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Machine Learning Monitoring Model for Fertilization and Irrigation to Support Sustainable Cassava Production: Systematic Literature Review

Ahmad Chusyairi[1], Yeni Herdiyeni[2], Heru Sukoco[3], Edi Santosa[4]
[1,2,3]Department of Computer Science, IPB University Bogor, Indonesia
[4]Department of Agronomy and Horticulture, IPB University Bogor, Indonesia

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ABSTRACT

The manual and time-consuming nature of current agronomic technology monitoring of fertilizer and irrigation requirements, the possibility of overusing fertilizer and water, the size of cassava plantations, and the scarcity of human resources are among its drawbacks. Efforts to increase the yield of cassava plants > 40 tons per ha include monitoring fertilization approach or treatment, as well as water stress or drought using UAVs and deep learning. The novel aspect of this research is the creation of a monitoring model for the irrigation and fertilizer to support sustainable cassava production. This study emphasizes the use of Unnamed Aerial Vehicle (UAV) imagery for evaluating the irrigation and fertilization status of cassava crops. The UAV is processed by building an *orthomosaic*, labeling, extracting features, and Convolutional Neural Network (CNN) modeling. The outcomes are then analyzed to determine the requirements for air pressure and fertilization. Important new information on the application of UAV technology, multispectral imaging, thermal imaging, among the vegetation indices are the Soil-Adjusted Vegetation Index (SAVI), Leaf Color Index (LCI), Leaf Area Index (LAI), Normalized Difference Water Index (NDWI), Normalized Difference Red Edge Index (NDRE), and Green Normalized Difference Vegetation Index (GNDVI).

Corresponding Author:

Ahmad Chusyairi,
Department of Computer Science, IPB University Bogor, Indonesia
Jl. Raya Darmaga, Kampus IPB, Darmaga, Bogor, Indonesia. 16680
Email: ahmadchusyairi@apps.ipb.ac.id

1. INTRODUCTION

Food is defined as anything derived from living things, such as food additives, foodstuffs, and other goods, and anything processed or unprocessed used in agriculture, forestry, plantations, fisheries, animal husbandry, and water and water. Components are utilized in the production, processing, or preparation of meals or beverages [1]. Especially for Indonesia, a tropical nation with a sizable population, food security is crucial [2]. Reconstruction after the COVID-19 epidemic can benefit from food security. With a score of 60.2, Indonesia is now rated 63 out of 113 nations in terms of food security. Even while the scores seem to improve, this indicates that there is still much space for growth. Food security is based on three (three) pillars: 1) accessibility, 2) affordability, and 3) quality and safety [3].

Cereals (wheat, rice, and corn), tubers (cassava and sweet potatoes), nuts (soybeans, peanuts, and long beans), and other plants are examples of plants that provide food security [4]. Since the cassava plant has a very high output potential (> 40 tonnes/ha), it was selected and developed to support Indonesia's food security [5]. Diversification is a common feature of industrial derivatives in the form of fuel, food, and feed [6]; simple farming is carried out [7] since there are abundant genetic resources in cassava plants [8].

The nation may continue to grow, the utilization of state-owned land must be maximized, and it is intended that import attempts from outside be restricted to preserve food security. Because it is well recognized that the agronomic practices used in these areas tend to be less sustainable, areas not too large for growing food crops typically have less than ideal sustainability in their use and utilization. There are currently weaknesses in the monitoring process, such as manual fertilization and irrigation, that take a long time to implement. Other issues that should be taken seriously include the excessive or insufficient supply of water and fertilizer, the suboptimal use of large areas of land, and the lack of human resources, which make it more difficult to carry out efforts to ensure food security and therefore have an impact on the volatility of energy, costs, and mental energy.

Given that Indonesia is a tropical country where this plant may be grown, the cassava plant is used for study [9]. Therefore, there is a lot of possibility for agricultural sustainability by integrating technology and analysis with the right applications; blockchain and artificial intelligence are two examples of this [10] various techniques for forecasting the prices of agricultural products [11], and analysis is to review data while monitoring to address the relevant issues quickly.

