Weed detection using machine learning: A systematic literature review

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Abstract

Recently, many researchers and practitioners used Machine Learning (ML) algorithms in digital agriculture to help farmers in decision making. This study aims to identify, assess and synthesize research papers that applied ML algorithms in weed detection using the Systematic Literature Review (SLR) Protocol. Based on our defined search string, we retrieved a total of 439 research papers from three electronic databases, of which 20 papers were selected based on the selection criteria and thus, were synthesized and analyzed in detail. The most applied ML algorithm is Neural Networks in these models. Thirteen evaluation parameters were identified, of which accuracy is the most used parameter. 75% of the selected papers used cross-validation as the evaluation approaches, while the rest used holdout. The challenges most encountered were insufficient data and manual labeling of the pixel during image segmentation. Based on the ML algorithms identified, we concluded that supervised learning techniques are the most used techniques in weed detection.

Keywords: *Weed detection, Machine Learning, Systematic literature review, digital agriculture, pest*

1. Introduction

According to the United Nations, the global population will be around 8.5 billion, 9.7 billion, and 10.9 billion by 2030, 2050, and 2100, respectively [1]. Because of the global rapid population growth, a food insecurity crisis is possible. The global population and the agriculture product demands need to be at equilibrium to avert this crisis. The production of agricultural products needs to be increased by about 70% [2] to attain an equilibrium state. However, agriculture is facing some challenges that, if not addressed, will negatively affect agricultural product demand. Climate change, weeds, diseases, soil erosion, and other issues are among the challenges [3].

Weeds are considered among the greatest threat to crop production [4] as they compete for survival with plant crops. Weed contributes 30% of the total global crop losses caused by pests [3], [5]. Thus, early detection and control of weeds are of great importance to both the plant crop and the farmer. Early detection of weed will positively affect crop yield and crop quality [6]. Furthermore, reduce the cost of labor. Weed is unwanted plants that grow

spontaneously on the agriculture field and compete with economic plant crop for elements; such as light, nutrients, water, and space [7]. Weed detection is the processing of identifying or detecting weed in the agriculture field [8]. Weeds can be identified and controlled in a range of methods [9]. Manual weeding [9], [10] is considered the first method used in weeding. Manual weeding involves agricultural workers using hand or simple tools to manage weed. However, this method is tedious, inefficient, and almost impossible for modern agriculture. Manual weeding exposes agricultural workers to serious health challenges [10]. Mechanical weeding is another method used in weed detection and control [11], [12], followed by the chemical method. Chemical methods harm the environment. Digital agriculture provides solutions to the challenges faced by the earlier methods [2]. Digital agriculture uses technologies and data to improve farm activities and minimize threats from weeds, diseases, and many more. The sources of this data are instrumental sensors. Digital agriculture enables farmers to make sound decisions at the right time. ML algorithms are used on the collected data to extract useful information and help the farmer in decision making.

ML is a subset of Artificial Intelligence (AI) that enables a machine to learn from experiences like humans. ML used data to interpret patterns or extract knowledge from them. ML algorithms have been used in many fields to extract information ranging from health care [13]–[16], [52], education [17]–[19], finance [20]–[23], agriculture [4], [24]–[26] and many other fields.

Numerous ML algorithms are already being used to detect weed in the agriculture field. Nevertheless, a study on systematic literature review on machine learning algorithms and weed detection is lacking. In this work, we aimed at conducting a systematic literature review to highlight the ML algorithms applied in weed detection, evaluation parameters, and evaluation approaches as well as the challenges encountered when applying machine learning algorithms on weed detection. The following is how the paper is structured: Section 1 introduces the study, Section 2 the background and related work, Section 3 the research methodology used, and Section 4 the results and discussion. Lastly, section 5 is the conclusion and recommendations.

2. Background and Related Work

A Systematic Literature Review (SLR) is a scientific method for identifying, evaluating, and interpreting primary studies to answer a specific question [27]. When identifying and evaluating literature, SLR should be objective and comprehensive [28]. SLR assists researchers and practitioners in identifying research gaps and trending issues.

