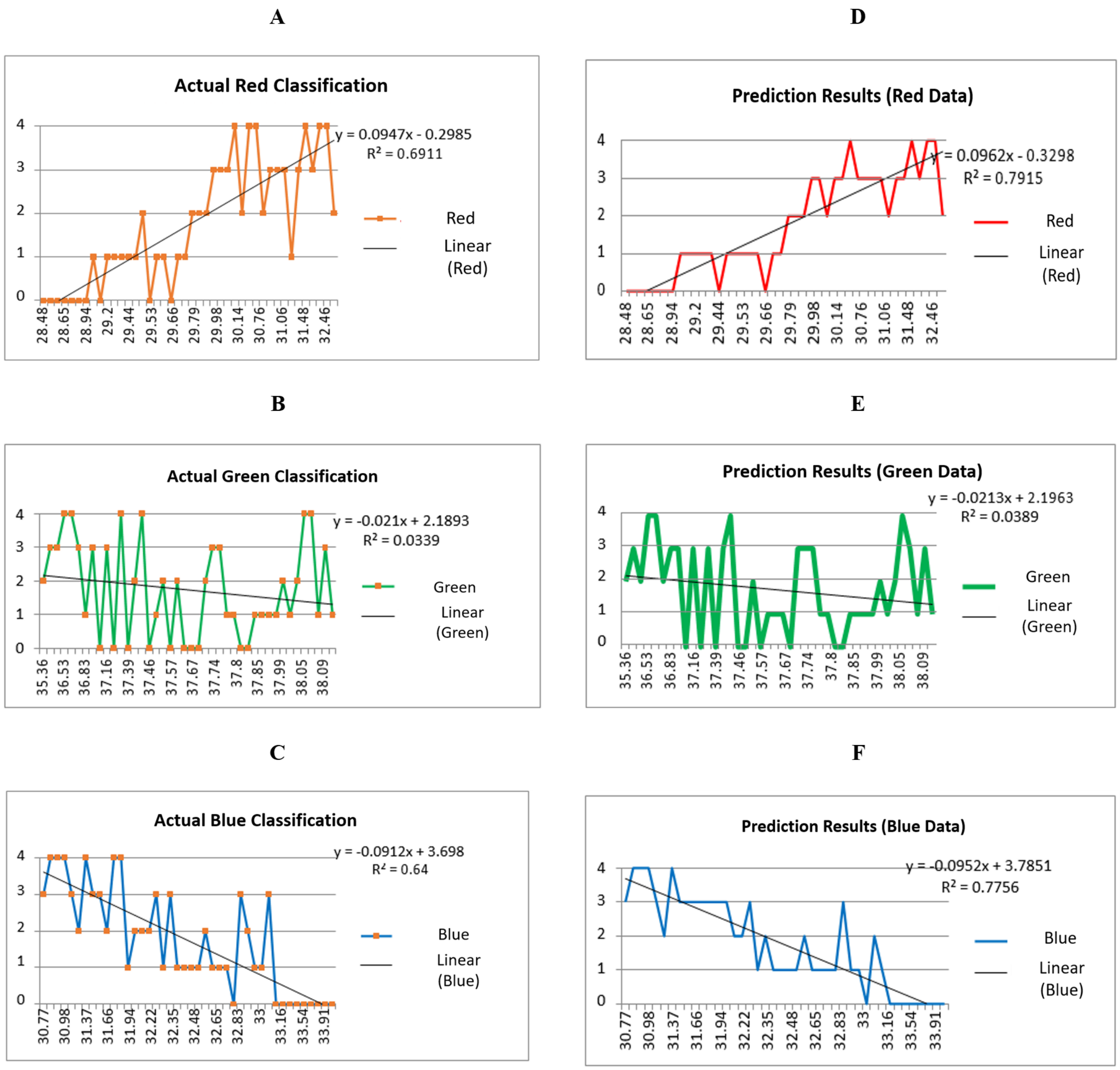

FIGURE 3. The correlation test of classification results from Red (A), Green (B), and Blue (C) data, compared to the prediction results from Red (D), Green (E), and Blue (F).