Water electrical conductivity (EC) has previously been predicted using machine learning models, with decision tree-based models like XGBoost being among the most popular. EC is the primary factor guiding fertigation strategies in operational settings. Yet, its measurement in the drainage water may not entirely indicate the root zone in the growing medium [12].

Researchers monitor the availability of plants and other factors related to the targets they are studying to make sure they are satisfied [1] (using cassava plants in this study), fertilizing practices [13], conduits for irrigation are accessible [14], and wooded regions [15], particularly with low levels of production. A machine learning model is required to apply the technology, and this study addresses the models that may be applied to manage the outcomes of gathering analytical data. Geological mapping or area exploration must be done to gather this data. Given the size of the area that the research objective is, remote sensing is employed in conjunction with drone technology to facilitate mapping [16] to speed things up. After obtaining the data, researchers must process the information gathered, going through several phases such as data collecting, pre-processing, modeling, and monitoring.

A machine learning method called Random Forest (RF) has shown to be extremely accurate in several agricultural applications. The individual correlation parameters, or Vegetation Indices (VI), are the foundation of this methodology. Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE), and Green Normalized Difference Vegetation Index (GNDVI) were the top three indices in rank-based analysis using VIs extracted from UAV-based multi-spectral imagery—their combination with RF-enhanced crop yield prediction. Higher accuracy was obtained using additive regression, which used RF as the foundation for weak learning. Its correlation coefficient and mean absolute error, or MAE, were 0.78 and 853.11 kg ha-1, respectively [17].

Deep learning is the most extensively utilized application in agriculture. Consequently, increasing, regulating, and enhancing agricultural production is possible. Integrating deep learning into modern agricultural tools, technologies, and algorithms—such as image classification, feature extraction, transformation, and pattern analysis—is crucial for smart agriculture. Deep learning is frequently used to solve these problems [18].

Researchers are looking for a good and efficient way to monitor the agricultural development process based on the literature study that has been completed. This is because there aren't many resources available that can be used to monitor the development of food crops efficiently and quickly. Most of the literature research that is now available takes the form of in-depth analyses of connected topics. As previously mentioned, this article explains how technology can be used to monitor initiatives because agricultural technology can now boost farmer production and improve the agricultural sector's efficiency. The present research positions and future research proposals for applications conducted by researchers in relevant domains constitute the contribution of this article. Hopefully, this paper can provide light on appropriate plant monitoring techniques. The introduction, methods, discussion results, conclusions, and relevance to earlier research are applied according to the article's structure. This paper's innovation is developing a monitoring model for cassava plants' irrigation and fertilization to support sustainable cassava production. This study highlights the use of imagery from Unnamed Aerial Vehicles (UAVs) to assess cassava crops' irrigation and fertilization levels.

2. METHOD

Researchers use a research method called the Systematic Literature Review, or SLR, based on a systematic literature study that requires consecutive steps to be completed. Planning is the initial step in any research activity; it entails defining the topic, setting goals, locating the most recent publications, and making field observations.

Creating a plan is the first step to take. Creating research questions (RQ) and deciding on the review process are the two steps that will be completed in this part. Getting the RQ ready is the first step. This step is crucial because RQ is used to direct the literature search and excavation. Table 1 displays the research question that was developed.

Table 1. Research question

	Research Question
RQ1:	What cases can be solved by machine learning with remote sensing implemented in plants?
RQ2:	What is xception deep learning and how does it work?
RQ3:	What is the vegetation index and explain its types?
RQ4:	How to develop a model for monitoring the watering and fertilizing to support sustainable cassava production?

This study poses three research topics: machine learning ideas, case studies, and research questions. Using remote sensing on crops, RQ1 explains which scenarios can be resolved by machine learning. The operation of deep learning is explained using RQ2. The creation of a model to track the fertilizing and watering to support sustainable cassava production is explained by RQ3. Formulating the study scope to identify the problem boundaries is one method of determining the review protocol. By choosing the terms to be used in the article search, the research problem here is limited. In Table 2, the keywords are displayed.

