Oil Palm and Machine Learning

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Machine learning (ML) offers new technologies in the precision agriculture domain with its intelligent algorithms and strong computation. Oil palm is one of the rich crops that is also emerging with modern technologies to meet global sustainability standards. This entry presents a comprehensive review of research dedicated to the application of ML in the oil palm agricultural industry over the last decade (2011–2020).

oil palm machine learning systematic review agriculture sustainability

1. Introduction

Palm oil is a key source of edible vegetable oil extracted from fruits of the oil palm tree. It has emerged as an important feedstock and biofuel raw material [1][2]. Cultivated on millions of hectares in the world, oil palm has a noticeable part of the volume of world trade. The oil palm started its journey from West Africa and has become a hope for the economy of many countries. However, Southeast Asia is considered the hub of the palm oil industry, with Indonesia and Malaysia being the major exporters [3]. The growing demand for the palm oil threatens the future of the rain forests because expanding oil palm cultivations tend to replace existing forestry. To overcome the negative impacts of oil palm farming by making it a key element of building a future sustainable world, plant science faces three major challenges. The global average palm oil yield of 3.5 tons per hectare should be elevated to the full yield potential around 11–18 t. The tree architecture must be changed to low labour intensity and high mechanization of the harvest. Oil composition should be tailored to the evolving demands of oleochemical, fuel industries, and, most importantly, food [4]. Thus the use of technology is inevitable to deal with these challenges through the sustainable intensification of oil palm [5]. The application of powerful, intelligent ML methods has the potential to transform the current productive agriculture into sustainable agriculture. In precision agriculture, complex tasks such as land classification, soil management, crop selection, seasonal variations, fertilizers management, crop yield forecasting, and yield gap analysis are effectively evolving with ML methods [6][7][8][9]. Because of incredible learning and high computational power, ML approaches have also been adopted in the field of oil palm for the mechanization of several tasks such as tree counting and plant health assessment [10][11]. However, the broader inspiration of modern agriculture is to examine all factors that cause gaps in crop yield. Agricultural productivity is subject to several stressors, including biotic and abiotic risk factors, many of which are intensified by a changing climate, thereby affecting durable sustainability. The productivity of tree crops such as oil palm is particularly complex. To comprehend and mitigate these risk factors, a collection of multi-layered large data sets is required. Additionally, advanced analytics is also critical to integrate those highly heterogeneous datasets to generate insights about the key constraints on the yields at tree and field scales. Since yield gap analysis deals with interdependent and irregular elements, it becomes difficult to map their dependencies with conventional methods. Thus, ML application is an efficient way to obtain precise outcomes and appropriate solutions for such convoluted problems. Previously, micro-components analysis was performed to study the overall yield gap by the commonly used “divide and conquer” ML strategy [12][13]. The studies concluded that the investigation of individual yield-reducing factors could provide insight into the overall impact. On the other hand, ML application to evaluate the correlation among different factors such as soil moisture and rainfall, day length and solar radiation, fertilization frequency, and plant growth provides better quantitative understandings [14][15][16]. The aforesaid statement necessitates bringing such research directions to light. In this regard, a domain-based scientifically structured review article can provide insightful information to new researchers based on compiled results. It enables depicting the state-of-the-art, highlighting the strategic matters raised by the scientific community and cluster analysis [17]. Researchers can identify research gaps with reference to discussed systems, concepts, and propositions. The review also helps to build a research roadmap with knowledge of formerly applied theories and existing techniques [18].

In the literature, some authors have reviewed the application of effective tools and ML techniques in oil palm. For instance, Chong et al. conducted a review on applications and practices of remote sensing for oil palm plantations monitoring [19]. Accordingly, the technologies developed for the processing of fruit and palm oil waste management by converting it to biofuel are reviewed in [20]. The application of ML for detecting nutrition deficits in oil palm with the help of proximal images are explored in [21]. Besides, the technical review of sensors and techniques for oil palm plants’ disease detection is performed in [22]. Subsequently, ML features are reviewed for automatic fruit grading with the help of image processing [23]. Recently, Rashid et al. reviewed ML application for yield prediction of different crops, including oil palm [24]. From the reviewed literature, it is observed that present studies did not systematically search the literature in most cases. Moreover, only specific aspects (such as yield prediction, crop monitoring, and nutrient deficits, etc.) of oil palm using ML are reviewed. Although the cited works provide deep insight into existing studies, to date, unidimensional reviews lack a full presentation of the overall ML-based research in the oil palm domain. The literature search reveals that a broader overview of the current research trends and the extent of ML application for oil palm is missing.