Secondary studies, such as surveys and reviews that were excluded from the study due to the selection criteria outlined in section 3, are discussed here. [29] Conducted a comprehensive survey on deep learning techniques to detect and classify weed. The survey focuses on datasets (sources and pre-process), deep learning techniques applied, location, and deep learning evaluation approach. According to the findings, supervised learning techniques are the most commonly used technique in weed detection and classification. [9] Reviewed machine vision techniques and image processing techniques applied in weed detection. The study reveals that the most challenging task in weed detection is the segregation of plant crops and weeds. A detailed review paper was written by [4] to study the application of ML to the agricultural sector. The researchers categorized agricultural products into four main categories. Namely: livestock, crops, soil, and water management. [30] Surveyed the extraction of hidden patterns from agriculture datasets using deep learning techniques. The authors compared the performance of deep learning techniques to traditional image processing techniques, and the study reveals that deep learning techniques outperform the other techniques. [31] Reviewed automatic weed and crop discriminations using machine learning and sensing method. The report highlighted three types of sensing methods (spectroscopy, color imaging, and hyperspectral imaging) as the potential techniques for automatic classification of weed and crop.

To the best of our knowledge, the application of ML algorithms to detect weed using the SLR protocols have not been performed. Addressing this research gap is the main purpose of this study.

3. Methodology

Guidelines written in [27] were used to conduct this study. SLR is divided into three phases [27]. The initial phase is planning. The first task in this stage is to identify why the research work is needed and the definition of the research questions the study is to address. Also, the systematic search protocols are determined. These protocols involve: deciding on the databases to use, identification of keywords and composition of the search string, and finally, decide on the selection criteria to use in determining which publications are relevant to the study. The second phase is conducting the review. In this phase, the selected databases are searched based on the composed

search string, and the search result is saved. Some retrieved papers are chosen based on selection criteria defined and information extracted from them. The final phase is reporting the review. The research questions are answered by synthesizing and analyzing the extracted pieces of information, and the results are presented in tables and figures.

3.1.1. Research Questions

The questions this paper is addressing are as follows:

RQ1: What machine learning algorithms were applied in weed detection?

RS2: Which evaluation parameters and evaluation approaches are used?

RQ3: What are the challenges?

3.1.2. Search strategy

An automated search strategy is used to identify relevant literature for this systematic search. This search strategy was tailored to three databases (see Table 1). Initially, the search terms used were “machine learning” and “weed detection”, and these terms were used to have a broad picture of the study. Volumes of publications were returned, and the abstract of some returned papers was read to find synonyms of the search terms. The search term identified were “weed identification”, “weed classification”, “weed recognition”, “weed mapping”, “neural network”, and “deep learning”. A complex search string (see Table 2) was developed using the identified keywords and logical operators, and this is done to avoid missing relevant studies. All searches in the databases spanned from 2010 to 2020 and included primary studies published in English only. A specific description of the search string per database is shown (see Table 2). A total of 439 studies were retrieved after executing the search.

Table 1: Use databases.

S/N	Database Name	Link
1	Google Scholar	https://scholar.google.com/
2	Dimension	https://www.dimensions.ai/
3	Science Direct	https://www.sciencedirect.com/

Table 2: Search string formatted from the identified keywords

S/N	Database Name	Search String	CONDITIONS
1	Google Scholar	<i>allintitle: "machine learning" OR "deep learning" OR "neural network" "weed detection" OR "weed recognition" OR "weed classification" OR "weed mapping"</i>	2010-2020, UNCHECK INCLUDE CITATION BOX
2	Dimension	<i>"weed detection" "deep learning" (title and abstract)</i>	2010-2020
3	Science Direct	<i>["machine learning" OR "deep learning"] and ["weed detection" OR "weed identification" OR "weed recognition"]</i>	2010-2020

3.1.3. 3.3. Selection Criteria

Selection criteria are used to set boundaries between the relevant and irrelevant research papers. The irrelevant research papers are discarded from the study while the relevant research papers are processed. A research paper is relevant in this study if it answers the study questions. Both relevant and irrelevant research papers were retrieved using the literature search string in Table 2. To determine the relevant research papers that will address our RQs, inclusion, and exclusion criteria were applied to these papers.

