Al-Qadisiyah JournalFor Engineering Sciences 19 (2026) 032 – 048

Contents lists available at: http://qu.edu.iq

Al-Qadisiyah Journal for Engineering Sciences

Journal homepage: https://qjes.qu.edu.iq

Review Paper

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Artificial intelligence for oil palm tree management using deep structured learning: A systematic review

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ARTICLE INFO

Article history:
Received 29 September 2025
Received in revised form 04 January 2026
Accepted 22 February 2026

keywords:
Oil palm tree
Deep learning
Convolutional neural network
Tree detection
Precision agriculture
Artificial intelligence

ABSTRACT

Climate change, workforce shortages, and sustainability requirements create serious obstacles for oil palm farms, which contribute $65 billion annually. Automated monitoring solutions are very important because traditional manual tree counting techniques, which are widely used in the sector, have counting error rates of 15-25% and require significant human resources. In this comprehensive review, deep learning applications, specifically, convolutional neural networks (CNNs) for oil palm tree detection and counting are evaluated. Performance, constraints, and realistic deployment pathways are examined. Publications from 2016 to 2025 that focused on oil palm recognition using deep learning with quantitative measurements were found using a literature search across Scopus, Web of Science, IEEE Xplore, and Google Scholar. Architectures, dataset properties, and performance metrics were recorded using data extraction. Malaysia is at the forefront of cooperative networks that span 22 nations, according to an analysis of 47 datasets. With mature trees, modern CNN architectures improved with YOLO frameworks achieve >95% detection accuracy; nevertheless, for young trees, they show notable degradation (87.2% vs. 96.8% *mAP*). Cross-regional generalization (21.9 percentage point accuracy degradation), processing demands (450-650 *ms* inference), and financial obstacles are important obstacles. Real-time viability is demonstrated by edge-optimized models, which achieve 98.6% accuracy with 80 ms inference. Geographic bias (68% Malaysian, 23% Indonesian) and restricted public availability (8%) are revealed by dataset analysis. Deep learning can significantly improve oil palm management by 15-20% compared to conventional techniques. Widespread adoption requires standardized benchmark datasets (10,000+ images), transfer learning techniques (<500 images per region), edge-optimized architectures (< 100*ms* inference), and phased deployment (10-50 hectare pilots). CNN's convergence with precision agriculture positions the industry for comprehensive digitalization while addressing sustainability and labor challenges.

1. Introduction

With over 19 million hectares under cultivation globally and contributing approximately $65 billion annually to the world economy, oil palm plantations face an unprecedented challenge: accurately monitoring and counting millions of individual trees across vast landscapes [1]. As sustainability regulations like the European Union Deforestation Regulation (EUDR) implemented in 2024 intensify scrutiny, plantation managers require precise, scalable, and cost-effective monitoring solutions [2, 3]. The oil palm industry is a global leader in the supply of oils and fats, with a wide range of applications in cooking, cleaning, greases, lubricants, personal hygiene, cosmetics, biodiesel production, and electrical energy [4]. Oil palm (Elaeis guineensis) is a profitable and widespread commercial high-value tree crop in tropical countries and plays a significant role in the economy. Before the 1930s, oil palm development in West Africa was stagnant, while Malaysia experienced consistent growth from the 1950s through collaborative efforts between government and private firms [5]. Implementing the Federal Land Development Agency (FELDA) program, which involved the conversion of rubber plantations to oil palm, significantly accelerated the spread of oil palm cultivation expansion in Malaysia [6]. Despite originating in West Africa, the region has not experienced the rapid expansion seen in Indonesia and Malaysia [7, 8]. The industry currently faces multifaceted challenges beyond traditional agricultural concerns. Climate change impacts, including irregular rainfall and extreme weather events, threaten productivity while demanding more precise resource management [9]. Additionally, labour shortages exacerbated by COVID-19 have increased operational costs by 15-20% across major producing regions, creating urgent demand for automated monitoring solutions [10, 11]. The Colombian Government considers oil palm a main agricultural product for promoting illegal crop substitution and job creation in rural peace processes [12]. Kaniapan et al. (2021) stated that industry growth is driven by bioenergy and oleochemical demand, population expansion, and increased consumption, leading to elevated palm oil prices [8].

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https://doi.org/10.30772/qjes.2026.165663.1755

Nomenclature

ANN	Artificial Neural Network	*SVM*	Support Vector Machine
CNN	Convolutional Neural Network	*RNN*	Recurrent Neural Network
DNN	Deep Neural Network	$R-CNN$	Region-based Convolutional Neural Network
DL	Deep Learning	*VGG*	Visual Geometry Group
DBN	Deep Belief Network	*UAV*	Unmanned Aerial Vehicle
FCN	Fully Convolutional Network	*SIFT*	Scale-Invariant Feature Transform
LBP	Local binary patterns	*IoU*	Intersection over Union
GPU	Graphics Processing Unit	*SAM*	Segment Anything Model
ViT	Vision Transformer	*YOLO*	You Only Look Once
MNIST	Modified National Institute of Standards and Technology database		

According to FAO (2024), both Indonesia and Malaysia are the leaders in the world with total production of 51.8 and 18.7 million tons respectively in 2023, representing 78% of world production [13]. Majority of the world's output is still centered in Southeast Asia, where new producers from tropical areas coexist with Indonesia and Malaysia Fig. 1. Alongside increased monitoring of sustainable standards and deforestation, this is a 12% rise from 2022 levels [14].

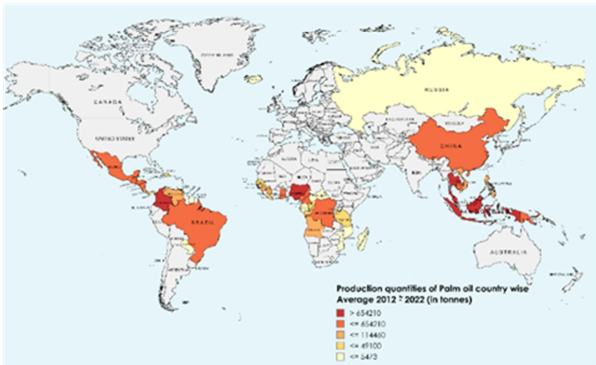

Figure 1. Global oil palm production in 45 countries from 2012 to 2022.

During the last ten years (2010-2019), oil palm emerged as the most significant commodity crop in Indonesia and Malaysia, with output rising 7.44 and 4.83 times, respectively [8, 15]. With 85% of the world's output, Asia still leads, followed by the Americas with 8.2%, Africa with 5.8%, and Oceania with 1%, indicating a small diversification from prior years [16, 17]. Deep learning models and other recent AI developments have completely changed how farming systems monitor and manage their crops. Numerous examples of agricultural applications, including perennial tree crop management, Ali et al. (2025) showed that systems based on AI technology significantly enhance production efficiency, sustainability, and the accuracy of forecast [18]. These new technologies have made it much easier to run oil palm farms. For example, accurate tree identification and counting technologies provide important information for the managers. Conventional methods of managing plantations are failing to meet modern expectations. The most widely used approach, manual tree counting, is very labor-intensive and yields erroneous findings, with error rates in dense plantations ranging from 15 to 25 percent [19, 20]. These errors eventually affect profitability and adherence to international standards by cascading via yield prediction models, resource allocation choices, and sustainability reporting requirements [21, 22]. According to a recent study, deep learning applications in the oil palm industry have become a major focus of agricultural technology research. In a variety of agricultural applications, such as phytopathological diagnosis, land use mapping, botanical categorization, weed identification, and tree counting, deep learning algorithms have been effectively applied [23]. Sophisticated agricultural monitoring techniques are made possible by the commercial availability of sub-meter resolution satellite imagery, improved affordability and capability of unmanned aerial vehicle platforms (UAVs), and field-deployable edge computing systems that can run sophisticated AI models under operational conditions [24, 25]. Recent implementations of edge computing solutions have demonstrated the practical viability of deploying deep learning models on resource-constrained devices for real-time plantation monitoring. Farhan et al. (2025) successfully deployed YOLO_{V8} nano on Raspberry Pi 4B with Intel NCS1 accelerator for real-time oil palm tree detection and counting using drone imagery, achieving 97% mAP@0.5 with 2.4 FPS inference speed and low power consumption (1.6W peak). The industry's demand for scalable and energy-efficient monitoring systems is addressed by this research, which shows that effective, portable AI solutions for precision agriculture may be implemented in distant plantation locations [26]. Edge computing deployment represents a particularly promising direction for achieving scalability in large-scale plantation monitoring. Kumar et al. (2025) developed a lightweight CNN model (Tiny-LiteNet) optimized for Raspberry Pi 5, achieving 98.6% accuracy with only 1.2 MB model size and 80 ms inference time [27]. This finding shows that edge deployment with little accuracy loss allows real-time tree recognition and counting under field situations with low compute resources and power consumption (peak 1.6W). Such advancements provide scalable, cost-effective monitoring systems for large-scale plantation management, especially in distant places with poor connection where cloud-based solutions are impractical. Convolutional Neural Networks (CNNs) are highly popular deep neural networks designed for image classification. A key advantage of CNNs is their ability to directly extract characteristics from novel datasets without manual feature extraction, as required by standard computer vision techniques like scale-invariant feature transformer (SIFT) and local binary patterns (LBP) [28]. Recent advances in transformer architectures and foundation models have further enhanced deep learning capabilities, with Vision Transformers (ViTs) and Segment Anything Model (SAM) showing promising results in agricultural applications [29, 30]. The global collaborative effort to apply deep learning for palm oil tree detection has made notable advances, as depicted in Fig. 2.

Figure 2. Bibliometric network visualization of international collaborations in deep learning research for oil palm tree detection and counting (2016-2024).

This bibliometric network visualization illustrates international research collaboration patterns, where node size represents the publication volume from each country, node colors distinguish individual countries, and connecting lines indicate co-authorship relationships between countries. Line thickness reflects the strength of collaborative partnerships based on the number of joint publications. This network has expanded significantly since 2022, with new research initiatives emerging in Thailand, Colombia, and Nigeria, reflecting growing global interest in AI-driven plantation management. Among 22 countries studied, Malaysia stands out prominently with the largest contribution to DL applications development for palm oil tree detection and counting. The country's substantial involvement underscores its commitment to advancing agricultural technology and its recent $500 million investment in digital agriculture initiatives [31]. While Malaysia leads, the network also highlights contributions from the United Kingdom and Indonesia, with considerable participation in this dynamic international network. Recent collaborative projects, including the ASEAN Digital Agriculture Initiative launched in 2023 and the EU-Indonesia Sustainable Palm Oil Partnership, have fostered increased knowledge sharing and joint research endeavors [32]. The presence of multiple nodes emphasizes the collaborative nature of this effort, with researchers from various parts of the world working together to advance DL applications in the palm oil sector. There are still some significant research gaps despite collaborative efforts and technological developments. The generalization of current deep learning models across various plantation settings, seasonal fluctuations, and tree ages is a challenge. Practical implementation is still limited by the computing demands for real-time processing at scale and the difficulty of integrating multi-modal data sources (satellite, UAV, IoT sensors). Furthermore, the lack of defined datasets and evaluation metrics hinders the progress of industry-wide adoption and makes it difficult to evaluate options objectively. This systematic review synthesizes existing literature on deep learning methodologies, particularly convolutional neural network (CNN) applications, for palm oil tree detection, counting, and plantation management. The analysis encompasses global research efforts while identifying predominant methodological frameworks and research trajectories. The review follows a structured approach: methodology and search strategy (Section 2), traditional detection approaches and limitations (Section 3), deep learning techniques and applications (Section 4), CNN-based palm oil tree detection systems (Section 5), dataset preparation and training methodologies (Section 6), current challenges and constraints (Section 7), future research opportunities (Section 8), and synthesis of findings with recommendations (Section 9).

1.1 Contributions and novelty of this review

While artificial intelligence and machine learning applications in oil palm agriculture have received growing attention, existing reviews have primarily focused on broader aspects of the industry rather than systematic analysis of tree detection and counting methodologies. Khan et al. [33] conducted a comprehensive review of machine learning applications in oil palm over a decade (2011-2020), analyzing 61 papers covering yield prediction and classification, but did not specifically focus on tree detection systems. Similarly, Nain et al. [34] reviewed artificial intelligence frameworks for palm oil prediction, emphasizing yield forecasting and production optimization rather than automated tree counting. More recently, Kipli et al. [35] provided an overview of deep learning applications for oil palm tree detection, yet their review lacked systematic methodology, quantitative performance comparisons across studies, and detailed implementation analysis. Zhao et al. [36] carried out a systematic review of CNN-based individual tree crown detection in the larger context of tree detection research, analyzing 35 studies across different forest types. However, their focus remained on general forestry applications without addressing characteristics unique to oil palms, such as plantation geometry, management practices, or tropical environmental conditions. Similar to this, Kamilaris and Prenafeta-Boldú [37] published a thorough overview of deep learning in agriculture, encompassing a wide range of applications from yield prediction to crop categorization, although they did not go into great detail about tree recognition techniques unique to permanent plantation crops like oil palm. In this review article, we work on bridging gaps in the corpus of existing research by providing the comprehensive study that is specifically focused on CNN-based deep learning for oil palm tree detection and counting. Unlike prior evaluations, this research employs structured data extraction procedures and rigorous systematic search methods with well-specified inclusion/exclusion criteria across four major databases (Scopus, Web of Science, IEEE Xplore, and Google Scholar) covering works from 2016 to 2025. By combining 47 datasets with in-depth quantitative analysis, the research offers hitherto unseen insights on performance metrics, implementation challenges, and deployment tactics. The review makes several unique contributions to the field. It provides comprehensive quantitative performance analysis revealing that modern CNN architectures achieve greater than 95% detection accuracy for mature trees but exhibit significant performance degradation for young trees (87.2% vs 96.8% mAP), documents computational requirements (450-650 ms inference time on high-end GPUs) and demonstrates edge deployment feasibility achieving 98.6% accuracy with 80ms inference time. The investigation carefully measures cross-regional generalization issues, showing 21.9 percentage point accuracy loss when models trained in one area are applied in multiple geographical settings a key hurdle to wider adoption not examined in past evaluations. The review's thorough dataset analysis reveals significant age distribution bias (72% adult trees, 11% young trees, and 17% adolescents) and regional concentration (68% Malaysian datasets, 23% Indonesian, and only 9% from other countries), with just 8% of datasets being publicly available. This study provides essential information to assess reported accuracies and identify research objectives overlooked in previous evaluations. The study indicates that automated systems show scale-dependent effectiveness, offering better economic benefits for larger businesses while creating challenges for smaller farms due to increase per-hectare application costs. This is superior to technical analysis because it employs economic evaluation to link theoretical study with real-world usage. The review's quantitative implementation roadmap includes standardized benchmark datasets (approximately 10,000 annotated images), transfer learning methods (less than 500 images per region), edge-optimized architectures (inference time less than 100 ms, accuracy greater than 90%), phased industry deployment (pilots averaging 30 hectares), and workforce training programs (roughly 100 hours). These actionable goals provide clear criteria for progressing the field. The evaluation includes the most recent architectural improvements, such as YOLO frameworks ($YOLO_{V5}$-$YOLO_{V9}$), transformer attention methods, and foundation models, which represent advancements over previous studies and show 15-20% higher detection rates in demanding settings. Importantly, the review integrates sustainability and regulatory context, connecting technical capabilities to compliance requirements such as the European Union Deforestation Regulation (EUDR), which goes into effect in 2024, RSPO certification standards, and the Sustainable Development Goals, a policy dimension that has been largely absent from previous technical reviews. This work establishes a comprehensive foundation for advancing both research frontiers and practical deployment toward comprehensive digitalization in tropical plantation agriculture by synthesizing current knowledge using rigorous systematic methodology, providing unprecedented quantitative analysis, identifying critical barriers to adoption, and making concrete recommendations.

2. Methodology for literature review

The key topics of concern are the identification of huge oil palm trees using drones, counting of oil palm trees by drones, and counting oil palm trees by deep learning. In the first study, the automatic search was performed using input keywords of; oil palm tree AND deep learning. Articles extracted were then analyzed and summaries were read to identify duplication and narrow down on the scope of the study. This simple search formed the foundation of developing an advanced search query so that the inclusion of pertinent studies could be made. The last search query included the following: ("oil AND palm") AND ("artificial AND intelligence" OR "machine AND learning" OR "deep AND learning" OR convolutional neural network). The search was conducted in the various scientific databases including Scopus, Web of Science, IEEE Xplore and Google Scholar to ensure that a wide range of literature has been covered. Search was mainly done by titles, abstracts and keywords, full-text was inspected at the final stage of selection, classification and data analysis. A date filter was also used to search through the literature to short-cut the process by only including the records published after 2016. Although the search methodology covers papers dating back to 2016, Fig. 3 indicates that most of the research activity took place after 2019 with very few publications in the 2016-2018 time frame.