In need of a comprehensive analysis, this review article brings together the application of ML in the oil palm agricultural industry. To the best knowledge of the authors, there is no detailed review until now that has explored multiple aspects of the oil palm domain within the framework of artificial intelligence (AI). The present state-of-the-art review synthesizes all prominent studies published throughout an entire decade (2011–2020) concerning oil palm in the ML context. It stands out from other review studies as the literature search was performed through a systematic protocol to ensure unbiased data base retrieval. Moreover, the standard protocol was extended to perform qualitative and quantitative assessment of the searched literature. This technique allows detailed and impartial insight into contemporary studies in the domain. The goal of writing this review was to analyse major progress, current trends, research gaps, and pioneering concepts intended for stimulating research on oil palm with the application of modern techniques. This research was envisaged to produce high-quality recommendations for novice researchers based on a scrupulous evaluation of the available works.

The remaining article is organized as follows. Section 2 provides the background of oil palm and ML. Section 3 explains the review scope and the proposed methodology. It provides the step-by-step procedure followed during the design and implementation phase. Accordingly, results are demonstrated in Section 4 , while detailed discussion is presented in Section 5 . Finally, Section 6 concludes the article.

2. Background of Oil Palm and Machine Learning

The Elaeis guineensis , commonly known as oil palm, is a single-stemmed branchless tree, which takes several years of investment and labour work before producing harvestable oil containing fresh fruit bunch (FFB) [25]. Two different kinds of vegetable oils are produced from oil palm fruit at first, namely, crude palm oil (CPO) and palm kernel oil. CPO is extracted from the pulp (mesocarp) of fruit, while its seeds provide palm kernel oil. Average annual raw crop production remains 12–18 tons h −1 in industrial oil palm under favourable conditions [26]. Besides its profitability and high production, some complex characteristics distinguish it from other crops. Unlike annual, biennial, and perennial crops, the oil palms are permanent plants [27] harvested twice a month throughout the plant's lifespan (except the initial growing period) [28][29]. Although some seasonal variations exist in oil palm yield, this divergence is limited to production capacity [30]. The seasonal impacts are considered a noticeable factor in contributing to yield decline. Some additional yield-reducing factors are fertilizers' limitations, irrigation limitations, pests, and infections. Careful regular analysis for disease assessment, fertilization, and timely harvesting contributes to high oil palm yield. Conversely, inappropriate field management and incorrect harvesting strategies restrict the oil quality and quantity [31]. Besides all efforts to enhance oil palm crop production, the yield-reducing factors influence the outcomes significantly. However, the factors mentioned above are variable and interdependent but are not unpredictable. Indeed, these sensitive issues are associated with some complicated parameters. As for fertilizer, its type, adequate quantity, and application frequency require precise optimization. At the same time, the estimation of harvesting time [32] is achieved with predictive analysis. Similarly, during disease assessment, healthy and unhealthy plants are classified. A decisive solution to such a complex problem is rendered in machine learning algorithms (MLAs) that perform prediction, classification, clustering, and optimization. Depending on research requirements, an ML model can be predictive or/and descriptive. A predictive model is used to forecast what is likely to happen in the future. On the other hand, a descriptive model gathers knowledge from the collected data to describe what happened in the past [33]. For solving the problems at hand, selection of the right algorithms is the key. Moreover, the utilized tools and chosen algorithms need to have the capability of handling bulk data. Aided by such intelligent algorithms, well-calculated field management strategies can boost the revenue through enhanced yield and optimized expenses. In addition, the oil palm as a profitable crop also needs technology-oriented tools (to reduce labour costs) and cerebral systems (to avoid the risk of human error) for decision-making.

3. Review Scope and Methodology

To conduct this review, first of all, a domain-specific less intact research topic was carefully chosen after a deep study of existing literature related to latent advancement in oil palm with the help of ML. In the quest of exploring the studies that have been published in the domain of oil palm and ML, this review topic is appropriate to analyse several dimensions.