Inclusion Criteria

IC1: Published papers from 2010 to 2020 AND

IC2: Published research papers that are primary studies AND

IC3: Published research papers that implement ML algorithms on agriculture datasets to detect weed

Exclusion Criteria

EC1: Published research papers not written in English Language OR

EC2: Unpublished research papers OR

EC3: Published research papers outside the scope of this study OR

EC4: Published research papers that are duplicate OR

EC5: A published research paper that is a secondary study (review or survey paper) OR

EC6: Unable to access the full text of the research paper

3.1.4. Studies Selection

This section described the process of selecting the relevant research papers. Initially, the primary author searched the three databases (see Table 1) using the defined search string (see Table 2), and the outcome of each database search was saved in separate files of the same format (excel format). Later, combine them into a single excel spreadsheet. The search yielded 439 research papers. Table 3 displays a breakdown of the search results. The excel spreadsheet is checked for duplication. A total of 44 duplicates were discovered and eliminated from the list. A total of 395 research papers were scaled to the next stage of selection. The authors independently access the titles and abstracts of the selected research papers to determine their relevance to this study based on the predefined selection criteria. As a result, 336 research papers eliminated, leaving 59 research papers. The full text of the 59 papers was read by the authors independently to determine their relevance to the research goal. Based on the authors' recommendations, 39 research papers were excluded from the study, while 20 research papers scaled to the final stage. The list of the relevant research papers is shown in Table 4. Fig. 1 uses a flowchart diagram to summarize the selection process. Section 4 analyses the relevant research papers.

Table 3: Search Space Results

S/N	Database	Date Search	Results
1	Google Scholar	2021-04-12	43
2	Dimension	2021-04-12	26
3	Science Direct	2021-04-12	370
Total			439

Fig. 1. Selection process using flowchart diagram.

3.1.5. Data extraction, synthesis, and reporting

Relevant data are extracted from the selected papers to help answer the research questions **RQs**, which was accomplished by reading the full text of the research papers. Data extracted are the source

of the research data (database), publications type, Author (s) name, publication year, the title of the paper, abstract, ML techniques, and evaluation performances. Then, synthesized the collected data which helps in understanding the data. To address RQ1, the ML algorithms were divided into smaller groups. Regression, decision trees, clustering, Bayesian models, instance-based models, neural networks (NN), support vector machines (SVM), and ensemble learning are among them. Prior knowledge is used to make this classification [4].

3.1.6. Results and Discussion

The research findings are analyzed in this section of the paper. During the search, 439 papers were retrieved from the databases and 20 papers were selected for the analysis based on the study selection criteria. Table 4 lists the relevant research papers with the author(s)' names, years of publication, the title of the research paper, and the ML algorithm used. The analysis includes document type, publication year, and source of research data. In addition, the research questions (RQs) are answered here.

3.1.7. Publication Document Types

The selected studies were published in a variety of publication categories. Journal articles, proceedings, books, and reports are the categories in this study. 70% of the research papers were published in journal articles (see Fig. 2). Research papers published in proceedings account for 15% of all research papers, while research papers published in books and reports account for less than 16% of all research papers. Figure 2 depicts the documents. The majority of the research papers chosen came from journal articles because academicians and researchers believe their findings are more accurate and significant.

Fig. 2. Publication Document Type

3.1.8. Publications Based on Year

Fig. 3 depicts the number of publications from the year 2010 to 2020. The graph shows that most of the papers (30%) are from 2020. The year 2019 is the year that follows with 25%. The years with fewer publications are 2016 and 2012 with 5%. However, the years 2010, 2011, 2013, 2014, and 2015 have zero and are not shown in the graph. From the graph, we deduct that the number of papers published

on the application of the ML algorithm to detect weed is increasing. The increases are due to the demand for intelligent tools to help farmers make decisions.

Fig. 3. Selected papers distributed over the year

3.1.9. Source of Research Data

The three data sources used in the study were Dimension, Google Scholar, and Science Direct. Google scholar provided 40% of the research papers, while Dimension and Science Direct provided 60% of the research papers. Figure 4 summarises the distribution.

Fig. 4. Database Distribution of papers

4. RQ1: What machine learning algorithms were applied in weed detection?

In addressing this question, the ML algorithms were classified into eight categories: regression, clustering, Bayesian models, instance-based models, neural networks (NN), support vector machines (SVM), decision trees, and ensemble learning. Other classifications were possible, but the authors recommended this after some deliberations and are based on a literature review of existing

knowledge [4]. The algorithms classification, the applied algorithms, and the number of times the algorithms are applied are shown in Table 5. The total numbers of applied algorithms exceed the total number of selected research papers because some algorithms appear in more than one paper. Neural network categories were the most applied follows by support vector machines and the least among the categories is clustering with zero number of an applied algorithm. From this, we conclude that researchers preferred NN and SVM. The majority of the authors preferred NN over other algorithms because neural networks are good in image classification.

Table 5: Algorithms per category.