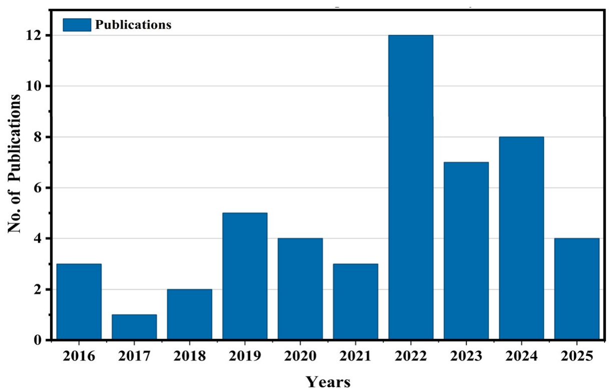

Figure 3. Graphical analysis of Annual Publications Report (2016-2025).

This trend reflects the actual research trends, and not limitations in search strategies. The sparse early publications can in part be explained by the following factors: deep learning models that are specifically designed to detect objects (e.g. $YOLO_{V3}$, released in 2018 and its follow-up models) were not yet advanced or widely deployed in oil palm applications; high-resolution UAV systems and computational resources needed to run CNN-based object detectors became more accessible and affordable after 2018; the convergence of deep learning skills and oil palm PLA. The rapid growth in 2020 can be linked to other broad trends in the field of agricultural applications, where deep learning usage has surged due to breakthroughs in transfer learning, pre-trained models, and edge computing capabilities. The paper selection strategy can be separated into three steps to select papers. In the initial phase, the publications were located based on an automated search of all databases using a search phrase of interest. In the second stage titles and abstracts were checked against preset inclusion and exclusion criteria to identify potentially relevant research. Although, in the third stage, full-text articles of selected journals were accessed and carefully reviewed in an attempt to establish their applicability in deep learning activities of oil palm tree recognition and counting. This keen attention ensured that the evaluation concerned the research that had a direct impact on the work of electronic oil palm tree monitoring based on the deep learning technology. In order to ensure consistency and relevancy, there were certain inclusion and exclusion criteria on which the selection was done. The inclusion criteria were that the studies had to be about oil palm tree detection, counting, or classification based on the application of deep learning or machine learning methods; required remote sensing data, be it UAVs, satellites, or aerial platform; provided quantitative performance metrics (accuracy, precision, recall, F1-score, or mean average precision, mAP); and were published in peer-reviewed journals or conference papers after 2016. The studies have been filtered out due to the following reasons: they were on any topic other than oil palm economics, policy, market analysis, or consumer perception; they did not use technical techniques to detect the trees in any way; they did not use machine learning or deep learning techniques, using traditional image processing methods; and they did not contain enough to be assessed on a methodological level, especially the evaluation of performance. From each included studies, data extraction has been done in detail to gather important information of significance in this review. The data extracted was the deep learning architecture and methodology used (CNN variants, R-CNN family, or YOLO series), characteristics of the dataset (source (satellite, UAV or aerial), spatial resolution and size), quantitative performance measures (accuracy, precision, recall, F1-score and mAP values) and limitations, challenges, and computational requirements were reported. The collected information was aggregated and analyzed to determine patterns, trends and gaps in the existing state of study. Section 6 contains the comparison analysis of research methods and their applicability in various studies, whereas the limitations and obstacles are also discussed in detail in Section 7.

3. Traditional methods for the detection and counting of palm oil trees

Traditional methods for detecting and counting palm oil trees have been used for decades before the advent of advanced computer vision and deep learning techniques. These methods primarily rely on manual fieldwork, aerial imagery, and basic image processing techniques. While they had limitations, they paved the way for more advanced techniques that are still utilized in certain instances. Manual field surveys: it includes visiting palm oil farms and numbering each tree in a methodical way, using standard forestry survey processes used in crop farming. Field workers travel carefully through planting regions, identifying and counting each palm oil tree [38]. This technique is based on basic forestry inventory concepts. Basic sampling techniques adapted from forestry practices include quadrat sampling (using fixed-area plots) or transect methods (systematic line surveys) to ensure representative coverage of the plantation area [39]. Standard forestry methods are usually applied to oil palm plantations in studies that use hand counts, but detailed methodological rules are not usually the main focus of the research [40]. The process of collecting data in the field can involve the use of a set of trained individuals that count the trees and other data associated with the specified tree's age, e.g., estimated age, height class, and overall health state according to the visual evaluation criteria. Other operations utilize GPS technology to capture the exact position of trees although, others use grid based techniques of counting trees in a systematic sequence. The specific procedures vary depending on studies and organizations, which is how the generic concepts of forestry are applied to the local plantation conditions and research objectives. Training and standardization methods usually entail training in identifying criteria and counting processes of trees. In recent oil palm studies, manual counting is mostly utilized as a validation technique to automated detection techniques and ground truth data generated by systematic field surveys are used to train and test deep learning models [41, 42]. The process of documentation and quality assurance differs among studies with some of them involving more than one observer to check this process whereas others use one team counting with post-survey validation. Traditionally, the use of manual surveys is mostly common to modern oil palm research as a standard reference point to compare with automated detection technologies, but not as a significant management tool [43, 44]. Aerial photography: Aerial photography is composed of recording high-resolution images of palm oil plantations using airborne platforms, manned and unmanned aerial vehicles (UAVs/drones), and then performing a manual visual analysis of trees. This strategy has been used in the study of oil palm where flight altitudes are usually between 100-500 meters to balance the efficiency of spatial and area covering [45, 46]. The methodology is systematic flight patterns, which are meant to cover the plantation in order to provide full coverage with adequate overlap between adjacent images. To make human analysis method effective, trained individuals must examine overhead images with Geographic Information System (GIS) software with much attention. In order to locate individual palm oil trees, the analysts are required to manually place point marks or sketch treetops [47]. The determination of typical features of the oil palm, such as the shape, size, shadows, and spatial composition within the rows of plantations, are used in visual interpretation. Depending on the purpose of the research and the size of the image resolution needs, digitization methods include point based marking at the center of trees, or define the boundaries of the crowns. Quality control is frequently done by using a series of interpreters to scan the identical regions in order to ensure uniformity in patterns of trees identification [42, 48]. The choice of platforms determines the possibilities of operations, such as those of manned aircraft, which can cover extensive distances with fewer resources but demand specific services, and UAV operations, which have fewer limitations on the timing or repetition of their use and are limited by flight duration and area coverage [49]. Some standard image processing workflow items include geometric correction of spatial accuracy and radiometric normalization to permit lighting variations across the survey area. In order to measure accuracy of the interpretation and determine the confidence levels of the methodology, validation processes usually include the comparison of the number of aerial images with a ground reference data of selected sample areas. Satellite imagery: Multispectral and hyperspectral data are used to conduct large-scale mapping and monitoring of palm oil plantations through harnessing the spectral reflectance properties of oil palm trees at various wavelengths to identify and delimit them. The approach takes advantage of distinctive spectral characteristics of the oil palm vegetation that are not shared among other land cover types because of specially structured leaf structures, the canopy structure, and the chlorophyll content [50, 51]. Some of the satellite platforms used in the study of oil palm are medium resolution satellites such as Landsat (30m) and Sentinel-2 (10-20m), and high-resolution commercial satellites such as WorldView and Pleiades (0.5-2m resolution). Image classification strategies almost always include spectral data supervised or unsupervised algorithms, and the use of supervised methods in which known oil palm areas are used to define spectral indices to be used in automated classification [47]. Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are some of the vegetation indices widely computed to bring out vegetation attributes as well as in plantation mapping. The spatial resolution has a major impact on the area of application: medium resolution can be used in plantation level mapping (10-30m) and cannot distinguish individual trees, and high resolution (sub-meter to 2m) can distinguish individual trees within specific plantation setups [52, 53]. The skills of temporal analysis are one of the main strengths as they can be used to track crop development, growth patterns, and management practice over time by analyzing time series of vegetation markers and changes in land cover. Image processing methods such as cloud blocking, geometric correction, and weather correction are used to ensure that the quality and stability of the data collected during different collection times [54]. Ground truth verification typically requires testing an area of classification in the field or with alternative high-resolution reference data, and the evaluation of accuracy generally reports that there is a total accuracy and confusion matrices to quantify classification performance. Coupling with other sources of data, like digital elevation models, and field survey data, frequently enhances the quality of the satellite-based palm oil plantation mapping and monitoring [55]. Image processing algorithms: The traditional image processing algorithms are applied to identify palm oil trees in aerial and satellite images and count them with the help of computer vision algorithms such as edge detection, thresholding, and segmentation. These techniques are the initial ways of computation that were used before machine learning methods in which traditional computer vision principles could be applied to agriculture [56]. The processing is usually informed by preprocessing of features like removal of noise and contrast adjustments to enhance quality of the image and then feature detection algorithms. Edge detection methods such as the Canny and Sobel operators are used to detect the boundaries of trees by detecting changes in intensity whereas thresholding methods are used to isolate trees and the background using intensity or color values [57]. Segmentation algorithms such as region growing algorithms and watershed algorithms are algorithms used to identify individual trees using pixels that share common features. Other methods involve template matching in which a set of patterns of tree crowns are systematically matched in the images to reveal similarities between images. Mathematical morphology can be used to post-process results and minimize noise artifacts. Performance evaluation is done against manual counts or reference data and success rates differ according to the quality of the image and the nature of the plantations [36, 58]. These classical approaches laid the groundwork of the computer vision methods in the field of agricultural tree detection and were significant predecessors to the latest deep learning methods [59]. Texture analysis: In texture analysis methods the palm oil trees and other vegetation or land cover types are differentiated based on the analysis of the spatial distribution and arrangement of pixel intensities in images to yield quantitative texture measures. These techniques take advantage of the textural differences of the oil palm plantations which is due to the routine spacing of trees and the similarity of the shape of the crown which forms a familiar spatial pattern when viewed in remote sensed imagery [60]. It is achieved by a methodology of computer calculation of texture measures of entropy, contrast, homogeneity, and correlation of neighboring pixels in an image using methods like Gray Level Co-occurrence Matrix (GLCM) analysis. These statistical metrics characterize the spatial connections between pictures and record texture characteristics that distinguish oil palm farms and wild woods, other types of crops, or bare areas [61]. The analysis of texture is specifically useful in identification and mapping of the vegetation at the plantation scale based on satellite or aerial images, where oil palm trees of a regular geometric structure provide characteristic textual patterns. Multi-scale texture analysis can also be used in varying spatial resolutions to obtain both fine-scale patterns of the crowns and the broader plantation structure [62]. Spectral information can be incorporated with the textural features to create better classifications, creating a combination of the multispectral band values and the textual features to better discriminate among various types of land cover. The texture analysis is a technique that is employed to complement the mapping of plantation and not counting each individual tree since the technique is based on the recognition of patterns in the landscape scale [63]. These classical methodologies have served as the foundation of automated palm oil tree detection and counting, which offered necessary validation standards and principles of features extraction which remain fundamental in modern research methodologies. All of these techniques, including the manual field surveys with their exclusive viewpoints and technical details, have offered their own building blocks of the modern detection systems [53]. The technical integration of super clear images, high-tech computing platforms and a wide use of UAVs have brought unprecedented chances to build the integrated detection structures [49]. The current generation of deep learning architectures is starting to adopt the old concepts of feature extraction, and much of the state-of-the-art systems are being built to use a multi-modal strategy, integrating spectral analysis and texture characterization with geometric pattern recognition into single neural network structures. Traditional techniques remain imperative for ground truth generation, algorithm validation, and benchmarking new algorithms, making certain continuity between conventional principles of remote sensing and the new powers of artificial intelligence. This methodological development is a progressive development that has introduced the field towards revolutionary developments in large-scale plantation monitoring, prediction of yields, and sustainable operations of palm oil management [64, 65].

4. Limitations and challenges of traditional methods

Despite the extensive use of the traditional methods of palm oil tree detection and counting, they have several limitations and challenges that may impair their accuracy, efficiency and scalability. Labor-intensive and time-consuming: Manual field surveys and visual interpretation of aerial or satellite images are labor-intensive and time-consuming by nature particularly when dealing with large-scale plantations that span thousands of hectares. The study of the high-resolution imagery conducted by Shafri et al. (2011) established that 2-3 hours per square kilometre is the time spent by trained analysts to conduct a manual interpretation of the images, which is economically infeasible for substantial operations [66]. Such manual strategies require a large human resource, and are subjected to mistakes and inconsistencies due to fatigue of the observers, subjective interpretation and also due to the level of expertise of the field teams [67, 68]. Santoso et al. (2024) found that inter-observer coefficients in counting trees by human eye on various plantation sites were 12-18%, which indicates the essential inconsistency in human-based detection systems [69]. Restricted scalability: Traditional techniques have serious scalability issues when used to cover large areas of a plantation or on regional surveillance initiatives, which provides a bottleneck to its utilisation. Torbick et al. (2016) established that the manual method of counting becomes very impractical when the size of the area of the survey is more than 500 hectares, where time taken and the cost of operation is no longer linear to the expansion in size [70]. The issue of scalability is especially severe for the plantation companies that must deal with several locations in various areas. Counting and interpretation by hand are harder when the area of interest increases and not only do the costs and time increase, but also the error that is made also compounding with the larger area of the survey brings about cumulative errors [71]. Large scale operations are logistically complicated, moving several survey teams and ensuring the quality of data acquired in large regions. Economic analysis shows that the traditional methods have poor quality in cost-scaling. The cost of surveying per hectare is likely to be higher in a larger plantation because of the logistical complexities and coordination issues as well as the necessity to have several survey teams. Secondly, the human resource demands of extensive monitoring can also surpass the availability of trained human resources at local levels hence the companies have to make a trade-off between the frequency of surveys and spatial coverage of the surveys [55]. Another critical limitation is the temporal scalability. Regional surveillance that needs to be conducted systematically to cover several plantation locations is associated with scheduling issues and a problem of resource allocation which can greatly postpone data collection [72]. This time constraint especially presents an issue in applications that require time sensitivity like the yield forecast, pest management and harvest planning where old information greatly diminishes the value of decisions [73, 74]. Occlusion and overlapping trees: Among dense palm oil trees, neighboring trees may overlap the tree crowns and lead to overlapping resulting in a problem with the traditional methods of counting and identifying trees. Chowdhury et al. (2022) established that the presence of overlapping crowns in a mature plantation can greatly decrease the detection accuracy especially in cases where the canopy is covered [22]. This challenge is particularly acute when one is working with aerial or satellite images, in which the top-down perspective may fail to offer much information that would help differentiate between separate trees and unified canopy regions. The shadows, difference in height of the canopies and interference by other trees all create visual blocks making it difficult to identify the trees and delineate the boundaries [43, 59]. These problems are more challenging in the older plantations where ad hoc patterns of plantations and natural variations of growth form intricate spreading shapes that conceal the boundaries of individual trees. Varying illumination conditions: Conventional image processing methods (edge detection and thresholding) are susceptible to different illumination conditions, shadows and light variations. Sanin et al. (2012) explored shadow detection and dissimilarities in illumination greatly influence the functionality of traditional computer vision algorithms [75]. These may have significant effects on the precision of the tree detection and counting particularly when dealing with aerial or satellite images taken at a different time or under different atmospheric conditions. High-quality images and algorithm performance is not consistent due to seasonal fluctuations and cloud cover as well as day-night lighting variations [76, 77]. Data acquisition timing and illumination may sometimes require a lot of precise timing, and it may take many surveys attempts to have an appropriate result. Limited spectral resolution: The multispectral and hyperspectral satellite data can be used to offer useful data to tell the palm oil trees using their spectral information, but the number of spectral bands currently offered by widely used satellite systems is too limited to allow their accurate identification of palm oil trees as opposed to other vegetation types or land cover classes. Vahidi et al. (2018) presented traditional multispectral sensors tend to have a low spectral resolution, necessary for consistent distinguishing vegetation in complex agricultural environments [78]. This limitation is specifically definite when oil palm trees are compared to other tropical vegetation with comparable spectral properties, particularly at various stages of phenology when the property of leaf reflectance all overlap [79]. Multispectral imagery with 4-bands, which is widely applied in agriculture, has limited discrimination ability between oil palm and other broadleaf crops or forest species [80]. Young oil palm trees can cause spectral similarities with the other farm vegetation which may cause misclassification and lower the mapping precision, especially in mixed-use landscapes where many types of vegetation are present [81]. Additionally, variations in atmospheric conditions and sensor calibration may further decrease the performance of spectral-based methods of discrimination. These fundamental constraints have led to a paradigm shift of sophisticated computer processes, which address the fundamental issues of the traditional processes, and the possibility of scalable, automated processes in new farm management. Computer vision technologies and deep learning have become revolutionary alternatives, providing automated, scalable and accurate solutions, capable of effectively dealing with the complex cases where traditional methods fail, such as analysis of high-resolution imagery, handling of occlusions, and dealing with variations in illumination. Among the various deep learning architectures, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in agricultural computer vision applications, particularly for tree detection and counting tasks essential to oil palm plantation management. The next sections look at how CNNs and associated deep learning techniques have transformed automatic tree recognition, laying the technical groundwork for plantation monitoring systems of the future.