The basic searching was done by an automated search. The starting input for the search was “oil palm” AND “machine learning.” Articles were retrieved, and abstracts were read to find the synonyms of the keywords. The search input was used to obtain a broad view of the studies. From the basic search experiment, a more complex search string was built in order to avoid missing relevant studies. The final search string was as follows: (“machine AND learning” OR “deep AND learning” OR “artificial AND intelligence”) AND (“oil AND palm” OR “Elaeis AND guineensis”). After executing iterated combinations of defined search strings in five databases, 1060 studies were retrieved through advance search with the title, abstract, and keywords. The “anywhere” option in Google Scholar and Springer Link was selected. Inserted keywords included “oil palm,” “Elaeis guineensis,” “machine learning,” “deep learning,” and “artificial intelligence” as search strings according to the procedures defined in [34] with the AND keyword for the exact combination of two strings and OR for flexible searches. The initial search was performed based on the title, abstract, and keywords; however, the full text was considered for final selection, categorization, and information extraction.

The available literature on the topic was collected within a unique range of ten years. Only technical papers that propose the application of any MLA to explore oil palm were considered. On the other hand, all the articles that did not apply ML for agricultural oil palm as a special case were discarded. This was done to narrow down the search because applications of ML occur in numerous fields that do not serve our domain-specific investigation. For instance, a study was not included if it investigated public opinion (consumer perception) on the impacts of palm oil using ML methods [35].

This section covers the procedures to acquire relevant literature. Primarily, the articles that contained standalone or hybrid ML models integrated with other methods, precisely applied on oil palm, were searched. The choice of articles included literature with macro-level (country or state) , meso-level (entire plantation), and micro-level (tree or part of tree) oil palm assessment with multidimensional application of statistical, ML, or deep learning (DL) algorithms.

4. Results

All above results provided insights into statistics of the literature on ML and oil palm to encounter our seven defined research questions. The specified qualitative review of individual articles from the subcategories can be extracted from Tables 2–7, and the brief precedent description of important studies is provided prior to each table.

The concept of UAV for crop monitoring is not quite new in modern agricultural practices. Aerial colour and colour-infrared imaging have been used to track crop growth for more than 50 years. These methods are currently being re-evaluated for analysis in precision agriculture. UAVs are becoming more popular due to their low cost and ability to fly on low altitudes, which increases the spatial resolution [36]. The aerial imagery can be acquired rapidly during crucial periods of crop development. For oil palm field monitoring through UAV and classification of crop segments based on resulting images, linear regression was performed in [37]. Similarly, ref. [38][39][40][41] collected images of oil palm from UAV for counting or detection of oil palm trees by applying different ML techniques. The articles that suggest automated oil palm canopy monitoring using UAV are included in **Table 1** as an imperative part of this review. agriculture-11-00832-t004_**Table 1** Automated canopy segmentation/crop monitoring using UAV. Articles Dataset Model/Algorithm(s) Objective(s) [37] Images of 2-, 4-, and 7-year-old trees Linear regression (LR) Automatic canopy segmentation [38] Plantation images Visual geomatry group-single shot detector (VGG-SSD), faster-RCNN, YOLO-V3, Retina-net, Mobilenet-SSD Fast and robust detection of oil palm [39] Oil palm images Histogram of oriented gradients (HOG-SVM), SVM Detecting Individual oil palm tree [40] Oil palm images SVM Counting oil palm inventory [41] Oil palm images CNN Oil palm tree detection

Table 1. Automated canopy segmentation/crop monitoring using UAV.

Articles	Dataset	Model/Algorithm(s)	Objective(s)
[37]	Images of 2-, 4-, and 7-year-old trees	Linear regression (LR)	Automatic canopy segmentation
[38]	Plantation images	Visual geomatry group-single shot detector (VGG-SSD), faster-RCNN, YOLO-V3, Retina-net, Mobilenet-SSD	Fast and robust detection of oil palm
[39]	Oil palm images	Histogram of oriented gradients (HOG-SVM), SVM	Detecting Individual oil palm tree
[40]	Oil palm images	SVM	Counting oil palm inventory
[41]	Oil palm images	CNN	Oil palm tree detection

Prediction/estimation.