The results of the manual classification were then analyzed using the artificial neural network (ANN) method. The results of the prediction classification using ANN identified the sample points that had the scores 0, 1, 2, 3, and 4 were 10, 11, 7, 8, and 6 points, respectively. However, there were 11 sample points that were falsely predicted, suggesting that the accuracy of the prediction was 73,8%. The accuracy results reveal a little higher value than earlier research with an identical research problem and the deployment of the ANN model. Ahmadi et al. [37] used the UAV platform to detect *Ganoderma* by implementing a more complicated approach. The ANN model's integration of information from digital cameras and UAV platforms reveals slightly lower accuracy than our result. The application of the red, green, and near-infrared bands features shows an accuracy of 72.73% from testing the ANN model with the Levenberg-Marquardt training algorithm. Supervised classification with diseases that attack nut tree leaves showed lower results in detecting red leaf blotch (*Prunus amygdalus*) [38]. The accuracy result for the forward stepwise discriminant classification method that integrates the vegetation indices feature is 59.6%. As a result, our research accuracy is slightly more accurate than the two previous studies. Our approach, which focuses on supervised labeling for a more precise categorization, is comparatively greater than using more sophisticated models and gathering satellite photos.

Then, we also performed a correlation test on prediction classification data. The correlation test of the Red (R) color of prediction showed that the Red value had a positive correlation with the *Ganoderma* score, suggesting that the lower the R-value, the lower the *Ganoderma* score (Figure 3D). This is in contrast to the result of Blue (B) color (Figure 3E), which indicated a negative correlation between Blue value and *Ganoderma* score. In addition, the correlation test of the Green (G) color suggested that the Green value did not correlate with the *Ganoderma* score (Figure 3F). Overall, the prediction results are in agreement with the actual/manual classification. Red and Blue as parameters have a strong correlation in differentiating immature and mature leaves compared to Green in the study of Barman and Choudhury [39]. The RGB parameter used as the primary color was developed into 17 indexes in this study. The combination of the three in the NRI index (R/R+G+B) shows the highest correlation with tender leaves. A similar association result in Barman and Choudhury's study [39] between tender leaves and the R parameter also has positively correlated with BSR disease in our research. Meanwhile, the negative correlation of the Blue parameter indicates the detection of healthy plants, which is shown by the high vegetation index with the dominance of mature leaves in an area of oil palm plantations.

3.4. Prediction without Green. As the Green color did not show a clear correlation between the value and the *Ganoderma* score, we then performed a prediction without Green color values. The results identified the sample points with the scores 0, 1, 2, 3, and 4 were 8, 5, 13, 12, and 4 points, respectively. Thus, the accuracy of the prediction was 59,5%, which was lower than the prediction using the Green color. The result suggested that the Green color is essential for predicting the presence of BSR disease. This may be because one of the main symptoms of BSR disease is the loss of chlorophyll in plants, leading to the change of color in plant leaves [23]. Overall, our result agreed with the previous research by Hushiarian et al [40].

In addition to the chlorophyll index, the vegetation index affects the accuracy of the model performance in detecting and classifying diseases and the physical condition of plants. In several studies, feature important analysis shows that RGB parameters individually show lower predictive scores compared to complex color combinations as features. The NIR and Red value as features measurement in the study by Raza et al. [41] in detecting soybean sudden death syndrome. Research by Ciocîrlan et al. [42], the combination of RGB parameters as a complex index shows a higher scoring than the simple RGB index in the Random Forrest model. In the future, multiple indexes for color normalization methods will be used for measuring the variables. In addition to using sophisticated machine learning models, it is envisaged that using these variables as features can enhance the performance of ANN models.