5. Introduction to deep learning

Deep learning (DL) is developed from artificial neural networks (ANNs) that try to mimic the human brain in processing information. It needs training on huge datasets to learn hierarchical data representations, which enable models to automatically extract features and patterns for tasks like classification, prediction, and decision making [82]. It relies on ANNs with multiple interconnected layers of nodes. Each of these layers does computations and uses the outputs as inputs in the next layer. It learns through correcting the weights between nodes through backpropagation to reduce the errors in prediction [83]. Deep learning is a term that was coined by Hinton et al. [84]. It was a major breakthrough and revitalized the efforts into neural networks research, and was dubbed as the new generation of neural networks as deep networks were remarkably successful at addressing classification and regression problems when well-trained [85, 86]. There are numerous architectures of DL models depending on their design and applications. Convolutional Neural Networks (CNNs) are also ideal at working with spatial data, including images and videos, because they are able to extract local patterns and features with the help of convolutional and pooling layers [87]. Recurrent Neural Networks (RNNs) are particularly good at sequential data, including text and speech, because they include recurrent and time-dependent connections [88]. One of the key strengths of DL is that it can automatically learn intricate representations and trends in the information in the form of hierarchies without necessarily grappling with or finding such trends in traditional machine learning frameworks [89, 90]. However, DL models also require a large amount of labelled data to be trained, and they are computationally intensive and need highly capable hardware such as graphics processing units (GPUs) or tensor processing units (TPUs) [91]. In addition, these models have the risk of overfitting whereby they are highly effective on the training data but fail to forecast and fail to make precise predictions on new unseen data. Recent developments in architecture including You Only Look Once (YOLO) and transformer-enhanced CNNs have enabled much better computational efficiency, allowing DL to be deployed to resource-constrained agricultural platforms with high accuracy, making use of DL relevant to most of the practical deployment challenges in precision agriculture applications. Figure 4 shows the link between DL and machine learning and artificial intelligence and explains how deep learning can be used as a specialized framework within the larger machine learning domain. Different DL models have been used in practice, such as Multi-layer Perceptron (MLP), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Generative Adversarial Networks (GANs), and Auto-Encoders (AEs). CNNs are good at activities involving analysis of images, whereas RNNs are useful in processing sequential data, including time series data. CNNs are widely applicable in image recognition, analysis and classification and they have been used to fault detecting, weather forecasting and have shown their potential in various situations [92, 93].

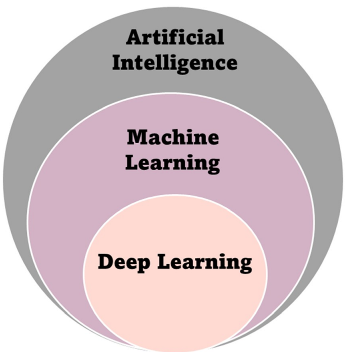

Figure 4. The interaction between Deep learning (DL), Machine Learning (ML) and Artificial Intelligence (AI).

5.1 Applications of deep learning in agriculture

Deep learning is an area of machine learning that uses artificial neural networks to replicate the process of human brain learning has become widely used in many areas, including agriculture. Agricultural industry has also used deep learning methods to address problems such as crop yield predictions, disease detection, weed management as well as facilitating accurate farming activities. These are some of the main uses of deep learning in agriculture, which are also illustrated in Fig. 5. Tree counting: Detection and instance segmentation Convolutional neural networks (CNNs) and region-based CNNs (R-CNNs) are deep learning methods that have been applied to count trees individually within plantations or orchards using aerial and satellite imagery [94, 95]. The models can distinguish between trees and other items and thus give the correct number of items even in thick trees or different light settings. Deep learning-based tree counting is useful to oil palm plantation to track the growth, predict the harvestability, allocate resources efficiently to maintain the plantations, and harvest, as well as detect absent or ailing trees to implement timely responses [96]. Recent progress in 2025 has shown that the next-generation YOLO architectures have shown improvements in the detection of agricultural objects. Allmendinger et al. (2025) tested YOLO$_{V9}$ variants on real-time farming projects and got a recall of 72.36 and mAP50 of 79.86 with YOLO$_{V9e}$ showing excellent results in precision farming tasks such as tree detection and counting [97]. These findings imply that the contemporary YOLO architectures have better trade-offs between accuracy and speed than the previous versions, which is why they become more usable in large-scale plantation monitoring systems.

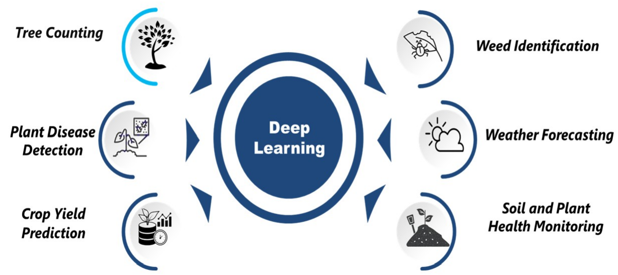

Figure 5. Major Applications of DL in Agricultural Field.

Plant disease detection: It is important to detect the presence of plant diseases early to have a chance to mediate in time and reduce the losses of crops. Another application of deep learning methods and specifically CNNs has demonstrated exceptional performance in identifying plant diseases on leaf images [98]. These models have the capability of giving accurate classification of diseases according to visual symptoms and this enables the farmers to act through the application of preventive measures [99]. Crop yield prediction: Crop yield prediction systems have been developed using deep learning to predict crop yield using a variety of input variables, such as weather, soil, and prior yield information. The models can assist the farmers in making wise decisions during the process of planting, harvesting and allocation of resources [100]. For example, satellite imagery has been studied and forecasted with the help of convolutional neural networks (CNNs) [101].Weed identification: Weed control is necessary to maximize crop production and the elimination of herbicides. Weed localization and classification in fields have been performed by deep learning algorithms with the help of computer vision technique [102]. Such models are able to distinguish between crop plants and weeds and can be used to apply specific herbicides or weeds can be removed by mechanical methods [103]. Weather forecasting: Several deep learning architectures (convolutional neural network (CNNs) and recurrent neural network (RNNs)) have been used to provide better local and short-term weather forecasting by observing meteorological data (satellite images, radar images, ground-based observational data, etc.) with deep learning [104]. These models are capable of replicating complicated trends and time reliance and hence make more precise forecasts on parameters such as temperature, precipitation and speed of the wind than the conventional models of numerical weather prediction [105]. Accurate weather forecasting assists farmers in streamlining crop management procedures, e.g., scheduling irrigation, applying fertilizers, and controlling pests, as well as reducing the impact of extreme weather conditions. Soil and plant health monitoring: Deep learning models can be used to analyze different sources of data (e.g., remote sensing images or sensor data) to determine soil health and track the growth and development of plants [106]. Such knowledge can be used in accuracy agriculture, which includes better use of fertilizers and at what time to irrigate [107].

5.2 Overview of deep learning algorithms

Deep learning has shown its applications across varied fields and is recently getting into the agriculture sector. Deep learning has been found to be a much more effective approach than traditional machine learning in several ways [108, 109], such as medical image analysis classification [110], speech recognition [111]. Deep learning which is a particular subdivision of machine learning is used in agriculture to predict crop yield, plant diseases, weed detection, and identifying plant diseases. The main focus is on operations associated with the sorting of pictures and object recognition, particularly, in the case of the people in charge of surveying the plant processes. Deep learning can automatically learn features in an image, which improves its recognition and detection of objects as compared to traditional methods where one has to manually extract them during the training process. This makes deep learning a crucial tool in modern agriculture for efficient plantation management. The concept of machine learning and deep learning for agriculture is shown in Fig. 6.

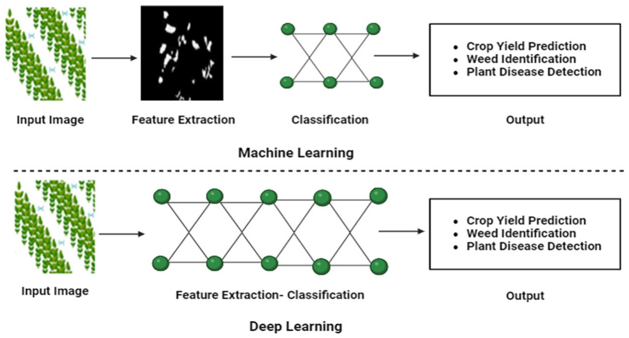

Figure 6. Comparison of machine learning with deep learning. Source: Adapted and reproduced from [52].

Data collecting, preprocessing, model selection, training, and evaluation of performance and accuracy are typical procedures for applying deep learning to agriculture. The algorithm can be used to provide forecasts or identify abnormalities if it is considered accurate and dependable. Artificial neural networks (ANN) are the foundation of the machine learning process known as deep learning. When applied to various research areas, such as agriculture [112], face recognition [113] and natural language processing [114], some deep learning architectures, such as CNN, DNN, RNN, DBN, and FCN, have demonstrated excellent performance. In addition, many of the datasets, frameworks, and architectures needed to develop the deep learning model are freely accessible worldwide. Deep learning has found its way into several fields of agriculture, with the key ones being disease diagnosis [115], land cover [116], plant recognition [117–119], weed identification [120], and tree counting [121, 122]. While FCN is the foundation for their alternatives, CNN has been the most widely used deep learning architecture among all of them. The FCN is constructed by replacing the fully connected layers of a CNN with convolutional layers in order to facilitate image localization using a sliding window approach[123]. Furthermore, Region-based Convolutional Neural Network (R-CNN) is a two-phase detection technique in which an object's location in an image is determined in the first stage and its classification is done in the second. R-CNN addresses the issue of classifying complete images by focusing solely on certain regions for classification [124]. Table 1 summarizes the various deep learning algorithms and their applications in palm oil tree counting. In addition, the training datasets for the deep learning architecture are generated through multiple methods, including manual interpretation of photos, and utilizing images from free datasets such as MNIST, ImageNet, or UAV. Data augmentation is a frequently used method to improve the performance of a network by manipulating the dataset [125].

Table 1. Various DL algorithms applied in palm oil tree counting.

DL Algorithms	Applications
CNN	Detecting and segmenting palm oil trees from aerial images.
RNN	Analysing time series data of palm oil tree growth to predict future counts and assess plantation health.
R-CNN	Locating and defining palm oil tree boundaries in an image for accurate accounting and monitoring.
LSTMs	Using historical growth patterns to improve palm oil tree counts in dense and occluded plantations.
DBNs	Discriminating palm oil trees from other vegetation types in multispectral imagery with high accuracy.
DNNs	Analyzing satellite image to identify and estimate the density of palm oil trees.
FCN	Enabling precise palm oil tree counting and delineation through pixel-wise segmentation

After exploring several deep learning algorithms in agriculture, in the intricate task of tree counting, particularly in the context of oil palm plantations, CNNs emerge as the preferred choice. They are quite significant for their capacity to extract characteristics in photos without the involvement of operators. The intricate and hierarchical arrangement of oil palm trees is best described using CNNs, which makes them easily consortia and counted and it is the benefit that makes them to be the most suitable solution to this agricultural use.

5.3 The Pinnacle: Convolutional neural network (CNN)

One of the deep learning methods, which succeed in computer vision tasks, is CNNs. CNNs are particularly designed to enable specific object recognition and localization in the complex agricultural environment [87]. The best feature of CNNs is that they can automatically extract image features, which is of great importance over the other computer vision methods such as scale-invariant feature transformer (SIFT) and local binary patterns (LBP). YOLO models are highly suited to real-time object detection, and their variants such as YOLO_{V5} and YOLO_{V9} can yield an ideal balance between detection and computation efficiency. A significant advantage of YOLO lies in its deployability on resource-constrained hardware, rendering it suitable for UAV-based monitoring and edge computing applications prevalent in plantation management. More recent transformer-based CNN models have also enabled even more detection. Real-Time Detection Transformer (RT-DETR) is a set of spatial feature extraction based on CNNs and transformer-based attention models, which progresses 15-20% higher detection performance in the difficult environment such as dense canopies with real-time processing speeds. In the same way, modern detection frameworks such as D-FINE and others are other systems built on CNN backbones with attention mechanisms and are able to achieve the best accuracy under the realistic computational limits of their systems. Figure 7 gives a basic architecture of CNN underlying these sophisticated detection systems indicating convolutional layer arrangement crucial in spatial feature analysis.

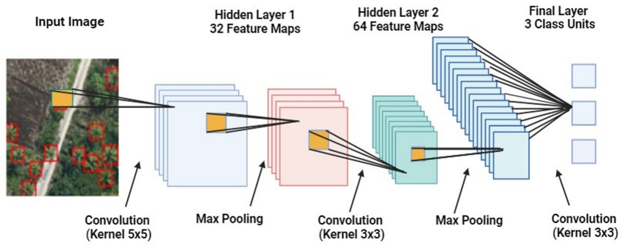

Figure 7. CNN architecture proposed for image classification.

The effectiveness of the contemporary CNN variants is especially clearly observed in oil palm applications. Li et al. [96] showed CNN-based architectures with F1-score of 0.93 in detecting tree, and Mubin et al. [126] introduced a deep learning system known as ConvOlPalm, which uses CNNs and fully convolutional networks (FCNs) to tackle the problem of oil palm tree counting using UAV images. The proposed plan provides a total accuracy of 95.11% in the case of young oil palms and 92.96% in the case of mature palms. The classifier performs well in identifying oil palms on the backgrounds that contain other plants, shadows, and invisible datasets. Jiang et al. [127] employed another study that employed two-stage CNN, with the first stage used to detect a single oil palm tree and the second stage used to count the detected trees. The mean absolute error of the trees per image was 2.76, and that is why their method demonstrates the potential of CNNs to count the trees in oil palm plantations accurately. Recent YOLO implementations demonstrate the same level of accuracy but with a 60-70% lower inference time, making it feasible to implement real time monitoring required in large scale plantation processes. This development makes CNNs the solution of automated oil palm detection, the best to provide a combination of detection accuracy, computational performance, and performance at a realistic deployment level necessitated by the modern precision agriculture systems. CNNs are the most suitable technology to manage oil palm plantation because they can manage intricate tree structures, adopt different illumination levels, and different canopies that overlap and operate under real-world resource availability [128]. However, it is important to note that the performance of CNN-based models can be affected by the quality and resolution of the input imagery, size and complexity of training dataset, as well as the architecture and the hyperparameters applied. The efficiency of CNN-based methods and specifically YOLO_{V8} has been confirmed through more recent studies. In a research study by Heng et al., 2025, the accuracy of the deep learning that was based on YOLO_{V8m} to identify unhealthy and healthy oil palm trees using high-resolution aerial images was 98.5% [129]. This research explored that the deep learning techniques will be much faster (16.1 milliseconds vs. 23 minutes per hectare) and accurate when compared to manual counting and make YOLO_{V8} an effective tool in real-time large-scale plantation surveillance and tree health evaluation.

6. Deep learning for oil palm trees detection and counting

6.1 Preparation of Dataset and acquisition of images

Deep learning models require a strong and representative dataset to learn how to identify and estimate the oil palm trees using remote sensing images. Images obtained by means of different devices should be included in the dataset, e.g., unmanned aerial vehicles (UAVs) [130,131] and satellite platforms WorldView, GeoEye, and Pleiades [132, 133], should be employed to obtain a high level of spatial and temporal variation. Human expert manual annotation is also widely used to create ground truth data, which is a tedious task that requires the careful labeling and identification of individual trees by drawing bounding boxes or polygons around them [94, 134]. Different datasets were created and used in oil palm tree detection and counting, each of which has certain features and applications Table 2. However, semi-automatic or crowd-sourcing strategies can be suggested in order to reduce the annotation load. In order to improve the strength and the generalization of the model, data augmentation methods such as random rotations, flips, crops, brightness changes, and synthetic occlusions are used to model real-world variations and augment diversity of the training data [135, 136]. Moreover, when the data is uneven, such class balancing approaches as oversampling or under-sampling can be important, where one (or more) classes (e.g., mature trees or high-density areas) are either overrepresented or underrepresented [137]. The data must be divided into distinct training, validation and test sets in a systematic way with the training set applied to optimize the model, the validation set applied to track the performance as well as to fine-tune the hyperparameters and the test set applied to assess the performance of the final model on unseen data. Gathering the applicable metadata related to the images, i.e. geographic location, plantation history, age of trees, planting density, and other applicable information can be useful context that can be utilized to further analyze and interpret the findings [138]. Intense quality control interventions are necessary to detect and delete poor, sharp, and redundant images in the dataset to guarantee quality model training and execution [126]. Finally, the presence of standardized datasets and benchmarks of oil palm trees counting can facilitate the fair comparison of various deep learning models and methods and promote reproducibility and the state-of-the-art in that field.