Table 2. Keywords Searching

Code	Keyword
Key1:	“Machine Learning” AND “Remote Sensing” or “Plants”
Key2:	“Deep Learning” or “Convolutional Neural Network”
Key3:	“Vegetation Index” or “Normalized Difference Vegetation Index” or “Green Normalized Difference Vegetation Index” or “Normalized Difference Red Edge Index” or “Normalized Difference Water Index” or “Soil-Adjusted Vegetation Index” or “Leaf Color Index” or “Leaf Area Index”
Key4:	“Monitoring Watering” or “Monitoring Fertilizing” or “Cassava Plants in Limited Production Forest”

To perform literature studies, publications pertinent to the research being done are gathered. The collection employs the following general classification techniques: 1) To find research relevant to the scope of this work, a systematic search was carried out for papers published in 2020–2024. Academic resources like Science Direct, IEEE Xplore, Google Scholar, and other Scopus-indexed journals and conferences were used, and 2) Articles are gathered according to subtopics, and the research output, benefits, and drawbacks are known. The results of the SCOPUS database search (n = 193) and other database search results (n = 50) are included in the Literature Review Systematics with PRISMA diagrams in the following stages: a) Identification (n = 203); b) Filtering (n = 146); these results show the number of articles remaining after duplicates are eliminated. With articles (n = 97) that do not pass the selection c) Complete articles that have been evaluated for suitability (n = 93), complete articles that fail the selection (n = 68), and articles that fail the selection (n = 97), d) At the inclusion/selection step, 78 articles are available for analysis and synthesis, as seen in Figure 1.

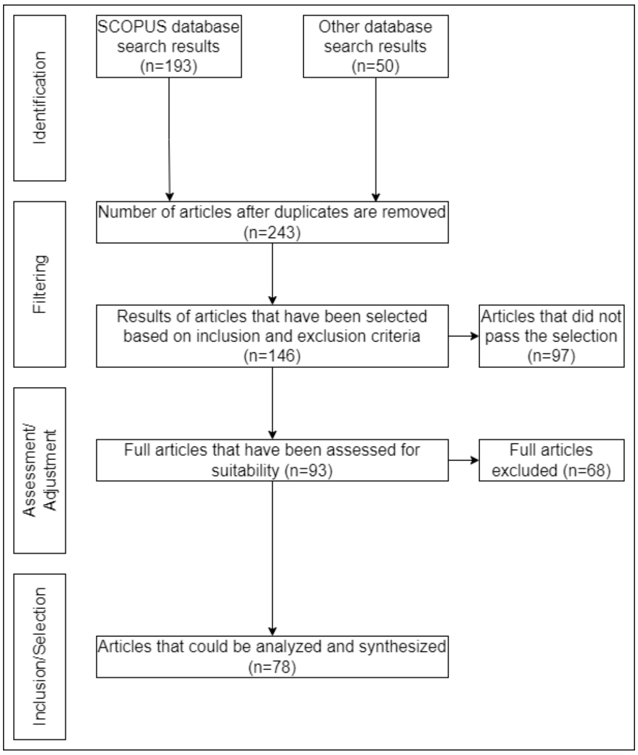

Figure 1. System Literature Review with PRISMA

Applying machine learning algorithm models for agricultural purposes, particularly for the watering and fertilization of cassava plants, has been identified as difficult. Large-scale land mapping requires the necessary data, which can be gathered by remote sensing. UAV drones are equipped with sensors that measure reflected light from objects, enabling them to cover broad regions quickly.

The study objectives were determined after the problem had been identified. This research expects that the machine learning-based monitoring model can address current issues in the agricultural industry, particularly in areas with limited output forests.