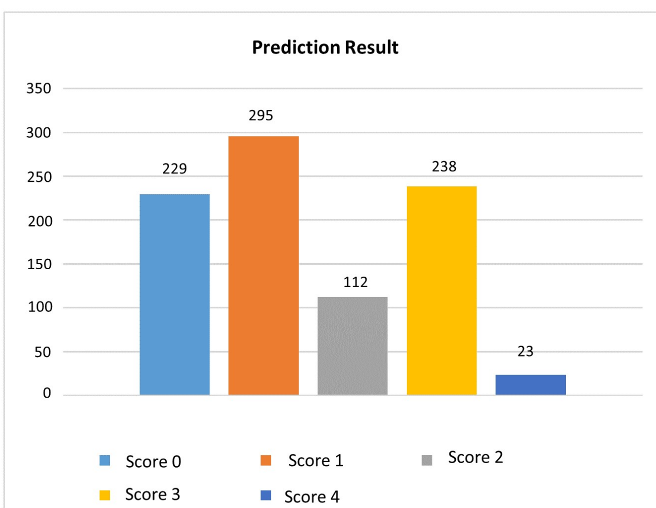

FIGURE 4. *Ganoderma* score prediction in all sample points

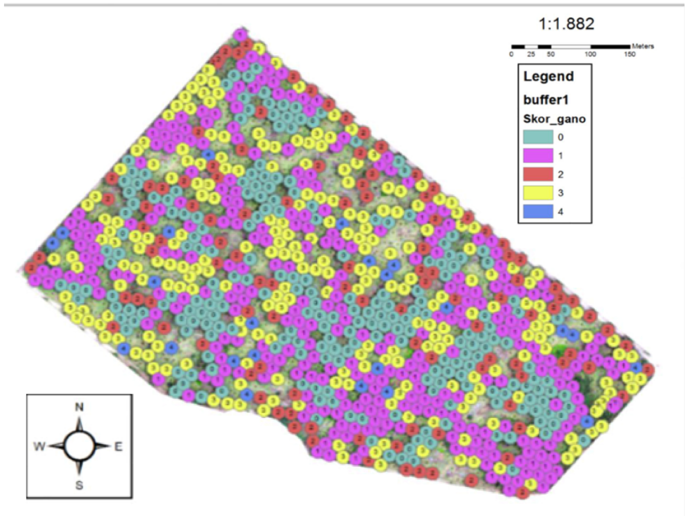

FIGURE 5. Plotted map showing *Ganoderma* score after prediction

3.5. Analysis of All Points Using ANN. After confirming that the Green color value is needed to obtain high accuracy, we then analyzed all sample points using ANN (Figure 4). The result showed that most of the sample points/oil palm trees had a *Ganoderma* score of 1 (295 trees), while the least sample points had the score 4 (23 trees). In addition, only a quarter of the sample points were not affected by *Ganoderma*, suggesting that the BSR disease dominated the oil palm plantation area. We further plotted the result from ANN analysis to the map to identify the spread of the *Ganoderma* attack (BSR disease). From Figure 5, it could be seen that the *Ganoderma* score was evenly distributed, indicating that the spread of BSR disease was not clumped in certain sample points. It is known that BSR could spread rapidly by physical contact with the infected root [11, 43]. Furthermore, the BSR disease could also spread from the basidiospores, which can easily travel through the air [44, 45]. Overall, the results showed that the majority of the sample points had been affected by the BSR disease.

4. CONCLUSION

This research has provided evidence that the machine learning approach, especially the Artificial Neural Network (ANN) method, could be used for analyzing the image of oil palm trees. The results of the analysis using the ANN method showed the distribution of *Ganoderma* disease in the plotted map. The result of the correlation test using a linear graph displayed that the lower the Red value, the lower the *Ganoderma* score. On the other hand, the correlation test of the Blue color displayed a negative correlation between the Blue value and the *Ganoderma* score. The Green value did not show a strong correlation with the *Ganoderma* score, which may be due to the dominance of the Green color in the canopy of the oil palm tree. In addition, the ANN analysis had identified the spread of BSR disease in all sample points, which was indicated by the *Ganoderma* scores: *Ganoderma* score 0 was 229 trees, score 1 was 295 trees, score 2 was 112 trees, score 3 was 238 trees, and score 4 was 23 trees. Overall, our research provided efficient and non-destructive ways to detect the spread of BSR disease in oil palm plantation sites. Further study should be undertaken to improve the accuracy of the prediction so that it can be implemented in a larger area.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

REFERENCES

[1] Badan Pusat Statistik, Indonesian oil palm statistics 2020, Indonesia Central Bureau of Statistics, Jakarta, Indonesia, 2020.

[2] Zulafwan, Web-based geographic information system for palm oil mapping, Riau J. Computer Sci. 2 (2016), 7-16.