Algorithm Categories	Applied algorithms	# of time applied
Neural networks	Convolutional neural network, Fully convolutional neural network, Artificial neural network, Deep convolutional neural network, AlexNet,	17
Support vector machines	Support vector machines	8
Bayesian model	Naïve Bayes Gaussian, Maximum likelihood classification	2
Ensemble learning	Random forest, XGBoost	2
Decision tree	Decision tree	1
Instant based models	K-nearest neighbour	1
Regression	Logistic regression	1
Clustering		0

5. RS2: Which evaluation parameters and evaluation approaches were used?

A total of 46 evaluation parameters were applied in the papers (see Table 6). The most used evaluation parameter was the accuracy used 13 times, followed by precision seven times and the F1-score six times. The least used parameters are specificity, coefficient of determination (r^2), Matthews's correlation coefficient (MCC), means squared error (MSE) which were applied one time in the study. Table 6 shows how many times a parameter was used. Cross-validation and hold-out approaches were the evaluation approaches identified. From the analysis, the hold-out evaluation approach is the least approach applied in the papers.

Table 6: Evaluation parameters that were applied in the papers.

Evaluation parameters	# of times used	Reference
Accuracy (ACC)	13	[32],[33],[34],[35], [36], [37],[38],[39][40], [41], [42], [43], [44]
Precision	7	[32], [7], [45], [46], [47], [48], [42]
F1-score	6	[46], [47], [49], [48], [41], [42]
Confusion Matrix	5	[33], [7], [35], [47], [39]
Recall (RC)	4	[32], [45], [46], [48]
Area under the curve (AUC)	2	[36], [50]
Receiver operating characteristic (ROC)	2	[36], [50]
Sensitivity	2	[7], [42]
Specificity	1	[42]

Coefficient of determination (R ²)	1	[35]
Matthews correlation coefficient (MCC)	1	[46]
Means squared error (MSE)	1	[34]
Root means squared error (RMSE)	1	[35]

6. RQ3: What are the challenges?

In answering this question, the selected research papers were thoroughly read to see if any author(s) mentioned any challenges encountered. Most of the research papers mention insufficient data to carry out the experience as the main challenge. Though they carry out the experience with limited data, a large amount of data is required for more accurate results. Few among the papers mention manual labeling of the pixel during the segmentation as the challenge face.

Table 4: List of selected papers.

Authors and year of publication	Title	ML algorithm(s) applied
Rumpf et al., (2012)	Sequential support vector machine classification for small-grain weed species discrimination with special regard to <i>Cirsium arvense</i> and <i>Galium aparine</i>	Support vector machines
Yano et al., (2016)	Identification of weeds in sugarcane fields through images taken by UAV and Random Forest classifier	Random forest
Tang et al., (2017)	Weed identification based on K-means feature learning combined with convolutional neural network	Convolutional neural network
dos Santos Ferreira et al., (2017)	Weed detection in soybean crops using ConvNets	Convolutional neural network
Dyrmann et al., (2017)	RoboWeedSupport - Detection of weed locations in leaf occluded cereal crops using a fully convolutional neural network	Fully convolutional neural network
Bakhshipour & Jafari, (2018)	Evaluation of support vector machine and artificial neural networks in weed detection using shape features	Support vector machines, Artificial neural network
Dian Bah et al., (2018)	Deep Learning with unsupervised data labeling for weeds detection on UAV images	Convolutional neural networks
Sandeep Kumar, (2018)	Convolution Neural Network-Based Weed Detection in Horticulture Plantation	Convolution neural network
Murawwat et al., (2018)	Weed Detection Using SVMs	Support vector machines
Jialin et al., (2019)	Weed Detection in Perennial Ryegrass With Deep Learning Convolutional Neural Network	Deep convolutional neural network
Yu et al., (2019)	Deep learning for image-based weed detection in turfgrass	Deep convolutional neural network

Bah et al., (2019)	Deep features and One-class classification with unsupervised data for weed detection in UAV images	Support vector machines,
Sarvini et al., (2019)	Performance Comparison of Weed Detection Algorithms	Support vector machines, Artificial neural network, Convolutional neural network
Forero et al., (2019)	Colour Classification Methods for Perennial Weed Detection in Cereal Crops	Naïve Bayes, Decision tree, K-nearest neighbor, Support vector machines, Artificial neural network
Espejo-Garcia et al., (2020)	Towards weeds identification assistance through transfer learning	Convolutional neural network, Support vector machines, XGBoost, logistic regression
Ofori & El-Gayar, (2020)	Towards deep learning for weed detection: Deep convolutional neural network architectures for plant seedling classification	Deep convolutional neural network
Asad & Bais, (2020)	Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network	Maximum likelihood classification, Deep convolutional neural network
Osorio et al., (2020)	A Deep Learning Approach for Weed Detection in Lettuce Crops Using Multispectral Images	Deep convolutional neural network, Support vector machines
Beeharry & Bassoo, (2020)	Performance of ANN and AlexNet for weed detection using UAV-based images	Artificial neural network, AlexNet
Gao et al., (2020)	Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields	Deep convolutional neural network