Filters are used to extract the necessary data from the publications' collection and the outcomes of observations. When a publication has multiple subtopics within a topic, the dominant subtopic is chosen to fill in research gaps that occur from variations in earlier research findings concerning concepts, hypotheses, data, and field issues. Making conclusions is the last stage, from which it is intended that fresh insights into the problem may be gained for both the agricultural industry and future studies on the same topic.

3. RESULT AND DISCUSSION

3.1. Machine Learning with Remote Sensing Implemented in Plants

Remote sensing is already desired for geological mapping or mineral exploitation, particularly in the key stages and during reconnaissance, where physical access is challenging and seasonal. Classifying land, vegetation, and water use or cover is a typical use of machine learning in remote sensing [19]. Table 3 lists a few papers that have been gathered about the use of remote sensing technology.

Table 3. Catalog of Research Papers

Author	**Technique Indexing**	**An example case study**	***Research Results***	***Research Gaps***
[20]	Deep Learning (DL) Convolutional Neural Network (CNN)	Broccoli multispectral image from a UAV	Accuracy of plant monitoring using UAV photography is 61.13%	Precision agriculture labor requirements can be decreased by optimizing irrigation and fertilization decisions, managing other crops, and keeping an eye on them.
[21]	Support Vector Machine (SVM)	Sugarcane multispectral picture	88% accuracy in RGB crop prediction using UAV	It was demonstrated that the area under the disease progression curve (AUDPC-reflectance) calculation used in this

Author	Technique Indexing	An example case study	*Research Results*	*Research Gaps*
				study was effective in classifying disease resistance.
[17]	Random Forest (RF)	forecast the maize yield	78% accuracy in RGB prediction using UAV	Assessment of various crop yields to support appropriate management and utilization in precision agricultural decision-making models
[22]	DL-YOLOv3	Corn multispectral image from UAV	80% accuracy in plant recognition using RGB from UAV	Following the pin-head square phase, model training and testing using volunteer cotton plants (VC) will guarantee that only plants that are hostable to Boll Weevil can be discovered, maybe with greater precision.
[23]	CNN-Long Short-Term Memory (LTSM)	Multispectral UAV photo of soybeans	Crop maturity estimation using RGB from UAV with 95% accuracy	By estimating soybean maturity using satellite data, further study in this field may be increased. Furthermore, by using this approach, researchers can find additional soybean qualities or traits from other crops that can be examined using drone photography to ultimately improve decision-making.
[24]	DL-CNN	UAV multispectral image of rice	Plant image classification using thermal photography with a 90.04% accuracy rate	Future study on deep learning and XAI techniques, classification research will be conducted to enhance the accuracy of the proposed CNN-16 and PlantDXAI to reduce classification errors.
[25]	DL- Artificial Neural Network (ANN)	Sugarcane multispectral picture	Indication of the condition of fertilization with 76% accuracy	The suggested method for estimating chlorophyll content has to be tested in several sugarcane fields with various types and verified at various stages of sugarcane plant growth.
[26]	DL-CNN	Multispectral UAV photo of cassava	Plant leaf stress can be identified with 93% accuracy.	A significant obstacle to the application of deep learning techniques in the field of plant leaf stress detection has been the lack of big data sets. Thankfully, Plant Village, a sizable database with thousands of photos, is now accessible; but a dataset with actual field photos is still unavailable.

Lee and colleagues' research [20] possesses the benefit of being able to gauge the ideal fertilizer dosage and the best time to harvest broccoli based on head size. There is a gap, which is the monitoring and management of other crops as well as optimizing irrigation and fertilization decision-making to increase efficiency and lower labor requirements for precision agriculture. The drawback is that the single plant detection method can be integrated with disease detection to measure the level of damage due to disease in the future. Moreover, Simões & Amaral's research [21] the research has drawbacks as well. Specifically, the multispectral reflectance data collected with UAV-based sensors is sensitive to infections caused by two rusts (orange and brown) simultaneously, but it is not specific to one of them, leaving a gap. Nevertheless, the area under the disease progression curve (AUDPCreflectance) calculation proposed in this study has proven to be effective in classifying disease resistance.