[3] R. Hafizi, B. Salleh, Z. Latiffah, Morphological and molecular characterization of Fusarium. solani and F. oxysporum associated with crown disease of oil palm, Braz. J. Microbiol. 44 (2013), 959-968. https://doi.org/10.1590/s1517-83822013000300047.

[4] G.A. Torres, G.A. Sarria, G. Martinez, et al. Bud rot caused by phytophthora palmivora: a destructive emerging disease of oil palm, Phytopathology. 106 (2016), 320-329. https://doi.org/10.1094/phyto-09-15-0243-rvw.

[5] C.L. Mohammed, A. Rimbawanto, D.E. Page, Management of basidiomycete root- and stem-rot diseases in oil palm, rubber and tropical hardwood plantation crops, Forest Pathol. 44 (2014), 428-446. https://doi.org/10.1111/efp.12140.

[6] A. Kandan, R. Bhaskaran, R. Samiyappan, Ganoderma- a basal stem rot disease of coconut palm in south Asia and Asia pacific regions, Arch. Phytopathol. Plant Protect. 43 (2010), 1445-1449. https://doi.org/10.1080/03235400802536527.

[7] Y. Siddiqui, A. Surendran, R.R.M. Paterson, et al. Current strategies and perspectives in detection and control of basal stem rot of oil palm, Saudi J. Biol. Sci. 28 (2021), 2840-2849. https://doi.org/10.1016/j.sjbs.2021.02.016.

[8] Z. Du, C.H. Dong, K. Wang, et al. Classification, biological characteristics and cultivations of ganoderma, in: Z. Lin, B. Yang (Eds.), Ganoderma and Health, Springer Singapore, Singapore, 2019: pp. 15–58. https://doi.org/10.1007/978-981-13-9867-4_2.

[9] H. Wirianata, F. Wilisiani, S. Gunawan, et al. Development of basal stem rot (Ganoderma boninense) of oil palm in peatland and minerals, Asian J. Appl. Res. Community Develop. Empower. 6 (2022), 30-33.

[10] E.M. Wakefield, Diseases of the oil palm in West Africa, Bull. Miscellaneous Inform. (Royal Botanic Gardens, Kew). 1920 (1920), 306-308. https://doi.org/10.2307/4107530.

[11] L. Naher, U.K. Yusuf, S.G. Tan, et al. Ecological status of Ganoderma and basal stem rot disease of oil palms (Elaeis guineensis Jacq.), Aust. J. Crop Sci. 7 (2013), 1723-1727.

[12] T.M. Azahar, J.C. Mustapha, S. Mazliham, et al. Temporal analysis of basal stem rot disease in oil palm plantations: an analysis on peat soil, Int. J. Eng. Technol. 11 (2011), 96-101.

[13] L.C. Wong, C.F.J. Bong, A. Idris, Ganoderma species associated with basal stem rot disease of oil palm, Amer. J. Appl. Sci. 9 (2012), 879-885.

[14] Lisnawita, H. Hanum, A.R. Tantawi, Survey of basal stem rot disease on oil palms (Elaeis guineensis Jacq.) in Kebun Bukit Kijang, North Sumatera, Indonesia, IOP Conf. Ser.: Earth Environ. Sci. 41 (2016), 012007. https://doi.org/10.1088/1755-1315/41/1/012007.

[15] R. Alviodinasyari, A. Martina, W. Lestari, Control of ganoderma boninense by trichoderma sp. SBJ8 on oil palm sprouts and seeds (Elaeis guineensis Jacq.) in Peat Soil, JOM MIPA, 2 (2015), 10-14.

[16] R.W. Rees, J. Flood, Y. Hasan, M.A. Wills, R.M. Cooper, Ganoderma boninense basidiospores in oil palm plantations: evaluation of their possible role in stem rots of Elaeis guineensis, Plant Pathol. 61 (2011), 567-578. https://doi.org/10.1111/j.1365-3059.2011.02533.x.

[17] A. Hamzah, R. Saputra, F. Puspita, et al. Ganoderma diversity from smallholder oil palm plantations in peatlands of Kampar District, Indonesia based on mycelia morphology and somatic incompatibility, Biodiversitas. 22 (2021), 16-22. https://doi.org/10.13057/biodiv/d220103.