7. Discussion

A threat to the systematic literature review is validity. Reliability, construct validity, and external validity are the potential threats to validity [51]. This research paper addresses the construct validity and external validity by retrieving a substantial number of studies: 439 research papers. The SLR adheres to the guiding line set by [27], which means that this study is clearly described and reproducible, thereby addressing the threat to reliability.

In this paper, we conducted a systematic review of research papers that use ML algorithms to detect the presence of weeds in agricultural datasets. As a result, we identified the ML algorithms used, the evaluation parameters, and the approaches. Furthermore, identified the challenges encountered during the studies. When interpreting the study's findings, keep the following in mind. Many ML algorithms were discovered, and for the sake of clarity and presentation, the algorithms were classified. The classification was done using pre-existing knowledge. Regression, clustering, Bayesian models, instance-based models, neural networks, support vector machines, decision trees, and ensemble learning were the eight groups of ML algorithms.

The ML algorithms identified were numerous. According to Table 4, the category with the highest number of applied ML algorithms is the neural network. In this classification, the neural network is a superset of traditional neural networks and deep learning. Furthermore, deep learning algorithms were the most used algorithms in the category (see Table 4) because of their performances and automatic feature extraction. Support vector machines are the second category in terms of the number of ML algorithms applied. Decision tree, instant-based modes, regression were all applied once. The least is clustering with zero algorithms. The ML algorithms indicate that weed detection is a predictive modeling problem.

Cross-validation and hold-out evaluation approaches were the approaches identified. The evaluation approaches are not clearly stated in the research papers. So, to find the approaches the method and result section of the research papers were read to deduct the method used. 75% of the research papers used cross-validation, 25% used holdout approaches. Various evaluation parameters were identified (see Table 6), and the most used parameter is accuracy. Accuracy is used 13 times in the papers. Others evaluation parameters are the precision, F1-score, and confusion matrix. Specificity, coefficient of determination (r^2), Matthews's correlation coefficient (MCC), and means squared error (MSE) were applied once. Most of the selected papers stated insufficient data as the main challenges. Another challenge is the manual labeling of the pixel during the segmentation of an image.

8. Conclusion and Recommendations

8.1. Conclusion

A systematic literature review on weed detection using machine learning algorithms was conducted. Based on the selection criteria defined, 20 papers were selected for the study and they were used to answer the research questions. The neural networks were the most used ML algorithms, 17 times. Accuracy and precision were the two most frequently used evaluation parameters, with each being used 13 and 7 times, respectively. The evaluation approaches used are cross-validation and holdout. 75% of the papers used cross-validation, while the rest of the research papers uses holdout. The challenges identified were insufficient data and manual labeling of a pixel. From the study, we conclude that weed detection is an example of supervised learning.

Nonetheless, a few of the research limitations associated with the present work include the exclusion of non-English publications in the systematic synthesis of the literature. Thus, looking at the diversification of the research area, possibly we have not captured other excellent studies published in other languages. Secondly, the complex search string used as depicted in Tables 2 limited the articles retrieved. Thirdly, another limiting factor is related to the duration range used in all the searches conducted across the databases; the searches spanned from 2010 to 2020 as stated in the methodology section. Nonetheless, the records retrieved are strictly limited to the three scientific databases mentioned. Accordingly, few recommendations are provided for future comparative studies.

8.2. Recommendations

The key recommendations for similar systematic literature reviews include relaxing the search filters across additional databases. This could yield additional relevant studies. Specifically, the present work reviewed only full-text online articles. Consequently, the findings are limited to the studies included. The future research agenda will be based on relaxing the search criteria to incorporate other scholastic databases for further comparative results. In addition, future studies could relax the search filters to include more books, conference papers, and so on. Noteworthy, to build on or replicate the reviewed studies, future research should explore other intelligent bibliographic techniques for in-depth analysis of the literature.

9. References

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