Studies conducted by Yadav and colleagues [22] based that an accuracy of 80% can be achieved in plant detection using RGB from a UAV. YOLOv3, which demonstrates the possibility of DL algorithms for real-time detection and mitigation using computer vision and spot-spray capable UAVs, is the research's benefit in identifying VC factories. The disadvantage is that, for all three input image sizes, the trained YOLOv3 model can be used for VC detection because there are no appreciable changes between these three scales. Therefore, it can be stated that using Volunteer Cotton (VC) plants for training and testing the model following the pin-head square phase guarantees the detection of only hostable boll weevil plants, possibly with increased accuracy.

Research by Moenizade et al. [23] his research's findings demonstrates that a UAV's RGB readings can estimate plant maturity with a 95% accuracy rate. His work has the benefit of supporting the CNNLSTM model's resilience to issues with data quality, such as dark and fuzzy images. One of the deep learning models also benefits from operating well on fewer frequent flights. Furthermore, the suggested approach is generalizable to data from different contexts. The study's shortcoming is that it was unable to pinpoint other traits unique to soybeans or traits of other plants whose drone photos may be used for analysis. By estimating soybean maturity using satellite data, further study in this field may be increased. Furthermore, by using this framework, researchers can find additional soybean qualities or traits from other crops that can be examined using drone photography to ultimately enhance decision-making.

The study conducted by Batchuluun and Park [24] yields a 90.04% accuracy rate in the image classification of plants using thermal imaging. The research's strength is that the suggested method for classifying plants and agricultural diseases outperforms other current methods, with an accuracy of 98.55% for the thermal plant image dataset and 90.04% for the rice plant dataset. One study shortcoming is that the Class Activation Map (CAM) and discriminator network additions do not result in longer processing times during testing. Future research on classification was conducted to enhance the accuracy of the proposed CNN-16 and PlantDXAI to reduce classification mistakes, utilizing deep learning and XAI techniques.

Studies conducted by Narmilan and colleagues [25] his research yielded a 76% accurate indicator of fertilization status. The results of his study demonstrate that in bigger sugarcane fields, the use of multispectral UAVs can be used to monitor plant health status and estimate chlorophyll content. By eliminating the requirement for traditional measurements of sugarcane chlorophyll concentration, this technology aids in the real-time management of plant nutrition in sugarcane plantations. Agronomic methods for gathering leaf tissue and conducting chemical analyses in the lab are time- and space-constrained due to practical constraints. The suggested method for estimating chlorophyll content must be tested in several sugarcane fields with various types and verified at various stages of sugarcane plant growth.

Investigation by Noon et al. [26] concluded that a 93% accuracy rate can be achieved in the identification of plant leaf stress. The benefit of this research is that it provides a brief overview of the trend of utilizing deep learning to identify plant leaf stress, which is helpful for researchers, especially those who are new to the subject. This research has certain limitations, specifically: a) One of the biggest obstacles to the application of deep learning techniques in the field of plant leaf stress detection has been the lack of large data sets. Thankfully, Plant Village, a sizable database with thousands of photos, is now accessible, but a dataset with actual field photos is still unavailable; b) Another research gap is the lack of real-world scenario photographs since most authors have only used pre-cropped and segmented synthetic images from publicly accessible databases. Certain writers do employ crowded background picture sets, but they do so using small data sets that self-assemble following the appropriate pre-processing. The authors take into consideration the fact that different lighting, lightning conditions, capture angles, and distances can result in different deep network/classification accuracy values for different plants on the same network when comparing the effectiveness of the proposed deep learning method on field and laboratory images. Almost everyone else has improved recognition accuracy by doing the required preprocessing procedures on self-collected field photos; c) Another issue that deep learning researchers with backgrounds in computer science encounter is annotating self-collected data with the assistance of subject matter experts; d) In this area of study, early identification of plant diseases is crucial because it enables farmers to implement less expensive corrective measures by identifying afflicted plants at an early stage. Although hyperspectral imaging has been utilized for this, it is difficult to detect disease or contaminated areas because of the vast areas that are captured on surfaces utilizing temperature sensors and light reflector sensors; e) Every published article examined for this review specifically suggests deep learning for plants. With changes in host-tissue pairs, classification accuracy is not guaranteed to remain the same. Another unresolved issue is the lack of universal CNN models whose performance is independent of plants or stress.