[18] M. Sinaga, P. Bonny, A. Susanto, Diversity of microorganisms oil palm rhizosphere and pathogenicity of Ganoderma boninense Pat. as the basis of control stem rot disease, Tech. Rep. 2003.

[19] H.P. Lim, Y.K. Fong, Research on basal stem rot (BSR) of ornamental palms caused by basidiospores from Ganoderma boninense, Mycopathologia. 159 (2005), 171-179. https://doi.org/10.1007/s11046-004-4440-6.

[20] P.K. Mandal, M.K. Babu, M. Jayanthi, et al. PCR based early detection of Ganoderma sp. causing basal stem rot of oil palm in India, J. Plant. Crops. 42 (2014), 392-394.

[21] N.H. Zainol Hilmi, A.S. Idris, M.N. Mohd Azmil, Headspace solid-phase microextraction gas chromatography-mass spectrometry for the detection of volatile organic compounds released from Ganoderma boninense and oil palm wood, Forest Pathol. 49 (2019), e12531. https://doi.org/10.1111/efp.12531.

[22] M.A. Markom, A.Y.M. Shakaff, A.H. Adom, et al. Intelligent electronic nose system for basal stem rot disease detection, Computers Electron. Agric. 66 (2009), 140-146. https://doi.org/10.1016/j.compag.2009.01.006.

[23] P. Ahmadi, F.M. Muharam, K. Ahmad, et al. Early detection of ganoderma basal stem rot of oil palms using artificial neural network spectral analysis, Plant Dis. 101 (2017), 1009–1016. https://doi.org/10.1094/pdis-12-16-1699-re.

[24] F. Zhang, N. Cao, Application and research progress of geographic information system (GIS) in agriculture, in: 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), IEEE, Istanbul, Turkey, 2019: pp. 1-5. https://doi.org/10.1109/Agro-Geoinformatics.2019.8820476.

[25] M.S. Aikal Baharim, N.A. Adnan, F.A. Mohd, et al. A review: progression of remote sensing (RS) and geographical information system (GIS) applications in oil palm management and sustainability, IOP Conf. Ser.: Earth Environ. Sci. 1051 (2022), 012027. https://doi.org/10.1088/1755-1315/1051/1/012027.

[26] Harsawardana, R. Rahutomo, B. Mahesworo, et al. AI-based ripeness grading for oil palm fresh fruit bunch in smart crane grabber, IOP Conf. Ser.: Earth Environ. Sci. 426 (2020), 012147. https://doi.org/10.1088/1755-1315/426/1/012147.

[27] T. Suparyanto, E. Firmansyah, T. Wawan Cenggoro, et al. Detecting hemileia vastatrix using vision AI as supporting to food security for smallholder coffee commodities, IOP Conf. Ser.: Earth Environ. Sci. 998 (2022), 012044. https://doi.org/10.1088/1755-1315/998/1/012044.

[28] H. Sastrohartono, A.P. Suryotomo, S. Saifullah, et al. Drone application model for image acquisition of plantation areas and oil palm trees counting, in: 2022 International Conference on Information Management and Technology (ICIMTech), IEEE, Semarang, Indonesia, 2022: pp. 167-171. https://doi.org/10.1109/ICIMTech55957.2022.9915223.

[29] E. Firmansyah, T. Suparyanto, A. Ahmad Hidayat, et al. Real-time weed identification using machine learning and image processing in oil palm plantations, IOP Conf. Ser.: Earth Environ. Sci. 998 (2022), 012046. https://doi.org/10.1088/1755-1315/998/1/012046.

[30] T.W. Cenggoro, A. Budiarto, R. Rahutomo, et al. Information system design for deep learning based plant counting automation, in: 2018 Indonesian Association for Pattern Recognition International Conference (INAPR), IEEE, Jakarta, Indonesia, 2018: pp. 329–332. https://doi.org/10.1109/INAPR.2018.8627019.