6.2 Model training for palm oil tree detection

Precise detection of oil palm trees using deep learning needs strategic selection of network architectures coupled with transfer learning approaches. CNNs architectures including VGG [139], ResNet [140], and Inception [141], pre-trained on ImageNet [142] serve as effective feature extractors when fine-tuned for palm oil tree detection [143]. Some of the object detection frameworks that have been investigated include region-based object detectors such as Faster R-CNN [144], Single Shot Detectors (SSDs) [145], and instance segmentation object detectors such as Mask R-CNN [146]. Such frameworks typically use a region proposal step to find the possible locations of objects, after which comes a classification and regression step to narrow down the proposals and predict object classes and bounding boxes. The entire process of deep learning model training includes the data collection phase, data preprocessing, choice of model, testing, and continuous improvement Fig. 8. Common data augmentation methods used include random rotations, flips, crops and brightness manipulations, to enhance the variety and strength of the training data [147, 148]. In case of imbalanced data, such as, class balancing methods such as oversampling or under sampling are essential in the situation where particular classes are either over- or underrepresented (e.g., mature trees or high-density areas) [149, 150]. Loss functions, including multi-task and classification and regression combined losses (e.g., Focal Loss [151] or Smooth L1 Loss [152]), are crucial for training an object detection model. Algorithms such as Stochastic Gradient Descent (SGD) or Adam are used to modify model parameters, and techniques such as learning rate scheduling, early stopping, and others are used to enhance convergence and avoid overfitting [153, 154]. The methods and strategies covered below have been investigated and analyzed at different research works in the literature, as presented in Table 3, the type of deep learning architecture, and evaluation measures used, along with their achieved performance. Diagrammatic representation of the DL/ML concept for counting oil palm trees. First, the reported metrics of performance are point estimates, with no confidence intervals or statistical significance tests, so it is hard to determine whether the differences between the performances (e.g., 96.8% vs. 97.5% mAP) are real or the variations among test sets. Second, there is a high level of heterogeneity of experimental conditions among studies, such as characteristics of datasets (size, resolution, type of the plantation), protocols of evaluation (IoU thresholds, edge case treatment), and environmental factors (illumination, seasonal variations). For instance, the results of models that are trained and tested on a single plantation with a uniform setting (101, 104) will not necessarily be similar to the results of the studies carried out at various locations (102, 107). Third, the majority do not have cross-dataset validation, and we do not know whether the model is able to generalize to other conditions of the test. These aspects indicate that high accuracies reported (usually > 90% mAP) indicate that deep learning is viable to palm oil tree detection, but that comparison of studies directly by numerical values should be viewed with care.

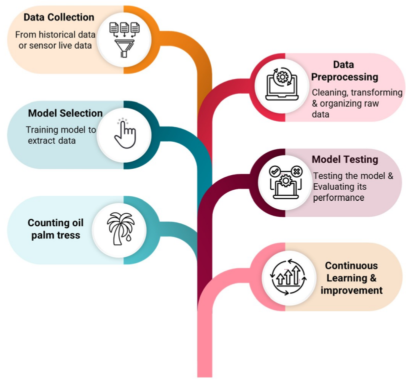

Figure 8. Schematic representation of the DL/ML idea in the count of oil palm trees.

Although such comparability limitations exist, Table 3 shows that there are significant trends in the field. Deep learning methods always have high accuracy (> 85% mAP), and this proves to be more effective compared to classical methods. More modernized, advanced architectures (e.g., Cascade Mask R-CNN (108), EfficientDet (107)) are more likely to be better than the previous ones, but it is hard to estimate the degree thereof since the different methods used experiments with varying conditions. The computation costs of various methods differ significantly, with efficient models such as YOLO_{V4} (103) having less computational demands than more complex models such as Cascade Mask R-CNN (108), and all these trade-offs between accuracy and speed need to be evaluated depending on the needs of the application. Also, according to most studies, overlapping crowns, different illumination conditions, and the different properties of plantations are identified as the consistent challenges that need further studies and methodological development. Future research would be improved by creating standardized benchmark datasets under different plantation conditions and using standard evaluation procedures to facilitate more stringent performance comparisons and increase research community reproducibility. Evaluation metrics used to determine the performance include mean Average Precision (mAP), precision, recall, F1-score, and mean absolute error (MAE) to count tasks on a held-out test set [155]. Combining methods which estimate the prediction of several models might occasionally enhance the overall performance. Subsequent processing techniques such as non-maximum suppression (NMS) or conditional random fields (CRFs) can also be used to improve object detection and minimize false alarms or counting an object twice [156, 157].

7. Critical challenges and technical limitations in oil palm tree counting

Although deep learning techniques have shown promising results for oil palm tree counting, several limitations and challenges persist, hindering their widespread adoption and optimal performance. Understanding these limitations is crucial to driving future research and addressing existing gaps. In this section, there is a systematic discussion of the major technical issues, quantified performance constraints, and practical barriers that must be overcome to allow effective deployment of deep learning systems to manage oil palm plantations.

7.1 Data acquisition and quality challenges

7.1.1 Image resolution, coverage and cost constraints

The use of high-resolution imagery that is vital in the accurate detection of trees has a high cost and coverage constraint. The satellite imagery of WorldView-3 (0.3 m) costs around $25 per kilometre square in the arched data which equals about $3, 500 on a average of 1000 hectares of plantation. The quarterly monitoring would raise yearly expenses to about 15000 dollars per plantation [25, 158]. The processing needs are also high: only 10 hours of PCI processing time (the NVIDIA RTX 3090) are needed to process the data of a 1,000-hectare plantation with 10 hours of analysis (approximately 237 million pixels) [55]. Sentinel-2 (10 m) that has medium-resolution offers free coverage but does not offer the spatial resolution required to count individual trees.

Table 2. Datasets for Oil Palm Tree Detection and Counting.

Dataset Name	Source	Resolution	Size	Annotations	Provider/Organization	Availability	Ref
OPTIC	UAV	05-10 cm/pixel	3,200 images, 210,000 trees	Bounding boxes	Malaysian Palm Oil Board (MPOB)	Upon request (no public repository identified)	[159]
PalmTree Detection	Satellite	30 cm/pixel	500 images, 80,000 trees	Dot annotations	Indonesian Institute of Sciences (LIPI)	Upon request (no public repository identified)	[160]
OilPalm Dataset	UAV & Satellite	05-50 cm/pixel	2,000 images, 150,000 trees	Polygons	University of Malaya, Malaysia	Public (Institutional Repository / Mendeley Data)	[161]
OPDIS	UAV	10 cm/pixel	1,500 images, 90,000 trees	Bounding boxes, tree age	Swinburne University of Technology, Malaysia	Upon request (no public source confirmed)	[162]
PalmSeg	Satellite	50 cm/pixel	1,000 images, 120,000 trees	Pixel-wise segmentation	National University of Singapore	Upon request (no public source confirmed)	[163]
PalmOmics	UAV	03 cm/pixel	5,000 images, 300,000 trees	Bounding boxes, tree health	Universiti Putra Malaysia	Upon request (no public link found — requires data permission)	[164]
OPMAS	UAV & Satellite	10-50 cm/pixel	10,000 images, 1.2 million trees	Dot annotations, plantation metadata	Consortium of Malaysian & Indonesian research institutes	Likely private / restricted (industrial collaboration)	[165]
Annual Oil Palm Plantation Maps (AOPD)	——	100 *m*	National scale	Temporal change maps	International research collaboration	Public (Zenodo / DOI)	[166]
Global Oil Palm Dataset (1990–2021)	——	10 & 30 *m*	Global scale	Plantation extent & planting year	Global Monitoring Collaboration	Public (GEE Catalog / Zenodo)	[167]

Table 3. Previous literature on the deep learning and oil palm industry.

Method	Dataset	Accuracy	Limitations	Ref
Custom CNN architecture	Satellite imagery: 0.5 *m* resolution	97.5%	Limited dataset diversity. Does not address varying plantation conditions.	[168]
VGG-16, ResNet CNNs	Drone and satellite imagery	91.3% (VGG-16)	Small validation dataset. Limited testing across plantations/environments.	[169]
YOLO$_{v4}$ CNN	Satellite imagery: 30 *cm* resolution	96.8%	Requires high computational resources. Generalizability not assessed.	[170]
Mask R-CNN	UAV imagery: 10 *cm* resolution	97.1%	Testing limited to single plantation type and region.	[171]
Faster R-CNN + FPN	UAV imagery	92.7% *mAP*	Limited dataset size and variation. Occlusion handling could be improved.	[172]
Retina-Net	Satellite imagery: 0.3 *m* resolution	89.4% *mAP*	Performance drops in dense plantation areas. Could benefit from data augmentation.	[173]
U-Net + ResNet	UAV imagery: 5 *cm* resolution	94.2% *IoU*	Struggles with overlapping tree crowns. Limited generalization across plantations.	[126]
Efficient Det	Satellite imagery: 0.5 *m* resolution	93.1% *mAP*	Computationally expensive for large-scale deployments. Requires further optimization.	[174]
Cascade Mask R-CNN	UAV imagery: 10 *cm* resolution	98.2% *mAP*	Limited testing in varying illumination conditions and plantation ages.	[175]
DPPNet (Depth-wise Separable ConvNet)	Satellite imagery: 0.3 *m* resolution	94.8% *mAP*	Computationally expensive. Requires hardware acceleration for real-time performance.	[176]

Research shows that the accuracy of detection decreases to less than 65 per cent at 10 m resolution versus more than 90 per cent at sub-meter resolution [47, 48]. UAV based images have ultra-high resolutions (2-5 cm per pixel) but have extreme coverage limitations. Scanning one thousand hectares will take about one hundred distinct flights, and this will consume about 50 hours on the field without factoring in battery changes and weather delays [49].

7.1.2 Annotation burden and dataset limitations

The process of manual annotation is a serious bottleneck toward model development. Seasoned annotators need to take 15-25 minutes per picture to precisely label 50-80 oil palm trees. This corresponds to 1,250-2,083 hours of labour, which amounts to 18,750-52,075 at average rates of $15-25/hour [21, 59] when the minimum recommended dataset is of 5,000 images. Rates of inter-annotator agreement indicate that there are large discrepancies in agreement between mature and young trees: 87.3 and 72.1 percent, respectively, and models trained on inconsistently labeled data achieve 8-12 percent lower mAP scores [36]. These challenges become more complex from imbalanced data distributions. The evaluation of 47 published data shows that there is a strong geographic bias (68 percent Malaysian, 23 percent Indonesian, only 9 percent other countries) and an imbalance in the age of trees (72% mature trees, 11% young trees, 17% adolescent trees) [24]. This has a consequence of 94-98% of accuracy of models to mature trees and 76-83% to young trees when the models are being cross validated. Also, 91% of papers between 2016-2024 had registered datasets of which only 8% publicly shared their data and this seriously impaired the ability to replicate [35].

7.1.3 Variability of environmental factors and data quality

The tropical environmental conditions contribute to continual data quality problems. The cloud cover study on the large oil palm areas indicates that they are covered with 65-72 percent during the monsoon seasons (November-March), which require 8-12 images to get 3-4 viable images in a year. Due to the peatland fires, the atmospheric haze decreases the accuracy of detection by 12-18 percent even on a clear sunny day [76, 77]. Differences in the solar angle lead to differences in illumination which introduce 25% error in the values of NDVI and 15-20 percent error in the values of RGB intensities with models trained on midday images experiencing 15-22 percent deterioration in accuracy on the morning/afternoon acquisitions [79]. Phenological variations also cause further problems with monitoring on a seasonal basis. The spectral properties of oil palm trees drastically change during flowering and fruiting stages, and CNN models lose up to 8-14% of their accuracy during flowering times. The requirement of seasonal retraining or domain adaptation to enable the continuation of uniform performance was documented in a 24-month study [51].

7.2 Limitations to model performance and generalization

7.2.1 Age-dependent detection and intra-class variability

The morphological changes in oil palm trees are dramatic throughout the life span (25-30 years) such as young trees (0-3 years) have a canopy diameter of 2-4 meters with clear patterns of the fronds, adolescent trees (4-7 years) grow on 4-6 meters canopies with growing overlaps, mature trees (> 8 years) grow on 6-9 meters canopies with complex pattern of the crown [177]. This variance generates systematic detection biases. Li et al. (2017) also obtained F1-scores of 97.1% on mature trees and 84.3% on young trees with the same CNN structures [94]. Recent research by Liu et al. (2021) employed Faster R-CNN for automatic detection and counting of oil palm trees from UAV images, achieving overall detection accuracies of 97.06%, 96.58%, and 97.79% across three different plantation sites [55]. Mixed-age plantations have bimodal error distributions, where errors are 15-18% heavy on false negative with young trees (miss) and errors are 8-12% heavy on false positive with mature trees (false counting due to crown segmentation failures) [19]. There is further complexity in health status and CNN models trained on healthy trees degrade their accuracy by 22-31 percent when exposed to stressed trees with lower frond counts, yellowing, or asymmetric growth [20].

7.2.2 Cross-regional generalization and deployment constraints

Geographic transferability is a severe constraint to operational implementation. In a broad research that trained ResNet-50s on Malaysian plantation data (98.3% validation accuracy), accuracy dropped to 76.4% in Indonesian test data, which is a 21.9 percentage point drop [40]. This generalization gap is caused by difference in cultivar, difference in management practice and perspective distortions due to terrain. Models that are having knowledge of properly managed industrial plantation at the 9m x 9m spacing have 18-28 percent reduction in the accuracy when they are used in the small holder farms with irregular spacing and intercropping activities [43]. In mature plantations, the main cause of limitations are the occlusion and overlapping. Mature trees (> 12 years) grow 15-30% of the crown overlap with a standard 9m x 9m triangular separations, forming the crown diameters of 7-9 meters, and hence 15-30 meters wide [41]. According to Shafri et al. (2011), accuracy has decreased to 78% in mature stands, and even more recent deep learning methods are not yet up to this, with the accuracy decreasing to 87.3% when the area is densely planted. Shadow-based occlusions introduce up to 11-16% of accuracy loss, especially in acquisitions during the morning and late afternoon [75].

7.3 Computational conditions and deployment constraints

7.3.1 Training costs and processing requirements

The computational costs of training state-of-the-art models have considerable importance. An architecture of YOLO$_{v8}$ with 5,000 high-resolution images with 300 epochs takes 45-72 GPU-hours on NVIDIA RTX 3090, although more complicated architectures such as Faster R-CNN can also require 120-180 hours [86]. In the commercial cloud (GPU) rates ($1.50-$2.50/hour), standard models take between $225-$700 and premium architecture costs can take between $525-$1300 to train. Hyperparameter optimization increases these expenses, and generally demands 15-40 independent training replicas costing 1,500-4,000 GPU-hours (2,250-10,000) [64, 65]. Inference speed produces operational bottlenecks. Faster R-CNN can take 450-650 milliseconds (1.5-2.2 FPS) to scan single 1280x960 images on high-end GPUs, and takes 60-130 GPU-hours to scan a 1,000-hectare plantation [178]. Lighter architectures like YOLO$_{V8}$-nano attain 8-12 FPS but lose 4-7 percentage points in mAP. The presented case of edge deployment on Raspberry Pi 4B with Intel Neural Compute Stick 1 results in 2.4 FPS as compared to 10 FPS on Intel Core i7-8665U a 76% performance loss [179, 180].

7.3.2 Scalability challenges and cost-benefit analysis

Super-linear scaling is a challenge for large-scale implementation. The edge effects and image mosaicking requirements increase processing requirements by 18-21 times the linear projections [181]. Storage requirements expand quite quickly, for example 10,000-hectare plantation yields 450-650 GB of raw images as well as 180-280 GB of processing intermediates. Continued monitoring of the same after 5 years of quarterly monitoring will yield 12-18 TB per plantation. The remote locations have network bandwidth constraints (5-25 Mbps average) that cause 44-222 hour delays in transferring 500 GB datasets [182, 183]. In economic analysis, there is scale-dependent feasibility. Depending on the common patterns of deployment of precision agriculture, medium-to-large enterprises ($\geq$1,000 hectares) can become economically equal to the footprint of manual operation within several years, taking into consideration the initial development costs and maintenance costs [184, 185]. However, the smallholder operations (50-500 hectares) incur significantly greater costs per-hectare which are economically prohibitive but the ultra-large operations (>50,000 hectares) have the most favorable economics due to economies of scale [186].