Large-scale land mapping is accomplished by remote sensing. Drones with sensors mounted may quickly traverse enormous regions by measuring light reflection from surfaces [27]. It is vital to use alternative spectral combinations, such as near-infrared (NIR) bands, to record plant growth and withering caused by water stress because standard aerial photographs (monochrome or visible in a spectrum of red (R), green (G), and blue (B) bands) cannot capture this information. Only a limited portion of the electromagnetic spectrum is visible because it consists of multiple bands with distinct wavelengths. Spectral reflection curve of vegetation with characteristics of absorption and reflectance. The wavelengths at which chlorophyll absorption occurs are $0.4 - 0.7\ \mu m$, $0.8 - 1.3\ \mu m$ for vegetation's near-cell structure infrared with high reflectance, and $1,4 - 2.4\ \mu m$ for water absorption in bands in the atmosphere related to biochemistry in leaves, protein, lignin, cellulose, and water content [28].

3.2. Xception Deep Learning and How Does It Work

Deeply separable convolution (convolution followed by vertex convolution), a considerably more computationally efficient alternative to conventional convolution, and shortcuts between convolution blocks, like those in ResNet, are the foundations of the effective architecture known as Xception Deep Learning. The unique feature of Xception's architecture, which consists of Deepthwise + Maxpooling separable convolution blocks connected by shortcuts akin to a ResNet implementation, is that Depthwise Convolution comes before Pointwise Convolution—rather, the sequence is inverted, according in Figure 2 [29].

Xception's network architecture is shown in Figure 2. First, n × n deep point convolution is conducted, followed by 1 × 1 point convolution. By using this method, the network becomes lighter and has fewer layers and parameters. Equations (1) and (2) follow this correlation [29].

$$f_{(l+1)}^{k}(p,q) = \sum_{(x,y)} f_{l}^{k}(x,y).\, e_{l}^{k}(u,v) \quad (1)$$

$$F_{(l+2)}^{k} = g_{c}(F_{(l+1)}^{k}, K_{(l+1)}) \quad (2)$$

Where (x, y) and (u, v) indicate the spatial index of the feature map F, and the kernel K has a depth of one. The feature map of the transform layer l is represented by F. The feature map F is spatially convolved across the kernel K, and the convolution of the operation is shown by $gc(.)$