[31] R. Rahutomo, A.S. Perbangsa, Y. Lie, et al. Artificial intelligence model implementation in web-based application for pineapple object counting, in: 2019 International Conference on Information Management and Technology (ICIMTech), IEEE, Jakarta/Bali, Indonesia, 2019: pp. 525–530. https://doi.org/10.1109/ICIMTech.2019.8843741.

[32] D.P. Putra, P. Bimantio, T. Suparyanto, et al. Expert system for oil palm leaves deficiency to support precision agriculture, in: 2021 International Conference on Information Management and Technology (ICIMTech), IEEE, Jakarta, Indonesia, 2021: pp. 33-36. https://doi.org/10.1109/ICIMTech53080.2021.9535083.

[33] D. Miljkovic, Brief review of self-organizing maps, in: 2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), IEEE, Opatija, Croatia, 2017: pp. 1061-1066. https://doi.org/10.23919/MIPRO.2017.7973581.

[34] N.M. Kebonye, P.N. Eze, K. John, et al. Self-organizing map artificial neural networks and sequential Gaussian simulation technique for mapping potentially toxic element hotspots in polluted mining soils, J. Geochem. Explor. 222 (2021), 106680. https://doi.org/10.1016/j.gexplo.2020.106680.

[35] H. Merdun, Self-organizing map artificial neural network application in multidimensional soil data analysis, Neural Comput. Appl. 20 (2010), 1295-1303. https://doi.org/10.1007/s00521-010-0425-1.

[36] T.D.S. Nasution, Supriadi, M.M.B. Damanik, Surveying and mapping K nutrient status and C-organic on oil palm plantations were attacked by ganoderma in PT. PD. PATI Aceh Tamiang, Agroecotechnol. J. 4 (2016), 2238-2244.

[37] P. Ahmadi, S. Mansor, B. Farjad, et al. Unmanned aerial vehicle (UAV)-based remote sensing for early-stage detection of ganoderma, Remote Sensing. 14 (2022), 1239. https://doi.org/10.3390/rs14051239.

[38] M. López-López, R. Calderón, V. González-Dugo, et al. Early detection and quantification of almond red leaf blotch using high-resolution hyperspectral and thermal imagery, Remote Sensing. 8 (2016), 276. https://doi.org/10.3390/rs8040276.

[39] U. Barman, R.D. Choudhury, Smartphone image based digital chlorophyll meter to estimate the value of citrus leaves chlorophyll using linear regression, LMBP-ANN and SCGBP-ANN, J. King Saud Univ. - Computer Inform. Sci. 34 (2022), 2938-2950. https://doi.org/10.1016/j.jksuci.2020.01.005.

[40] R. Hushiarian, N.A. Yusof, S.W. Dutse, Detection and control of Ganoderma boninense: strategies and perspectives, SpringerPlus. 2 (2013), 555. https://doi.org/10.1186/2193-1801-2-555.

[41] M.M. Raza, C. Harding, M. Liebman, et al. Exploring the potential of high-resolution satellite imagery for the detection of soybean sudden death syndrome, Remote Sensing. 12 (2020), 1213. https://doi.org/10.3390/rs12071213.

[42] M.I.C. Ciocirlan, A.L. Curtu, G.R. Radu, Predicting leaf phenology in forest tree species using uavs and satellite images: a case study for European beech (Fagus sylvatica L.), Remote Sensing. 14 (2022), 6198. https://doi.org/10.3390/rs14246198.

[43] E.A. Gorea, I.D. Godwin, A.M. Mudge, Ganoderma infection of oil palm - a persistent problem in Papua New Guinea and Solomon Islands, Australasian Plant Pathol. 49 (2019), 69-77. https://doi.org/10.1007/s13313-019-00673-9.

[44] H. Priwiratama, A.E. Prasetyo, A. Susanto, Incidence of basal stem rot disease of oil palm in converted planting areas and control treatments, IOP Conf. Ser.: Earth Environ. Sci. 468 (2020), 012036. https://doi.org/10.1088/1755-1315/468/1/012036.

[45] J. Kurihara, V.C. Koo, C.W. Guey, et al. Early detection of basal stem rot disease in oil palm tree using unmanned aerial vehicle-based hyperspectral imaging, Remote Sensing. 14 (2022), 799. https://doi.org/10.3390/rs14030799.