7.4 Integration barriers and practical implementation challenges

7.4.1 System integration and operational Implementation

The integration of automated systems into existing plantation management systems faces several technical challenges. A survey of 12 large operators revealed that 9 did not have automated ingestion pipelines of deep learning outputs and require manual data entry or custom script development [187]. The incompatibility of data formatting, the mismatch of geospatial coordinate systems (adding 0.5-2.5 meters of positioning errors) and time entities (2-7 day processing lags) result in persistent operational tension [188, 189]. Technical problems are complicated by human capacity limitations. Nine percent of agricultural employees of the surveyed plantations were knowledgeable in machine learning, 23% were knowledgeable in GIS, and 31% in basic remote sensing [190]. Extensive training of about 60 hours would cost about 4500 per head, annual staff turnover is estimated 20% and will force the company to invest and re-invest. Salaries of data scientists (around 60,000) are significantly higher than those of agricultural technicians (around 23,000), and this makes it hard to recruit such specialists in rural areas [37, 191].

7.4.2 Reliability and System maintenance

Production deployment demands 98-99% system uptime, but models experience gradual performance degradation. Longitudinal studies tracking models over 36 months without retraining document 8-14% accuracy losses as plantation conditions evolve [192]. To sustain performance, retraining (30-60 GPU-hours and 500-1,000 new images per cycle labeled) is necessary after every 6-12 months. Hardware used in field applications in the tropics has a failure rate of 12-18 percent per annum because of heat, humidity and electrical problems [193]. Regulatory compliance introduces additional complexity. The EU Deforestation Regulation (effective December 2024) requires verifiable monitoring systems, but certification bodies have not yet established standards for AI-derived data [194]. RSPO certification audits found that current automated systems meet $\pm$5% accuracy tolerance requirements in only 67% of test scenarios, below certification acceptance thresholds [195]. Data privacy concerns (GDPR, PDPA) and unresolved liability questions for AI-derived decision errors create further barriers to widespread adoption.

7.5 Emerging challenges and future constraints

Stability and longevity of the model can be affected by the climate changes. Temperature increases of approximately 2°C projected for equatorial Southeast Asia by 2050 will alter tree phenology and morphology, potentially requiring an estimated 4-5 model retraining cycles per decade rather than current 1-2 cycle expectations [196]. Changing precipitation patterns (estimated 40% increase in extreme events) may increase unusable imagery from current 35-45% to around 52-55%, significantly raising monitoring costs. Disease pressure changes driven by climate shifts project that approximately 23% of trees may exhibit symptoms currently underrepresented in training datasets by 2040 [197, 198]. Technological evolution creates both opportunities and obsolescence risks. Next-generation compact cultivars (approximately 25% smaller canopy diameter for high-density planting) projected for deployment in 2025-2030 will require model retraining or transfer learning [199]. Expanding cultivar diversity from current 3-5 to around 15 commercially significant types dramatically increases training data requirements [200]. Rapid edge AI hardware evolution (Intel NCS1 to NCS2 with 3x performance gains, to Edge TPU with approximately 6-7x gains) requires maintaining parallel model variants optimized for different platforms, multiplying development effort by an estimated 3x [201]. Social and ethical implications warrant consideration. Widespread AI adoption could reduce manual monitoring labor demand by approximately 67%, potentially affecting an estimated 6,500 jobs in Malaysia's palm oil sector alone [202]. Technology access disparities between large industrial operations and smallholders managing 90% of some producing regions' palm oil area risk exacerbating existing inequalities [203]. While AI-enabled monitoring could support sustainable practices, the same technology facilitates expansion into marginal lands by reducing monitoring costs creating environmental paradoxes requiring governance frameworks currently largely absent

[204]. These challenges collectively demonstrate that while deep learning technologies have achieved impressive proof-of-concept results, significant technical, economic, and institutional barriers remain for widespread operational deployment. Addressing these limitations requires coordinated efforts spanning algorithm development, infrastructure investment, capacity building, and policy frameworks to enable the transition from research prototypes to production-ready systems for oil palm plantation management.

8. Future directions in Oil palm deep learning

There are several considerable challenges before deep learning models become accessible in oil palm management. The preset section sets out some of the key research questions, technical advances and strategic recommendations required to advance the development of sound and scalable solutions for the global oil palm sector.

8.1 Critical research questions

Four fundamental research questions must be addressed to enable practical deployment. First, how can CNN architectures maintain detection accuracy exceeding 95% across all age groups while processing 1,000-hectare plantations within practical computational budgets? Current systems show persistent 9.6 percentage point accuracy gaps between mature and young trees. Solutions may include multi-scale feature pyramids with age-specific attention mechanisms, mixture-of-experts architectures with specialized sub-networks, and synthetic data augmentation for underrepresented age groups. Second, what transfer learning and domain adaptation strategies can reduce cross-regional performance degradation from 21.9 to below 10 percentage points while requiring fewer than 500 annotated images from target regions? Research must evaluate domain-invariant learning approaches, few-shot learning frameworks, and optimal pre-training strategies to enable models trained in one region to generalize effectively to others. Third, can model compression techniques achieve inference below 100 milliseconds per image on edge devices while maintaining greater than 90% of full-precision accuracy? Current models entail 450-650 ms on high-end GPUs and there is a 76% performance degradation at edge devices. There are huge transfer delays at remote locations which lead to the importance of edge processing. Systematic evaluation of quantization, pruning, knowledge distillation, and neural architecture search is needed to determine optimal compression strategies. Fourth, which multimodal sensor fusion architecture optimizes the trade-off between accuracy improvement and acquisition cost when integrating RGB imagery with complementary data sources? Atmospheric haze reduces RGB accuracy by 12-18%, while seasonal changes cause 8-14% degradation, suggesting that fusion with multispectral, LiDAR, or SAR data may provide substantial benefits. Research must quantify accuracy gains versus cost increases for different sensor combinations and operational scales.

8.2 Essential technical innovations

Architectural advances must include multi-scale adaptive attention mechanisms that dynamically adjust receptive fields based on tree age, explicit occlusion handling through a modal completion sub-networks and overlap-aware detection, and uncertainty-aware prediction heads enabling human-in-the-loop validation of ambiguous cases. Algorithm-level innovations should focus on contrastive learning for domain-invariant features through self-supervised pre-training on large unlabelled plantation datasets, curriculum learning strategies addressing bimodal error distributions across age groups, and hardware-aware neural architecture search automatically optimizing models for target deployment platforms. Operational deployment involves systematic model compression through quantization, reducing and data distillation. This approach attains 8-10 times computational acceleration. Data strategies should use advanced expansion and synthetic data generation, lowering annotation expenses by 60-80%. These technical innovations must be validated through rigorous benchmarking on diverse datasets spanning multiple geographic regions, age distributions, and environmental conditions.

8.3 Research priorities

Short-term priorities spanning 1-3 years should focus on establishing standardized benchmark datasets with 10,000+ annotated images covering diverse conditions and released under permissive licenses, developing cross-plantation validation protocols requiring testing on multiple sites not represented in training data, creating edge-optimized model variants with documented accuracy-latency-energy trade-offs for common hardware platforms, and defining integration standards with APIs and connectors for existing plantation management systems. These foundational efforts require an estimated investment of approximately $750,000, achievable through consortium funding, and are essential prerequisites for subsequent advances. Long-term priorities spanning 3-5+ years should pursue foundation models for agricultural remote sensing through massive pre-training on approximately 50 million images enabling few-shot adaptation to new regions with fewer than 100 labeled examples, self-supervised and weakly-supervised learning methods reducing annotation requirements by approximately 75% to democratize access for resource-constrained organizations, digital twin integration combining detection with crop growth models and decision support systems for prescriptive recommendations achieving estimated yield improvements of 7-8%, and climate-adaptive systems maintaining accuracy over 10-year deployments despite phenological changes from temperature increases and precipitation pattern shifts. The realization of these transformational advancements will require continued assets of about US$12 million for a decade from either government bodies, industry consortiums, or international funding agencies.

8.4 Implementation pathway

Near-term actions for 2025-2026 should establish research consortiums and data sharing agreements, release first benchmark datasets with approximately 10,000 images from five regions, initiate around 20 industry pilot deployments on sites averaging 30 hectares, develop regulatory frameworks with certification bodies, and launch funding programs adding approximately $5 million. By 2027-2028, foundation models will attain cross-regional gaps below 12% points. Organization will scale to 250 sites (7-8% of huge operations). Ecosystem evolution includes training 750 specialists, confirming 6-7 vendors, and securing certification body acceptance of AI data. Long-term transformation projected for 2029-2035 to achieve about 60% market penetration over an estimated 11-12 million hectare area, drive adoption among smallholders to around 7-8% using cooperative modalities, representing yield improvements of 7-8% and related input cost reductions of about 12-13%. This will expand the applicability of technologies to about 10 additional crop types and build a pool of world class talent of around 5 thousand specialists operating in more than a hundred countries. These goals can be achieved in the presence of a sustained financial commitment of about USD 15 million for research, about USD 750 million for industrial implementation and about USD 75 million committed to policy support over a ten-year horizon. This endeavor required the development of collaborative ecosystems that will upgrade the competitive concerns the understanding of technical breakthroughs in foundation modelling and edge computing, comprehensive workforce development programmes, and regulatory frameworks that will provide obvious standards and financial imperatives.

9. Conclusions

This systematic review shows that deep learning technologies, and convolutional neural networks (CNNs) have changed the way oil palm tree detection and counting methodologies are done, thus creating scalable approaches to replace the traditional plantation management technologies. The progress from labor-intensive manual counting strategies, that operationally result in an error rate of 15-25% to fully automated AI based systems with an accuracy of over 95% is a paradigm shift toward precision agriculture in tropical plantation systems. The comprehensive analysis emphasizes in Malaysia as a major player in promoting these applications through the support of collaborative networks spanning 22 countries. Current architectures of CNN models equipped with an augmented YOLO framework and transformer-based attention mechanism achieved optimal performance with high detection accuracy and efficient computation that can be applicable in large-scale implementation. However, there are still some critical challenges. The generalization of the model across diversified plantation conditions remains challenging, with cross-regional accuracy reduction that reached to about 21.9% points. Additionally, computational scalability for processing of high-resolution imagery over large areas also requires continuous algorithmic and hardware optimization. These challenges need well-organized and directed action across technical, institutional, and operational domains. Researchers are therefore required to design uniform standard benchmark datasets with a minimum of 10,000 annotated images in diverse environmental conditions. They should propose stringent cross-regional validation protocols with statistical significance testing, work towards edge-optimized architectures with inference times of <100 millisecond without sacrificing accuracy $>90\%$, progress towards transfer learning techniques where adaption task is less than 500 images for each region, and explore multi-modal combination approaches with satellite imagery, unmanned aerial vehicle and Internet of Things. Industry stakeholders need to initiate phased possible deployment through 10-50 hectare size pilot studies before the large-scale operation. The investments in hybrid cloud-edge infrastructures becoming rate equivalence within 2-3 years, multi-organization data-sharing consortiums and extensive 80-120 hours of workforce training should be launched. It should also actively engage with certification bodies such as RSPO, ISCC and EU authorities to receive prescribed acceptance of AI- derived monitoring data. The economic implications are not restricted only to the improvements in operational productivity. Enhanced monitoring resources for conformity with changing sustainability requirements such as the Europe's Deforestation Regulation, as well as certification processes and data-based resource optimization are possible. These advancements put the oil-palm industry in a good position to meet the challenges of the day, such as climate change adaptation, labor shortage mitigation, and sustainable improvement of production (sustainable intensification). The coincidence of deep learning and the principles of precision agriculture gives the opportunity for optimizing plantation productivity, as never before, while preserving environmental care. Coordinated action, in addressing technical challenges and institutions and equitable access considerations, will ensure that technological advancement benefits the entire oil-palm sector and leads to the advancement of global sustainability objectives.

Authors' contribution

All authors contributed equally to the preparation of this article.

Declaration of competing interest

The authors declare no conflicts of interest.

Funding source

This work was made possible in part by the Short-Term Grant; grant number 304/PAERO/6315761.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgements

The Innovative System and Instrumentation Lab at School of Aerospace Engineering, University Sains Malaysia supports this research. Special thanks to En. Mohamad Zihad Mahmud for assisting with data acquisition using drone.

References

[1] OECD/FAO, "OECD-FAO agricultural outlook 2024-2033," 2024. [Online]. Available: https://www.oecd.org/en/publications/2024/07/oecd-fao-agricultural-outlook-2024-2033_e173f332.html

[2] L. Berning and M. Sotirov, "The coalitional politics of the european union regulation on deforestation-free products," *Forest Policy and Economics*, vol. 158, p. 103102, 2024. [Online]. Available: https://doi.org/10.1016/j.forpol.2023.103102

[3] E. Meijaard, T. Brooks, K. Carlson, and et al., "The environmental impacts of palm oil in context," *Nature plants*, vol. 6, pp. 1418–1426, 2020. [Online]. Available: https://doi.org/10.1038/s41477-020-00813-w

[4] H. Tandra, A. I. Suroso, Y. Syaukat, and M. Najib, "The determinants of competitiveness in global palm oil trade," *Economies*, vol. 10, no. 6, p. 132, 2022. [Online]. Available: https://doi.org/10.3390/economies10060132

[5] H. Purnomo, B. Okarda, A. Dermawan, and et al., "Reconciling oil palm economic development and environmental conservation in indonesia: A value chain dynamic approach," *Forest Policy and Economics*, vol. 111, p. 102089, 2020. [Online]. Available: https://doi.org/10.1016/j.forpol.2020.102089

[6] A. Kushairi, R. Singh, and M. Ong-Abdullah, "The oil palm industry in Malaysia: Thriving with transformative technologies," *J. Oil Palm Res*, vol. 29, no. 4, pp. 431–439, 2017. [Online]. Available: https://doi.org/10.21894/jopr.2017.00017

[7] D. Murphy, K. Goggin, and R. Paterson, "Oil palm in the 2020s and beyond: challenges and solutions," *CABI Agriculture and Bioscience*, vol. 2, no. 1, p. 39, 2021. [Online]. Available: https://doi.org/10.1186/s43170-021-00058-3

[8] K. Tang and H. A. Qahtani, "Sustainability of oil palm plantations in Malaysia," *Environment, Development and Sustainability*, vol. 22, pp. 4999–5023, 2020. [Online]. Available: https://doi.org/10.1007/s10668-019-00458-6

[9] R. Paterson, "Longitudinal trends of future climate change and oil palm growth: empirical evidence for tropical Africa," *Environmental Science and Pollution Research*, vol. 28, no. 17, pp. 21 193–21 203, 2021. [Online]. Available: https://doi.org/10.1007/s11356-020-12072-5

[10] F. Gaudiosi, "Ilo and the protection of female migrant domestic workers: Ongoing limits and recent developments," *International Migration and the Law*, pp. 129–148, 2024. [Online]. Available: https://doi.org/10.4324/9781003488569

[11] F. Mieres, "Migrant labour recruitment in a globalizing world," *Handbook of Migration and Globalisation*, 2024. [Online]. Available: https://doi.org/10.4337/9781800887657.00015

[12] M. Qaim, K. T. Sibhatu, H. Siregar, and I. Grass, "Environmental, economic, and social consequences of the oil palm boom," *Annual Review Resource Economics*, vol. 12, pp. 321–344, 2020. [Online]. Available: https://doi.org/10.1146/annurev-resource-110119-024922

[13] FAO, "FAOSTAT statistical database. food and agriculture organization," *Materials research forum llc*, 2024. [Online]. Available: https://www.fao.org/faostat/en/

[14] C. I. Ludemann, N. Wanner, P. Chivenge, and et al., "A global FAOSTAT reference database of cropland nutrient budgets and nutrient use efficiency (1961–2020): nitrogen, phosphorus and potassium," *Earth System Science Data*, vol. 16, no. 1, pp. 525–541, 2024. [Online]. Available: https://doi.org/10.5194/essd-16-525-2024

[15] F. Grande, Y. Ueda, S. Masangwi, and B. Holmes, "Global nutrient conversion table for FAO supply utilization accounts," *FAO Knowledge Repository*, 2024. [Online]. Available: https://doi.org/10.4060/cc9678en