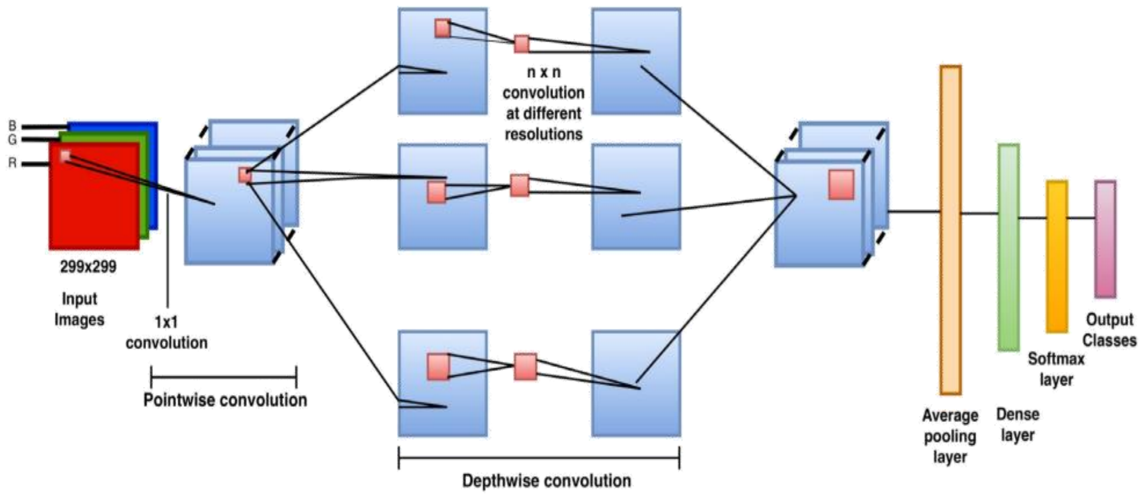

Figure 2. Xception Deep Learning

3.3. Vegetation Index and Explain Its Type

The vegetation index is a measure of the health of an ecosystem. It is crucial for preserving ecological balance, controlling the water cycle, and promoting the movement of materials and energy [30]. The following describes the many components of the vegetation index: Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Red Edge Index (NDRE), Normalized Difference Water Index (NDWI), Leaf Color Index (LCI), and Leaf Area Index (LAI). The formula of the vegetation index is explained in Table 4.

Even though the NDVI is a useful tool for communicating vegetation status and measured vegetation attributes, there is a chance that end users who have had little to no remote sensing education misuse it because of its widespread use and popularity, particularly in Unmanned Aerial Systems (UAS) applications. This is how the NDVI formula is explained (3) [31].

To forecast responses for the three phenological stages and their averages, the sole predictor of great significance was the vegetative GNDVI. Average Maize Streak Virus (MSV) may be predicted using CIgreen during vegetative stages, while average MSV and MSV at grain filling can be predicted most accurately with CIgreen during flowering. The following explains the GNDVI formula (4) [32].

Standardized Disparity, the NDRE yield estimator performs better than the NDVI. The red edge spectral region (690–730 nm) is covered by NDRE in its formulation. The red peripheral channel is more sensitive to the amount of chlorophyll, according to several studies. The NDRE formula (5) [33].

The NDWI is a widely used remote sensing indicator that enhances water features and removes the influence of plants and soil by using green bands and near-infrared (NIR) data. The NDWI formula is as follows (6) [34]. SAVI will remove the backdrop soil's silent vegetation cover. The formula for SAVI (7) [35] is as follows.

LCI uses RGB parameters as a foundation. The technology is more accurate and suitable for assessing apple tree nitrogen when the new LCI is integrated into a smartphone-based application interface. Furthermore, a low-cost, user-friendly Leaf Color Chart (LCC) has been created. The model's output is then fed into a straightforward conditional structure, which uses certain equations to recalculate the model's outputs and converts them into numerical LCI values between 0 and 10. The formula for LCI is as follows (8) [36].

Leaf Area Index (LAI) is a significant phenotypic trait that is closely related to photosynthesis, respiration, and water use. LAI is greatly affected by the similarity between synthetic multispectral data and observational multispectral data. Surface and canopy structure is also affected by ecological factors like rainfall, solar radiation, temperature, and soil moisture [37]. In land surface and terrestrial ecosystem models, LAI is a crucial variable for capturing the condition of the vegetation. It is intimately linked to the modeling of carbon and water exchange between the land and the surrounding atmosphere [38]. LAI to calculate the area of leaves. Equation (9) explains the LAI formula [39].