Oil palm is among the fastest-growing crops in terms of agricultural land use, and their development has been linked to substantial damage to the environment. As a result, this crop often appears in open and procedural discussions that are hindered or skewed by a lack of reliable conservational data. The shortage of consistent cultivation information in particular has continued to be a source of concern. Recent advances in remote-sensing data access and the ability of ML have played a remarkable role to address this issue. In this regard, the study in [10] has obviously contributed not only to oil palm tree detection, but it also incorporates ML for tree counting with adequate accuracy. Tree counting along with young and mature tree identification is carried out by Okoro et al. [42]. Some other studies [43][44][45][46] also performed similar work related to tree counting, age estimation, or tree detection but differ in study level, data sets, and algorithms. Another wide variety of researchers seems more concerned about oil palm area mapping, globally and locally, as [47][48] and many more have proposed models to monitor oil palm area expansion, covered land, plantation detection, patterns of land use for oil palm plantation, aboveground biomass, oil palm fields observation, and so on. Particulars on the above-discussed contributions are provided in **Table 2** . It covers all reviewed articles implementing various models to detect land cover, oil palm cultivation, or expansion. However, no model has been proposed to differentiate oil palm from other similar trees like date palm and coconut palm. This research gap may cause inaccurate classification of satellite images in case of analysing diversified cultivation on a large scale [49]. agriculture-11-00832-t006_**Table 2** Land cover/tree detection. Articles Dataset Model/ Algorithm(s) Objective(s) [47] GEE Sentinel-1,2 images DEEPLABV3 + CNN Worldwide map of oil palm plantations [48] GEE images RF Recording the spatial allocation of oil palm [50] WorldView-3 CNN Detecting young and mature oil palm trees [42] GEE images SVM Monitoring oil palm cultivation monitoring [51] Images captured at site Viola and Jones detector Oil palm map [52] Calculated biomass values, forest type, and soil information DA, logarithmic regressions Estimating aboveground biomass in oil palm plantation [53] Satellite imagery, time series data from MODIS, field data Moving average (MA) , DT Detecting land cover conversion to oil palm [10] Remote sensor images CNN Tree detection and counting [54] Images from Kaggle DenseNet, DenseNet with saliency and semantic parsing (SSP) Industrial oil palm monitoring [55] Earth Explore images SVM Oil palm distribution mapping [43] QuickBird satellite images Faster-CNN Detecting oil palm trees [73] QuickBird satellite images TS-CNN Detecting oil palm trees [71] WorldView-3, LiDAR SVM, RF Oil palm tree counting and age estimation [56] GEE Images, shuttle radar topographic mission (SRTM), NDVI, normalized difference water index (NDWI), digital elevation models (DEM) SVM, CART, RF Oil palm mapping [72] QuickBird imagery Vegitation indices, semi-variogram computation Detection of oil palm trees [57] GEE images SVM, RF, CART Monitoring oil palm farms in Malaysia [58] Land cover map, WorldView-2 image, field data SVM and maximum likelihood classifier (MLC) Mapping of oil palm [86] Site-specific agrometeorological data Dempster–Shafer Inference Irrigation management in oil palm crops [59] Palm trees images Logistic regression Validation of an oil palm detection system

Table 2. Land cover/tree detection.

Articles	Dataset	Model/ Algorithm(s)	Objective(s)
[47]	GEE Sentinel-1,2 images	DEEPLABV3+ CNN	Worldwide map of oil palm plantations
[48]	GEE images	RF	Recording the spatial allocation of oil palm
[50]	WorldView-3	CNN	Detecting young and mature oil palm trees
[42]	GEE images	SVM	Monitoring oil palm cultivation monitoring
[51]	Images captured at site	Viola and Jones detector	Oil palm map
[52]	Calculated biomass values, forest type, and soil information	DA, logarithmic regressions	Estimating aboveground biomass in oil palm plantation

Articles	Dataset	Model/ Algorithm(s)	Objective(s)
[53]	Satellite imagery, time series data from MODIS, field data	Moving average (MA), DT	Detecting land cover conversion to oil palm
[10]	Remote sensor images	CNN	Tree detection and counting
[54]	Images from Kaggle	DenseNet, DenseNet with saliency and semantic parsing (SSP)	Industrial oil palm monitoring
[55]	Earth Explore images	SVM	Oil palm distribution mapping
[43]	QuickBird satellite images	Faster-CNN	Detecting oil palm trees
[46]	QuickBird satellite images	TS-CNN	Detecting oil palm trees
[44]	WorldView-3, LiDAR	SVM, RF	Oil palm tree counting and age estimation
[56]	GEE Images, shuttle radar topographic mission (SRTM), NDVI, normalized difference water index (NDWI), digital elevation models (DEM)	SVM, CART, RF	Oil palm mapping
[45]	QuickBird imagery	Vegitation indices, semi-variogram computation	Detection of oil palm trees
[57]	GEE images	SVM, RF, CART	Monitoring oil palm farms in Malaysia
[58]	Land cover map, WorldView-2 image, field data	SVM and maximum likelihood classifier (MLC)	Mapping of oil palm
[60]	Site-specific agrometeorological data	Dempster–Shafer Inference	Irrigation management in oil palm crops
[59]	Palm trees images	Logistic regression	Validation of an oil palm detection system

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