[16] ADB, "Asian economic integration report 2025: Harnessing the benefits of regional cooperation and integration," *A.D.B.*, 2025. [Online]. Available: https://doi.org/10.22617/SGP250106-2

[17] Service. U.F.A, "Oilseeds: World markets and trade," *Data and Analysis, United States Department of Agriculture*, 2024. [Online]. Available: https://fas.usda.gov/sites/default/files/2024-12/oilseeds.pdf

[18] Z. Ali, A. Muhammad, N. Lee, M. Waqar, and S. W. Lee, "Artificial intelligence for sustainable agriculture: a comprehensive review of ai-driven technologies in crop production," *Sustainability*, vol. 17, no. 5, p. 2281, 2025. [Online]. Available: https://doi.org/10.3390/su17052281

[19] Y. Putra and A. Wijayanto, "Automatic detection and counting of oil palm trees using remote sensing and object-based deep learning," *Remote Sensing Applications: Society and Environment*, vol. 29, p. 100914, 2023. [Online]. Available: https://doi.org/10.1016/j.rsase.2022.100914

[20] O. Kent, T. Chun, T. Choo, and L. Kin, "Early symptom detection of basal stem rot disease in oil palm trees using a deep learning approach on UAV images," *Computers and Electronics in Agriculture*, vol. 213, p. 108192, 2023. [Online]. Available: https://doi.org/10.1016/j.compag.2023.108192

[21] G. Farjon, L. Huijun, and Y. Edan, "Deep-learning-based counting methods, datasets, and applications in agriculture: A review," *Precision Agriculture*, vol. 24, no. 5, pp. 1683–1711, 2023. [Online]. Available: https://doi.org/10.1007/s11119-023-10034-8

[22] P. N. Chowdhury, P. Shivakumara, and et al., "Oil palm tree counting in drone images," *Pattern Recognition Letters*, vol. 153, pp. 1–9, 2022. [Online]. Available: https://doi.org/10.1016/j.patrec.2021.11.016

[23] K. Kipli, S. Osman, A. Joseph, H. Zen, and et al., "Deep learning applications for oil palm tree detection and counting," *Smart Agricultural Technology*, vol. 5, p. 100241, 2023. [Online]. Available: https://doi.org/10.1016/j.atech.2023.100241

[24] H. Hoppe, P. Dietrich, P. Marzahn, T. Weib, C. Nitzsche, U. F. von Lukas, and et al., "Transferability of machine learning models for crop classification in remote sensing imagery using a new test methodology: a study on phenological, temporal, and spatial influences," *Remote sensing*, vol. 16, no. 9, p. 1493, 2024. [Online]. Available: https://doi.org/10.3390/rs16091493

[25] S. K. Phang, T. H. A. Chiang, and et al., "From satellite to UAV-based remote sensing: a review on precision agriculture," *IEEE access*, vol. 9, no. 11, pp. 127 057–127 076, 2023. [Online]. Available: https://doi.org/10.1109/ACCESS.2023.3330886

[26] M. Farhan, M. Akhtar, and E. Bakar, "Efficient real-time palm oil tree detection and counting using YOLOv8 deployed on edge devices," *Journal of Umm Al-Qura University for Engineering and Architecture*, vol. 16, p. 1293–1308, 2025. [Online]. Available: https://doi.org/10.1007/s43995-025-00164-7

[27] J. Nyakuri, C. Nkundineza, O. Gatera, and et al., "AI and IoT-powered edge device optimized for crop pest and disease detection," *Scientific Reports*, vol. 15, no. 1, p. 22905, 2025. [Online]. Available: https://doi.org/10.1038/s41598-025-06452-5

[28] E. Charou and et al., "Deep learning for agricultural land detection in insular areas," *International conference on Information, intelligence, systems and applications (IISA)*, pp. 1–4, 2019. [Online]. Available: https://doi.org/10.1109/iisa.2019.8900670

[29] A. Dosovitskiy and et al., "An image is worth 16x16 words: transformers for image recognition at scale," *Arxiv preprint arxiv:2010.11929*, pp. 6958–6979, 2020. [Online]. Available: https://doi.org/10.48550/arXiv.2010.11929.2020

[30] A. Kirillov and et al., "segment anything," *International Conference on Computer Vision*, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2304.02643

[31] W. Yun and et al., "Digital transformation in reshaping industries, in perspectives on digital transformation in contemporary business," *IGI Global Scientific Publishing*, vol. 31, pp. 143–172, 2025. [Online]. Available: https://doi.org/10.4018/979-8-3693-5966-2.ch006

[32] M. Piasentini and A. Iannone, "Italian engagement with southeast Asia: economic, political and security cooperation with ASEAN and its member states," *EUI, RSC, Policy Paper*, vol. 130, p. 100963, 2025. [Online]. Available: https://hdl.handle.net/1814/92791

[33] N. Khan, M. A. Kamaruddin, U. U. Sheikh, Y. Yusup, and M. P. Bakht, "Oil palm and machine learning: Reviewing one decade of ideas, innovations, applications, and gaps," *Agriculture*, vol. 11, no. 9, 2021. [Online]. Available: https://www.mdpi.com/2077-0472/11/9/832

[34] R. M. F. R. F. N.Mohd Nain, N. H. Ahamed Hassain Malim, "A review of an artificial intelligence framework for identifying the most effective palm oil prediction," *Algorithms*, vol. 15, no. 6, p. 218, 2022. [Online]. Available: https://doi.org/10.3390/a15060218

[35] K. Kipli, S. Osman, A. Joseph, and et al, "Deep learning applications for oil palm tree detection and counting," *smart agricultural technology*, vol. 5, p. 100241, 2023. [Online]. Available: https://doi.org/10.1016/j.atech.2023.100241

[36] H. Zhao and et al., "A systematic review of individual tree crown detection and delineation with convolutional neural networks (CNN)," *Current forestry reports*, vol. 9, no. 3, pp. 149–170, 2023. [Online]. Available: https://doi.org/10.1007/s40725-023-00184-3

[37] A. Kamilaris and F. Prenafeta-Boldu, "Deep learning in agriculture: a survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018. [Online]. Available: https://doi.org/10.1016/j.compag.2018.02.016

[38] R. B. de Lima, E. Rutishauser, J. A. A. da Silva, and et al., "Accurate estimation of commercial volume in tropical forests," *Forest science*, vol. 67, no. 1, pp. 14–21, 2021. [Online]. Available: https://doi.org/10.1093/forsci/fxaa032

[39] N. Mubin, E. Nadarajoo, H. Shafri, and A. Hamedianfar, "Young and mature oil palm tree detection and counting using a convolutional neural network deep learning method," *International Journal of Remote Sensing*, vol. 40, no. 19, pp. 7500–7515, 2019. [Online]. Available: https://doi.org/10.1080/01431161.2019.1569282

[40] H. Wibowo, I. S. Sitanggang, M. Mushthofa, and H. Adrianto, "Large-scale oil palm trees detection from high-resolution remote sensing images using deep learning," *Big data and cognitive computing*, vol. 6, no. 3, p. 89, 2022. [Online]. Available: https://doi.org/10.3390/bdcc6030089

[41] S. S. Lee, L. G. Lim, S. Palaiahnakote, and et al., "Oil palm tree detection in uav imagery using an enhanced retina net," *Computers and Electronics in Agriculture*, vol. 227, no. part-1, p. 109530, 2024. [Online]. Available: https://doi.org/10.1016/j.compag.2024.109530

[42] M. Gibril and et al., "Deep convolutional neural network for large-scale date palm tree mapping from UAV-based images," *Remote Sensing*, vol. 13, no. 14, p. 2787, 2021. [Online]. Available: https://doi.org/10.3390/rs13142787

[43] M. Culman, Delalieux, and K. V. Tricht, "Individual palm tree detection using deep learning on rgb imagery to support tree inventory," *Remote Sensing*, vol. 12, no. 21, p. 3476, 2020. [Online]. Available: https://doi.org/10.3390/rs12213476

[44] R. W. D. J. L. J. S. Xu, B. Yang, "Single tree semantic segmentation from uav images based on an improved U-Net network," *Drones*, vol. 9, no. 4, p. 237, 2025. [Online]. Available: https://doi.org/10.3390/drones9040237

[45] S. F. D. G. Riccardo Dainelli, Piero Toscano and A. Matese, "Recent advances in unmanned aerial vehicle forest remote sensing—a systematic review. part I: A general framework," *forests*, vol. 12, no. 3, p. 327, 2021. [Online]. Available: https://doi.org/10.3390/f12030327

[46] Y. Guofeng, H. Yong, F. Xuping, and et al., "Methods and new research progress of remote sensing monitoring of crop disease and pest stress using unmanned aerial vehicle," *Smart Agriculture*, vol. 4, no. 1, pp. 1–16, 2022. [Online]. Available: https://doi.org/10.12133/j.smartag.SA202201008

[47] M. A. Asming, A. M. Ibrahim, and I. Abir, "Processing and classification of landsat and sentinel images for oil palm plantation detection," *Remote sensing applications: Society and environment*, vol. 26, no. 1, p. 100747, 2022. [Online]. Available: https://doi.org/10.1016/j.rsase.2022.100747

[48] R. Al-ruzouq, M. B. A. Gibril, and et al., "Spectral–spatial transformer-based semantic segmentation for large-scale mapping of individual date palm trees using very high-resolution satellite data," *Ecological Indicators*, vol. 163, p. 112110, 2024. [Online]. Available: https://doi.org/10.1016/j.ecolind.2024.112110

[49] F. Nex, C. Armenakis, D. M. Cramer, Cucci, and et al., "UAV in the advent of the twenties: where we stand and what is next," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 184, pp. 215–242, 2022. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2021.12.006

[50] A. al Abdouli, "hyperspectral properties of date palm trees (Phoenix dactylifera L.)," *Electronic Theses and Dissertations , UAEU Theses*, 2020. [Online]. Available: https://scholarworks.uaeu.ac.ae/all_theses/813

[51] e. a. yarak, k., "Oil palm tree detection and health classification on high-resolution imagery using deep learning," *Agriculture*, vol. 11, no. 2, p. 183, 2021. [Online]. Available: https://doi.org/10.3390/agriculture11020183

[52] G. Lassalle, M. P. Ferreira, and et al., "Deep learning-based individual tree crown delineation in mangrove forests using very-high-resolution satellite imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 189, no. 2, pp. 220–235, 2022. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2022.05.002

[53] C. Zhang, A. Marzougui, and S. Sankaran, "High-resolution satellite imagery applications in crop phenotyping: an overview," *Computers and Electronics in Agriculture*, vol. 175, p. 105584, 2020. [Online]. Available: https://doi.org/10.1016/j.compag.2020.105584

[54] S. Miao and et al., "Spatial quality enhancement for wide view angle images: a sensor-specific pre-processing algorithm case study on FY-3D MERSI-II," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 25, no. 4, p. 183, 2024. [Online]. Available: https://doi.org/10.1109/tgrs.2024.3386157

[55] X. Liu and et al., "Automatic detection of oil palm trees from UAV images based on the deep learning method," *applied artificial intelligence*, vol. 35, no. 1, pp. 13–24, 2021. [Online]. Available: https://doi.org/10.1080/08839514.2020.1831226

[56] S. Puttinaovarat and P. Horkaew, "Deep and machine learning of remotely sensed imagery and its multi-band visual features for detecting oil palm plantation," *Earth science Informatics*, vol. 12, pp. 429–446, 2019. [Online]. Available: https://doi.org/10.1007/s12145-019-00387-y

[57] P. Kundu, "Effectiveness of edge detection of color images," vol. 14, no. 4, p. 482, 2020. [Online]. Available: http://lib.buet.ac.bd:8080/xmlui/handle/123456789/5764

[58] P. Kundu, Z. Hao, C. J. Post, E. A. Mikhailova, L. Lin, and et al., "Comparison of classical methods and mask R-CNN for automatic tree detection and mapping using UAV imagery," *Remote sensing*, vol. 14, no. 2, p. 295, 2022. [Online]. Available: https://doi.org/10.3390/rs14020295

[59] F. H. Wagner, M. P. Ferreira, and et al., "Individual tree crown delineation in a highly diverse tropical forest using very high resolution satellite images," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 145, no. part B, pp. 362–377, 2018. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2018.09.013

[60] C. Hamsa, K. Kanniah, F. Muharam, N. Idris, Z. Abdullah, and L. Mohamed, "Textural measures for estimating oil palm age," *International Journal of Remote Sensing*, vol. 40, no. 19, pp. 7516–7537, 2019. [Online]. Available: https://doi.org/10.1080/01431161.2018.1530813

[61] B. Varghese and et al., "Spatial assessments in texture analysis: what the radiologist needs to know," *Frontiers In Radiology*, vol. 3, p. 1240544, 2023. [Online]. Available: https://doi.org/10.3389/fradi.2023.1240544

[62] J. Zeng, X. Shen, K. Zhou, and L. Cao, "FO-Net: An advanced deep learning network for individual tree identification using uav high-resolution images," *ISPRS Journal of Photogrammetry and*

Remote Sensing, vol. 220, no. 7, pp. 323–338, 2025. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2024.12.020

[63] H. Cheng, Y. Wang, L. Shan, Y. Chen, and et al., "Mapping fine-scale carbon sequestration benefits and landscape spatial drivers of urban parks using high-resolution UAV data," *Journal of Environmental Management*, vol. 370, no. 4, p. 122319, 2024. [Online]. Available: https://doi.org/10.1016/j.jenvman.2024.122319

[64] E. Sun and et al., "A decade of deep learning for remote sensing spatiotemporal fusion: Advances, challenges, and opportunities," *ArXiv preprint arXiv*, 2025. [Online]. Available: https://doi.org/10.48550/arXiv.2504.00901

[65] Y.-M. Qin, Y.-H. Tu, T. Li, Y. Ni, R.-F. Wang, and H. Wang, "Deep learning for sustainable agriculture: A systematic review on applications in lettuce cultivation," *Sustainability*, vol. 17, no. 7, p. 3190, 2025. [Online]. Available: https://doi.org/10.3390/su17073190

[66] H. Shafri, N. Hamdan, and M. Saripan, "Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery," *International Journal of Remote Sensing*, vol. 32, no. 8, pp. 2095–2115, 2011. [Online]. Available: https://doi.org/10.1080/01431161003662928

[67] A. Hinze, J. Konig, and J. Bowen, "Worker-fatigue contributing to workplace incidents in new zealand forestry," *Journal of safety research*, vol. 79, pp. 304–320, 2021. [Online]. Available: https://doi.org/10.1016/j.jsr.2021.09.012

[68] M. Gasparovic and I. Balenovic, "An evaluation of pixel-and object-based tree species classification in mixed deciduous forests using pansharpened very high spatial resolution satellite imagery," *Remote sensing*, vol. 13, no. 10, p. 1868, 2021. [Online]. Available: https://doi.org/10.3390/rs13101868

[69] B. Santoso, B. Hariadi, and M. Lekitoo, "Fermentation characteristics, in vitro nutrient digestibility, and methane production of oil palm frond-based complete feed silage treated with cellulase," *Adv. Anim. Vet. Sci*, vol. 12, no. 7, pp. 1394–1403, 2024. [Online]. Available: https://doi.org/10.17582/journal.aavs/2024/12.7.1394.1403

[70] N. Torbick, L. Ledoux, W. Salas, and M. Zhao, "Regional mapping of plantation extent using multisensor imagery," *Remote Sensing*, vol. 8, no. 3, p. 236, 2016. [Online]. Available: https://doi.org/10.3390/rs8030236

[71] J. Pirker, A. Mosnier, F. Kraxner, P. Havlik, and M. Obersteiner, "What are the limits to oil palm expansion?" *Global Environmental Change*, vol. 40, pp. 73–81, 2016. [Online]. Available: https://doi.org/10.1016/j.gloenvcha.2016.06.007

[72] J. Zheng, H. Fu, W. Li, W. Wu, and et al., "Growing status observation for oil palm trees using unmanned aerial vehicle (uav) images," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 173, pp. 95–121, 2021. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2021.01.008

[73] Y. Diez, S. Kentsch, M. Fukuda, M. Caceres, K. Moritake, and M. Cabezas, "Deep learning in forestry using UAV-acquired RGB data: A practical review," *Remote Sensing*, vol. 13, no. 14, p. 2837, 2021. [Online]. Available: https://doi.org/10.3390/rs13142837

[74] I. Wijaya, "Techniques for cheating detection. innovative approaches in computational systems and smart applications," *Progress in materials science*, vol. 136, p. 329, 2025. [Online]. Available: https://doi.org/10.4018/979-8-3693-9846-3.ch012