Table 4. Formula Vegetation Index

Vegetation Index	Evaluated Qualities	Formula	Use	Equality
NDVI	canopy structure, leaf area, chlorophyll content, and biomass [40]	$\frac{(NIR-R)}{(NIR+R)}$	where Red (R) and Near-Infrared (NIR)	(3)
GNDVI	plant stress, photosynthetic process, leaf area, and biomass ratio of absorbing radiation [40]	$\frac{(NIR-G)}{(NIR+G)}$	where Near-Infrared (NIR) and Green (G)	(4)
NDRE	plant vigor, density and condition of the vegetation leaf area, chlorophyll [40]	$\frac{(NIR-RE)}{(NIR+RE)}$	where Red Edge (RE) and Near-Infrared (NIR).	(5)
NDWI	content, stress indication, fertilizer need, take-up of nitrogen [40]	$\frac{(G-NIR)}{(G+NIR)}$	where Green (G) and Near-Infrared (NIR).	(6)
SAVI	take silent vegetation cover out of the surrounding soil [35]	$\left(\frac{(NIR-R)}{(NIR+R+L)}\right)*(1+L)$	where Red (R), NIR (near infrared), and L represent the percentage of green vegetation cover, such as 0.5.	(7)
LCI	chlorophyll content in leaves [41]	$\frac{(NIR-RE)}{(NIR+R)}$	where Near-Infrared (NIR), Red Edge (RE) and Red (R)	(8)
LAI	simulated leaf area [39], carbon, and water exchange [38]	$-\frac{ln(0.69-SAVI)/0.59}{0.91}$	using In: SAVI = Soil Adjusted Vegetation Index and natural logarithm to the base Euler number (constant up to 2.71828)	(9)

3.4. Monitoring the watering and fertilizing requirements of cassava plants

There are significant obstacles to agricultural output due to the effects of global climate change on crop productivity and exponential population increase. Crop performance monitoring is becoming more and more important in order to address these problems [42]. Crop stress can be monitored by using sensors and near-field communication (NFC) [43]. Unmanned Aerial Vehicle (UAV) monitoring of crop growth is supported by fertilizer distribution management and remote sensing monitoring of chlorophyll content [44]. In a long-term experiment, the impacts of fertilizing with nitrogen, potassium, and phosphorus were evaluated for the UAV-derived spectral vegetation index using the Normalized Difference Vegetation Index (NDVI) [45].

In order to determine how much irrigation is necessary and to maintain ideal soil moisture conditions for maximum development potential, it is critical to monitor crop transpiration [46]. Studying the physiology of stress in plants requires identifying and observing drought stress in plants growing in their native environments [47]. Total dry biomass output of two field-grown cassava cultivars, both with and without fertilization and water stress, expressed in kg/m2. The values in the two cultivars at each harvest time for zero water stress that are indicated by the same capital letter do not differ substantially [48].

A plant water stress monitoring system that links the three variables-soil, plant, and weather-in real time by detecting plant Acoustic Emission (AE). In addition to affecting water stress and atmospheric drought, the automated monitoring system created with the help of the virtual instrument platform may also be used to automatically regulate the greenhouse environment [49].

Remote sensing and digital monitoring [50] offer an irrigation and fertilizing model. in order to create models for monitoring and detection that are utilized in limited-production forests. Accurately identifying plant water stress is the foundation of precision irrigation techniques, which are a key part of the water-saving approach in agriculture and a way to increase water-saving efficiency.

4. CONCLUSION

The novel aspect of this research is the creation of a monitoring model for irrigation and fertilizer to support sustainable cassava production. This study emphasizes the use of Unnamed Aerial Vehicle (UAV) imagery to evaluate the irrigation and fertilization status of cassava crops. Finding cassava land for drone flights is a challenge. After the drone is processed to create an *orthomosaic*, labeling, feature extraction, and CNN modeling are performed, and the results are examined to identify water stress and nutrient deficits. Important new information about the application of UAV technology, multispectral imaging, thermal imaging, vegetation index (NDVI, GNDVI, NDWI, NDRE, SAVI, LCI, and LAI), and deep learning in numerous facets of precision agriculture is offered by the study that the aforementioned researchers presented. Every study has benefits and drawbacks. The study has limitations in terms of generalizability, sensitivity to disease, and precise detection, for instance. Furthermore, this study needs to handle differences and problems, including using real-world data, identifying leaf stress in different crops, and optimizing deep-learning models. Nonetheless, this study opens the door for more advancements in precision farming and the application of cutting-edge technology to boost agricultural productivity and decision-making.

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