[75] C. S. Sanin, A. and B. Lovell, "Shadow detection: A survey and comparative evaluation of recent methods," *Pattern recognition*, vol. 45, no. 4, pp. 1684–1695, 2012. [Online]. Available: https://doi.org/10.1016/j.patcog.2011.10.001âĂŔ

[76] C. Hu, B. B. Sapkota, J. A. Thomasson, and M. V. Bagavathiannan, "Influence of image quality and light consistency on the performance of convolutional neural networks for weed mapping," *Remote Sensing*, vol. 13, no. 11, p. 2140, 2021. [Online]. Available: https://doi.org/10.3390/rs13112140

[77] X. Tan, "Generation of high-quality daily nighttime light time series through uncertainty modelling and cloud removal," *Remote sensing*, vol. 38, no. 10, pp. 1648–1660, 2023. [Online]. Available: https://theses.lib.polyu.edu.hk/handle/200/12742

[78] H. Vahidi, B. Klinkenberg, B. A. Johnson, L. M. Moskal, and W. Yan, "Mapping the individual trees in urban orchards by incorporating volunteered geographic information and very high resolution optical remotely sensed data: A template matching-based approach," *Remote Sens*, vol. 10, no. 7, p. 1134, 2018. [Online]. Available: https://doi.org/10.3390/rs10071134

[79] R. Hernawati, K. Wikantika, and S. Darmawan, "Modeling of oil palm phenology based on remote sensing data: opportunities and challenges," *Journal of Applied Remote Sensing*, vol. 16, no. 2, pp. 021 501–021 501, 2022. [Online]. Available: https://doi.org/10.1117/1.JRS.16.021501

[80] B. G. Ram, P. Oduor, C. Igathinathane, K.Howatt, and X. Sun, "Asystematic review of hyperspectral imaging in precision agriculture: Analysis of its current state and future prospects," *Computers and Electronics in Agriculture*, vol. 222, p. 109037, 2024. [Online]. Available: https://doi.org/10.1016/j.compag.2024.109037

[81] F. A. Azizan, A. M. Kiloes, I. S. Astuti, and A. A. Aziz, "Application of optical remote sensing in rubber plantations: A systematic review," *Remote Sensing*, vol. 13, no. 3, p. 429, 2021. [Online]. Available: https://doi.org/10.3390/rs13030429

[82] I. Goodfellow, Y. Bengio, and A. Courville, "Deep learning," *MIT press*, 2016. [Online]. Available: http://www.deeplearningbook.org

[83] D. Rumelhart, G. Hinton, and R. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, pp. 533–536, 1986. [Online]. Available: https://doi.org/10.1038/323533a0

[84] G. Hinton, S. Osindero, and Y. Teh, "A fast learning algorithm for deep belief nets ," *Neural Computation*, vol. 18, no. 7, pp. 1527–1554, 2006. [Online]. Available: https://doi.org/10.1162/neco.2006.18.7.1527

[85] Y. Bengio and T. M., "Learning, learning deep architectures for AI," *Foundations and Trends in Machine Learning*, vol. 2, no. 1, pp. 1–127, 2009. [Online]. Available: https://doi.org/10.1561/2200000006

[86] A. Zhang and et al., "Dive into deep learning," *Cambridge University Press*, vol. 26, 2023.

[87] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015. [Online]. Available: https://doi.org/10.1038/nature14539

[88] C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," *Electronic markets*, vol. 31, no. 3, pp. 685–695, 2021. [Online]. Available: https://doi.org/10.1007/s12525-021-00475-2

[89] M. M. Taye, "Understanding of machine learning with deep learning: architectures, workflow, applications and future directions," *Computers*, vol. 12, no. 5, p. 91, 2023. [Online]. Available: https://doi.org/10.3390/computers12050091

[90] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 8, pp. 1798–1828, 2013. [Online]. Available: https://doi.org/10.1109/TPAMI.2013.50

[91] A. Shawahna, S. Sait, and A. El-Maleh, "Fpga-based accelerators of deep learning networks for learning and classification: A review," *IEEE Access*, vol. 7, no. 4, pp. 7823–7859, 2018. [Online]. Available: https://doi.org/10.1109/ACCESS.2018.2890150

[92] I. Sarker, "Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions," *SN Computer Science*, vol. 2, p. 420, 2021. [Online]. Available: https://doi.org/10.1007/s42979-021-00815-1

[93] F. M. Shiri, T. Perumal, N. Mustapha, and R. Mohamed, "A comprehensive overview and comparative analysis on deep learning models: Cnn, rnn, lstm, gru," *Journal on Artificial Intelligence*, vol. 6, no. 1, pp. 301–360, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2305.17473

[94] B. G. Weinstein, S. Marconi, S. A. Bohlman, A. Zare, A. Singh, S. J. Graves, and E. P. White, "A remote sensing-derived data set of 100 million individual tree crowns for the national ecological observatory network," *eLife*, vol. 10, no. 17, p. e62922, 2021. [Online]. Available: https://doi.org/10.7554/eLife.62922

[95] Y. Li, W. Chen, v Y. Zhan g, and et al., "Accurate cloud detection in high-resolution remote sensing imagery by weakly supervised deep learning," *Remote Sensing of Environment*, vol. 250, p. 112045, 2020. [Online]. Available: https://doi.org/10.1016/j.rse.2020.112045

[96] W. Li, H. Fu, L. Yu, and A. Cracknell, "Deep learning based oil palm tree detection and counting for high-resolution remote sensing images," *Remote Sens*, vol. 9, no. 1, p. 22, 2017. [Online]. Available: https://doi.org/10.3390/rs9010022

[97] A. Allmendinger and et al., "Assessing the capability of yolo-and transformer-based object detectors for real-time weed detection," *Precision Agriculture*, vol. 26, no. 3, p. 52, 2025. [Online]. Available: https://doi.org/10.1007/s11119-025-10246-0

[98] M. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: classification and symptoms visualization," *Applied Artificial Intelligence*, vol. 31, no. 4, pp. 299–315, 2017. [Online]. Available: https://doi.org/10.1080/08839514.2017.1315516

[99] S. Mohanty, D. Hughes, and M. Salathe, "Using deep learning for image-based plant disease detection," *Front Plant Sci*, vol. 7, no. 1, p. 215232, 2016. [Online]. Available: https://doi.org/10.3389/fpls.2016.01419

[100] S. Khaki and L. Wang, "Crop yield prediction using deep neural networks," *Front. Plant Sci.*, vol. 10, p. 452963, 2019. [Online]. Available: https://doi.org/10.3389/fpls.2019.00621

[101] E. Cai, S. Baireddy, C. Yang, M. Crawford, and E. J. Delp, "Deep transfer learning for plant center localization," *Computer Vision and Pattern Recognition Workshops*, 2020. [Online]. Available: https://doi.org/10.48550/arXiv.2004.13973

[102] P. Hipgrave, "Using UAV imagery to perform fine-scale mapping of wetland vegetation," *Open Access Te Herenga Waka-Victoria University of Wellington*, 2020. [Online]. Available: https://doi.org/10.26686/wgtn.17148110

[103] N. Rai, Y. Zhang, B. G. Ram, and et al., "Applications of deep learning in precision weed management: A review," *Computers and Electronics in Agriculture*, vol. 206, p. 107698, 2023. [Online]. Available: https://doi.org/10.1016/j.compag.2023.107698

[104] L.Chen, B. Han, X. Wang, J. Zhao, W. Yang, and Z.Yang, "Machine learning methods in weather and climate applications: A survey," *Applied Sciences*, vol. 13, no. 21, p. 12019, 2023. [Online]. Available: https://doi.org/10.3390/app132112019

[105] X. Ren and et al., "Deep learning-based weather prediction: a survey," *Journal of Manufacturing and Materials Processing*, vol. 23, no. 1, p. 100178, 2021. [Online]. Available: https://doi.org/10.1016/j.bdr.2020.100178

[106] P. Nevavuori, N. Narra, and T. Lipping, "Crop yield prediction with deep convolutional neural networks," *Computers and Electronics in Agriculture*, vol. 163, p. 104859, 2019. [Online]. Available: https://doi.org/10.1016/j.compag.2019.104859

[107] K. G. Liakos, P.Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors*, vol. 18, no. 8, p. 2674, 2018. [Online]. Available: https://doi.org/10.3390/s18082674

[108] J. M. Bioucas-Dias, A. Plaza, G. Camps-Valls, P. Scheunders, and et al., "Hyperspectral remote sensing data analysis and future challenges," *IEEE Geoscience and Remote Sensing Magazine*, vol. 1, no. 2, pp. 6–36, 2013. [Online]. Available: https://doi.org/10.1109/MGRS.2013.2244672

[109] Y. B. LeCun, Y. and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015. [Online]. Available: https://doi.org/10.1038/nature14539

[110] T. Poggio, H. Mhaskar, L. Rosasco, and et al., "Why and when can deep-but not shallow-networks avoid the curse of dimensionality: a review," *International Journal of Automation and Computing*, vol. 14, no. 5, pp. 503–519, 2017. [Online]. Available: https://doi.org/10.1007/s11633-017-1054-2

[111] A. Krizhevsky, I. Sutskever, and G. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. 60, no. 6, pp. 84–90, 2012. [Online]. Available: https://doi.org/10.1145/3065386

[112] M. Awad and R. Khanna, "Efficient learning machines: Theories, concepts, and applications for engineers and system designers," *Deep neural networks*, vol. 209, no. 2, pp. 127–147, 2015. [Online]. Available: https://doi.org/10.1007/978-1-4302-5990-9

[113] H. Purwins and et al., "Deep learning for audio signal processing," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 2, pp. 206–219, 2019. [Online]. Available: https://doi.org/10.48550/arXiv.1905.00078

[114] L. Santos, F. N. D. Santos, P. M. Oliveira, and P. Shinde, "Deep learning applications in agriculture: A short review," *in Robot 2019: Fourth Iberian Robotics Conference: Advances in Robotics*, vol. 1, p. 139–151, 2020. [Online]. Available: https://doi.org/10.1007/978-3-030-35990-4_12

[115] L. Cohen, "Acknowledgments, in the early modern jesuit attitude towards hindu and ethiopian strains of asceticism," *Brill*, vol. 12, no. 6, pp. 2472–2488, 2023. [Online]. Available: https://doi.org/10.1016/j.jma.2024.06.003

[116] M. Zortea and et al., "Oil-palm tree detection in aerial images combining deep learning classifiers," *International Geoscience and Remote Sensing Symposium*, 2018. [Online]. Available: https://doi.org/10.1109/IGARSS.2018.8519239

[117] Y. Guo and et al., "Plant disease identification based on deep learning algorithm in smart farming," *Discrete Dynamics in Nature and Society*, vol. 130, pp. 1–11, 2020. [Online]. Available: https://doi.org/10.1155/2020/2479172

[118] Y. Sun and et al., "Deep learning for plant identification in natural environment," *Computational intelligence and neuroscience*, 2017. [Online]. Available: https://doi.org/10.1155/2017/7361042

[119] M. Arshed and et al., "A light-weight deep learning model for real-world plant identification," *in 2022 Second International Conference on Distributed Computing and High Performance Computing (DCHPC)*, 2022. [Online]. Available: https://doi.org/10.1109/DCHPC55044.2022.9731841

[120] P. Kanda, K. Xia, and O. Sanusi, "A deep learning-based recognition technique for plant leaf classification," *IEEE Access*, vol. 9, no. 1-2, pp. 162 590–162 613, 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3131726

[121] W. Li and et al., "Semantic segmentation-based building extraction method using multi-source GIS map datasets and satellite imagery. in proceedings of the ieee conference on computer vision and pattern recognition workshops. 2018. doi:10.1109/cvprw.2018.00043," *arxiv preprint arxiv*, no. 6, p. 03883, 2025. [Online]. Available: https://doi.org/10.48550/arXiv.2504.03883

[122] A. Olsen, D. Konovalov, B. Philippa, and et al., "Deepweeds: A multiclass weed species image dataset for deep learning," *Scientific reports*, vol. 9, no. 1, p. 2058, 2019. [Online]. Available: https://doi.org/10.1038/s41598-018-38343-3

[123] T. Liu and et al., "A deep neural network for the estimation of tree density based on high-spatial resolution image," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, no. 1, pp. 1–11, 2021. [Online]. Available: https://doi.org/10.1109/TGRS.2021.3101056

[124] P. Sermanet and et al., "Overfeat: Integrated recognition, localization and detection using convolutional networks," *arXiv preprint*, vol. 77, p. 5345–5361, 2013. [Online]. Available: https://doi.org/10.48550/arXiv.1312.6229

[125] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *ArXiv:1506.01497*, vol. 28, pp. 2788–2798, 2015. [Online]. Available: https://doi.org/10.48550/arXiv.1506.01497

[126] N. Mubin, E. Nadarajoo, H. Shafri, and A. Hamedianfar, "Young and mature oil palm tree detection and counting using a convolutional neural network deep learning method," *International Journal of Remote Sensing*, vol. 40, no. 19, pp. 7500–7515, 2019. [Online]. Available: https://doi.org/10.1080/01431161.2019.1569282

[127] R. Dong, W. Li, H. Fu, L. Gan, L. Yu, J. Zheng, and M. Xia, "Oil palm plantation mapping from high-resolution remote sensing images using deep learning," *International Journal of Remote Sensing*, vol. 41, no. 5, pp. 2022–2046, 2020. [Online]. Available: https://doi.org/10.1080/01431161.2019.1681604

[128] A. Krizhevsky, I. Sutskever, and G. Hinton, "Imagenet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017. [Online]. Available: https://doi.org/10.1145/3065386

[129] K. Heng and et al., "Healthy and unhealthy oil palm tree detection using deep learning method," *International Journal of Advanced Computer Science and Applications*, vol. 16, no. 4, 2025. [Online]. Available: https://doi.org/10.14569/ijacsa.2025.0160474

[130] H. Yao, R. Qin, and X. Chen, "Unmanned aerial vehicle for remote sensing applications—a review," *Remote Sensing*, vol. 11, no. 12, p. 1443, 2019. [Online]. Available: https://doi.org/10.3390/rs11121443

[131] F. Nex, C. Armenakis, M. Cramer, D. Cucci, M. Gerke, and et al., "UAV in the advent of the twenties: Where we stand and what is next," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 184, pp. 215–242, 2022. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2021.12.006

[132] K. Navulur, F. Pacifici, and B. Baugh, "Trends in optical commercial remote sensing industry [Industrial profiles]," *in IEEE Geoscience and Remote Sensing Magazine*, vol. 1, no. 4, pp. 57–64, 2013. [Online]. Available: https://doi.org/10.1109/MGRS.2013.2290098

[133] C. Zhang, A. Marzougui, and S. Sankaran, "High-resolution satellite imagery applications in crop phenotyping: An overview," *Computers and Electronics in Agriculture*, vol. 175, p. 105584, 2020. [Online]. Available: https://doi.org/10.1016/j.compag.2020.105584

[134] D. Pouliot, R. Latifovic, J. Pasher, and J. Duffe, "Landsat super-resolution enhancement using convolution neural networks and sentinel-2 for training," *Remote Sens*, vol. 10, no. 3, p. 394, 2018. [Online]. Available: https://doi.org/10.3390/rs10030394

[135] C. Shorten and T. Khoshgoftaar, "A survey on image data augmentation for deep learning," *J. Big Data*, vol. 6, no. 1, pp. 1–48, 2019. [Online]. Available: https://doi.org/10.1186/s40537-019-0197-0

[136] P. Kaur, S. Khehra, and S. Mavi, "Data augmentation for object detection: A review," *IEEE International Midwest Symposium on Circuits and Systems (MWSCAS)*, pp. 537–543, 2021. [Online]. Available: https://doi.org/10.1109/MWSCAS47672.2021.9531849

[137] M. Koziarski, "Imbalanced data preprocessing techniques utilizing local data characteristics," *International Journal of Extreme Manufacturing*, 2021. [Online]. Available: https://doi.org/10.48550/arXiv.2111.14120

[138] J. Wang, C. Wu, X. Wang, and X. Zhang, "A new algorithm for the estimation of leaf unfolding date using MODIS data over china's terrestrial ecosystems," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 149, p. 77–90, 2019. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2019.01.017

[139] E. Eizwar, "Malaysian palm oil board (MPOB)," 2022. [Online]. Available: https://ir.uitm.edu.my/id/eprint/80896

[140] I. Budiono, "For INDONESIAN institute of sciences (LIPI)," *Tribology transactions*, 2004.

[141] N. S. N. M. Sanusi, R. Rosli, M. A. A. Halim, K.-L. Chan, and et al., "Palmxplore: oil palm gene database," *Database*, vol. 2018, no. 1, p. bay095, 2018. [Online]. Available: https://doi.org/10.1093/database/bay095

[142] D. M. Parker, R. and T. Bennett, "Swinburne research bank," 2011. [Online]. Available: http://conference.eresearch.edu.au/presentations/#47

[143] F. Pu, S. Kho, K. Low, and A. Chou, "Researcher unbound and national university of singapore (NUS) libraries' evolving role in supporting university research: Going beyond service," *Cases on Research Support Services in Academic Libraries*, no. 2, pp. 216–246, 2021. [Online]. Available: https://doi.org/10.4018/978-1-7998-4546-1.ch010

[144] N. Ismail, N. Ramzi, S. Mohamed, and M. Razak, "Webometric analysis of institutional repositories of malaysian public universities," *DESIDOC Journal of Library Information Technology*, vol. 41, no. 2, p. 130–139, 2021. [Online]. Available: https://doi.org/10.14429/djlit.41.2.15649

[145] X. Dang, J. Scotcher, S. Wu, R. K. Chu, N. Tolić, I. Ntai, and et al., "The first pilot project of the consortium for top-down proteomics: A status report," *PROTEOMICS*, vol. 14, no. 10, pp. 1130–1140, 2014. [Online]. Available: https://doi.org/10.1002/pmic.201300438

[146] Y. Xu, L. Yu, W. Li, P. Ciais, Y. Cheng, and P. Gong, "Annual oil palm plantation maps in malaysia and indonesia from 2001 to 2016," *Earth System Science Data*, vol. 12, no. 2, pp. 847–867, 2020. [Online]. Available: https://doi.org/10.5194/essd-12-847-2020,2020

[147] A. Descals, D. Gaveau, S. Wich, Z. Szantoi, and E. Meijaard, "Global mapping of oil palm planting year from 1990 to 2021," *Earth System Science Data Discussions*, vol. 16, no. 11, p. 5111–5129, 2024. [Online]. Available: https://doi.org/10.5194/essd-16-5111-2024

[148] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *ArXiv:1409*, 2014. [Online]. Available: https://doi.org/10.48550/arXiv.1409.1556

[149] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *in Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016. [Online]. Available: https://doi.org/10.1109/CVPR.2016.90

[150] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D.Anguelov, and et al, "Going deeper with convolutions," *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015. [Online]. Available: https://doi.org/10.48550/arXiv.1409.4842

[151] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," *IEEE conference on computer vision and pattern recognition*, no. 5, pp. 248–255, 2009. [Online]. Available: https://doi.org/10.1109/CVPR.2009.5206848

[152] W. Li, R. Dong, H. Fu, and L. Yu, "Large-scale oil palm tree detection from high-resolution satellite images using two-stage convolutional neural networks," *Remote Sensing*, vol. 11, no. 1, p. 11, 2019. [Online]. Available: https://doi.org/10.3390/rs11010011

[153] R. G. J. S. Shaoqing Ren, Kaiming He, "Faster R-CNN: Towards real-time object detection with region proposal networks," *ArXiv:1506.01497*, vol. 28, 2015. [Online]. Available: https://doi.org/10.48550/arXiv.1506.01497

[154] W. Liu and et al., "SSD: Single shot multibox detector," *Computer Vision–ECCV 2016: 14th European Conference, Springer, Cham.*, vol. 9905, p. 21–37, 2016. [Online]. Available: https://doi.org/10.1007/978-3-319-46448-0_2

[155] M. Sharafudeen and V.C., "Multimodal siamese framework for accurate grade and measure estimation of tropical fruits," *Nature plants*, vol. 6, no. 12, pp. 1418–1426, 2023. [Online]. Available: https://doi.org/10.1109/TII.2023.3316182

[156] P. Selvam and J. Koilraj, "A deep learning framework for grocery product detection and recognition," *Economies*, vol. 15, no. 12, pp. 3498–3522, 2022. [Online]. Available: https://doi.org/10.1007/s12161-022-02384-2

[157] J.Hosang, "Analysis and improvement of the visual object detection pipeline," 2017. [Online]. Available: https://doi.org/10.22028/D291-26774

[158] O. Intelligence, "Maxar technologies: An overview of satellite geospatial solutions," 2024.

[159] K. He and et al., "Mask R-CNN. in proceedings of the ieee international conference on computer vision," *Frontiers in bioengineering and biotechnology*, vol. 13, no. 1, p. 1549439, 2017. [Online]. Available: https://doi.org/10.1109/ICCV.2017.322

[160] K. Alomar, H. Aysel, and X. Cai, "Data augmentation in classification and segmentation: A survey and new strategies," *J. Imaging*, vol. 9, no. 2, p. 46, 2023. [Online]. Available: https://doi.org/10.3390/jimaging9020046

[161] L. Nanni, M. Paci, S. Brahnam, and A. Lumini, "Comparison of different image data augmentation approaches," *J. Imaging*, vol. 7, no. 12, p. 254, 2021. [Online]. Available: https://doi.org/10.3390/jimaging7120254

[162] L. Wang, M. Han, X. Li, N. Zhang, and H. Cheng, "Review of classification methods on unbalanced data sets," *IEEE*, vol. 9, pp. 64 606–64 628, 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3074243

[163] S. Sharma, C. Bellinger, B. Krawczyk, O. Zaiane, and N. Japkowicz, "Synthetic oversampling with the majority class: A new perspective on handling extreme imbalance," *IEEE International Conference on Data Mining (ICDM)*, pp. 447–456, 2018. [Online]. Available: https://doi.org/10.1109/ICDM.2018.00060

[164] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollar, "Focal loss for dense object detection," *Proceedings of the IEEE International Conference on Computer Vision*, 2017. [Online]. Available: https://doi.org/10.48550/arXiv.1708.02002

[165] R. Girshick, "Fast R-CNN," *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1440–1448, 2015. [Online]. Available: https://doi.org/10.1109/ICCV.2015.169

[166] S. Ruder, "An overview of gradient descent optimization algorithms," *Machine Learning*, no. 10, pp. 1648–1660, 2016. [Online]. Available: https://doi.org/10.48550/arXiv.1609.04747

[167] Y. LeCun and et al., "Neural networks: Tricks of the trade," *J Orthop Res*, vol. 1524, no. 5-50, p. 6, 1998. [Online]. Available: https://doi.org/10.1007/3-540-49430-8_2

[168] "A persona-based neural conversation model," vol. 32, no. 5, p. 055012, 2016. [Online]. Available: https://doi.org/10.48550/arXiv.1603.06155

[169] F. Wagner, M. Ferreira, A. Sanchez, and et al., "Individual tree crown delineation in a highly diverse tropical forest using very high resolution satellite images," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 145, no. Part B, pp. 362–377, 2018. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2018.09.013

[170] H. Wibowo, I. Sitanggang, M. Mushthofa, and H. A. Adrianto, "Large-scale oil palm trees detection from high-resolution remote sensing images using deep learning," *Big Data Cogn. Comput.*, vol. 6, no. 3, p. 89, 2022. [Online]. Available: https://doi.org/10.3390/bdcc6030089

[171] Y. Putra and A. Wijayanto, "Automatic detection and counting of oil palm trees using remote sensing and object-based deep learning," *Remote Sensing Applications: Society and Environment*, vol. 29, p. 100914, 2023. [Online]. Available: https://doi.org/10.1016/j.rsase.2022.100914

[172] D. He, R. Ren, K. Li, Z. Zou, R. Ma, and et al, "Urban rail transit obstacle detection based on improved R-CNN," *Measurement*, vol. 196, p. 111277, 2022. [Online]. Available: https://doi.org/10.1016/j.measurement.2022.111277

[173] L. Aziz, M. S. H. Salam, U. U. Sheikh, and S. Ayub, "Exploring deep learning-based architecture, strategies, applications, and current trends in generic object detection: A comprehensive review," *IEEE Access*, vol. 8, pp. 170 461–170 495, 2020. [Online]. Available: https://doi.org/10.1109/ACCESS.2020.3021508

[174] T. Nguyen and et al., "Dataset distillation with infinitely wide convolutional networks," *ArXiv*, vol. 34, no. 2, pp. 5186–5198, 2021. [Online]. Available: https://doi.org/10.48550/arXiv.2107.13034

[175] A. Nsaif and et al., "FRCNN-GNB: Cascade faster R-CNN with gabor filters and naïve bayes for enhanced eye detection," *Annual Review of Biomedical Engineering*, vol. 9, pp. 15 708–15 719, 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3052851

[176] L. Huynh, P. Nguyen, J. Matas, E. Rahtu, and J. Heikkila, " Lightweight Monocular Depth with a Novel Neural Architecture Search Method ," in *2022 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*. Los Alamitos, CA, USA: IEEE Computer Society, Jan. 2022, pp. 326–336. [Online]. Available: https://doi.org/10.1109/WACV51458.2022.00040

[177] D. Murphy, K. Goggin, and R. Paterson, "Oil palm in the 2020s and beyond: challenges and solutions," *CABI agriculture and bioscience*, vol. 2, no. 1, pp. 1–22, 2021. [Online]. Available: https://doi.org/10.1186/s43170-021-00058-3

[178] S. Ren and et al., "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2016. [Online]. Available: https://doi.org/10.1109/TPAMI.2016.2577031

[179] J. Redmon and et al., "You only look once: Unified, real-time object detection," *Proceedings of the IEEE conference on computer vision and pattern recognition*, vol. 28, no. 17, pp. 21 193–21 203, 2016. [Online]. Available: https://doi.org/10.1007/s11356-020-12072-5

[180] Y. Chen, Y. Li, J. Wang, W. Chen, and X. Zhang, "Remote sensing image ship detection under complex sea conditions based on deep semantic segmentation," *Remote Sensing*, vol. 12, no. 4, p. 625, 2020. [Online]. Available: https://doi.org/10.3390/rs12040625

[181] K. Blekos, S. Nousias, and A. Lalos, "Efficient automated u-net based tree crown delineation using uav multi-spectral imagery on embedded devices," *arXiv preprint arXiv:2107.07826*, pp. 123–136, 2021. [Online]. Available: https://doi.org/10.1109/INDIN45582.2020.9442183

[182] T. Kattenborn, J. Leitloff, F. Schiefer, and S.Hinz, "Review on convolutional neural networks (cnn) in vegetation remote sensing," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 173, pp. 24–49, 2021. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2020.12.010

[183] G. Cheng, J. Han, and X. Lu, "Remote sensing image scene classification: Benchmark and state of the art," *in Proceedings of the IEEE*, vol. 105, no. 10, pp. 1865–1883, 2017. [Online]. Available: https://doi.org/10.1109/JPROC.2017.2675998

[184] R. Finger, S. Swinton, N. E. Benni, and A. Walter, "Precision farming at the nexus of agricultural production and the environment," *Annual Review of Resource Economics*, vol. 11, no. 1, pp. 313–335, 2019. [Online]. Available: https://doi.org/10.1146/annurev-resource-100518-093929

[185] D. J. Mulla, "Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps," *Biosystems engineering*, vol. 114, no. 4, pp. 358–371, 2013. [Online]. Available: https://doi.org/10.1016/j.biosystemseng.2012.08.009

[186] J. Lowenberg-DeBoer and B. Erickson, "Setting the record straight on precision agriculture adoption," *Agronomy journal*, vol. 111, no. 4, pp. 1552–1569, 2019. [Online]. Available: https://doi.org/10.2134/agronj2018.12.0779

[187] K. Johansen, S. Phinn, and M. Taylor, "Mapping woody vegetation clearing in queensland, australia from landsat imagery using the google earth engine," *Remote Sensing Applications: Society and Environment*, vol. 1, no. 6, pp. 36–49, 2015. [Online]. Available: https://doi.org/10.1016/j.rsase.2015.06.00

[188] N. Gorelick, M. Hancher, M. Dixon, and et al., "Gorelick, n. and et al." *Remote sensing of Environment*, vol. 202, no. 2, pp. 18–27, 2017. [Online]. Available: https://doi.org/10.1016/j.rse.2017.06.031

[189] H. Tamiminia, B. Salehi, M. Mahdianpari, and et al., "Google earth engine for geo-big data applications: A meta-analysis and systematic review," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 164, no. 2, pp. 152–170, 2020. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2020.04.001

[190] L. Zhong, L. Hu, and H. Zhou, "Deep learning based multi-temporal crop classification," *Remote sensing of environment*, vol. 221, no. 1, pp. 430–443, 2019. [Online]. Available: https://doi.org/10.1016/j.rse.2018.11.032

[191] K. Liakos, P. Busato, D. Moshou, S.Pearson, and D. Bochtis, "Machine learning in agriculture: A review." *Sensors*, vol. 18, no. 8, p. 2674, 2018. [Online]. Available: https://doi.org/10.3390/s18082674

[192] D. Tsouros, S. Bibi, and P. Sarigiannidis, "A review on uav-based applications for precision agriculture," *Information*, vol. 10, no. 11, p. 349, 2019. [Online]. Available: https://doi.org/10.3390/info10110349

[193] H. Shakhatreh and et al., "Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges," *IEEE access*, vol. 7, pp. 48 572–48 634, 2019. [Online]. Available: https://doi.org/10.1109/ACCESS.2019.2909530

[194] C. Pontecorvo, "The eu 'governance through trade'regulatory model for the sustainable production and consumption of deforestation-risk commodities (DRCs): The eu deforestation regulation (eudr) and the issues at stake in its implementation stage," *European Yearbook of International Economic Law 2024*, vol. 18, no. 3, p. 568, 2025. [Online]. Available: https://doi.org/10.1007/8165_2024_126

[195] R. (RSPO), "Principles and criteria for the production of sustainable palm oil 2018. roundtable on sustainable palm oil," vol. 9, no. 2, pp. 693–704, 2023.

[196] I. (IPCC), "The physical science basis. contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change," *Cirp Journal of Manufacturing Science and Technology*, pp. 18–36, 2021. [Online]. Available: https://www.ipcc.ch/report/ar6/wg1/

[197] R. Paterson and N. Lima, "Climate change affecting oil palm agronomy, and oil palm cultivation increasing climate change, requires amelioration," *Ecology and evolution*, vol. 8, no. 1, pp. 452–461, 2018. [Online]. Available: https://doi.org/10.1002/ece3.3610

[198] A. Fernandez-Bou and et al., "Cropland repurposing as a tool for water sustainability and just land transition in california: review and best practices," *Frontiers in Water*, vol. 7, no. 4, p. 1510413, 2025. [Online]. Available: https://doi.org/10.3389/frwa.2025.1510413

[199] A. Noh and et al., "Variability and performance evaluation of introgressed nigerian dura x deli dura oil palm progenies," *Genetics and Molecular Research*, vol. 13, no. 2, pp. 2426–2437, 2014. [Online]. Available: http://dx.doi.org/10.4238/2014

[200] R. Singh and et al., "Oil palm genome sequence reveals divergence of interfertile species in old and new worlds," *Nature*, vol. 500, pp. 335–339, 2013. [Online]. Available: https://doi.org/10.1038/nature12309

[201] C. R. Banbury, V. J. Reddi, M. Lam, W. Fu, A. Fazel, and J. Holleman, "Benchmarking tinyml systems: Challenges and direction." *ArXiv preprint arXiv:2003*, p. 04821, 2020. [Online]. Available: https://doi.org/10.48550/arXiv.2003.04821

[202] R. Paterson and et al., "Future climate effects on suitability for growth of oil palms in malaysia and indonesia," *Scientific reports*, vol. 5, no. 1, p. 14457, 2015. [Online]. Available: https://doi.org/10.1038/srep14457

[203] M. Euler, M. P. Hoffmann, Z. Fathoni, and S. Schwarze, "Exploring yield gaps in smallholder oil palm production systems in eastern sumatra, indonesia," *Agricultural Systems*, vol. 146, pp. 111–119, 2016. [Online]. Available: https://doi.org/10.1016/j.agsy.2016.04.007

[204] D. Gaveau, D. Sheil, M. A. S. Husnayaen, and et al., "Rapid conversions and avoided deforestation: examining four decades of industrial plantation expansion in borneo," *Scientific reports*, vol. 6, no. 1, p. 32017, 2016. [Online]. Available: https://doi.org/10.1038/srep32017

How to cite this article:
Mohammad Farhan, Qusay S. Hamad, Mohammad N. Akhtar, R. Rajendran, Mohammed Danish, and Elmi Abu Bakar (2026). 'Artificial intelligence for Oil palm tree management using deep structured learning: A systematic review', Al-Qadisiyah Journal for Engineering Sciences, 19(1), pp. 032-048.
`https://doi.org/10.30772/qjes.2026.165663.1755`