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ARTIFICIAL INTELLIGENCE AND ITS TOOLS IN PEST CONTROL FOR AGRICULTURAL PRODUCTION: A REVIEW

INTELIGÊNCIA ARTIFICIAL E SUAS FERRAMENTAS NO CONTROLE DE PRAGAS PARA PRODUÇÃO AGRÍCOLA: UMA REVISÃO

INTELIGENCIA ARTIFICIAL Y SUS HERRAMIENTAS EN EL CONTROL DE PLAGAS PARA LA PRODUCCIÓN AGRÍCOLA: UNA REVISIÓN

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ABSTRACT
Artificial Intelligence (AI) and its tools are being widely used worldwide. In the area of agriculture, AI is being widely studied and expanding. The use of AI in agriculture is being widely studied and expanding from pre-harvest to post-harvest. The increase in world population has triggered the need to increase food production. This need has triggered a search for solutions that promote increased food production and quality. One way to increase food production and quality is pest control. AI and its tools have proven to be a growing and rising solution in controlling and combating pests. This research focuses on reviewing and demonstrating the advances in combating and controlling pests using AI tools and images. It stands out: the classification of pests; insect identification; use and capture of Unmanned aerial vehicle (UAV) footage; using Deep Learning (DL) and Convolutional Neural Network (CNN). A search engine was applied to 5 databases. Cutting criteria were applied in 3 stages, and there were 71 papers at the end. The 71 went through 3 quality assessment questions, leaving 47 works for final analysis. This study demonstrated that the DL and the CNN tool using real images have the potential for insect control and combat solutions. Another tool in recent studies associated with CNN is the attention mechanism, improving pest identification results. Identification of insects through leaf images using CNN requires.

KEYWORDS: Deep Learning. CNN. Intelligence Agriculture. Pests. Image.

RESUMO
A inteligência artificial e suas ferramentas estão sendo amplamente utilizadas em todo o mundo. O seu uso na agricultura está sendo amplamente estudado e expandido, abrangendo desde a pré-safra até o pós-safra. O aumento da população mundial tem desencadeado a necessidade de aumentar a produção de alimentos. Essa demanda desencadeou uma busca por soluções que promovam o aumento da produção e qualidade dos alimentos. Uma forma de alcançar esse objetivo é o controle das pragas. A inteligência artificial e suas ferramentas têm demostrado ser uma solução em crescimento e ascensão no controle e combate às pragas. Esta pesquisa concentra-se em revisar e demostrar os avanços no combate e controle de pragas, utilizando ferramentas de inteligência artificial e imagens. Destacam-se atividades como classificação de pragas, identificação de insetos, uso e captura de imagens por *Unmanned Aerial Vehicle*, além da utilização *deep learning* e *convolutional neural network*. O estudo apresenta a atual utilização da inteligência artificial, *machine learning* e *deep learning*, identificando as ferramentas em uso e as soluções propostas ou desenvolvidas para o combate e controle de pragas. Esta pesquisa serve como base para abordar futuros desafios referentes ao uso de inteligência artificial e suas ferramentas na identificação de pragas em imagens reais, fornecendo *insights* para pesquisadores interessados em desenvolver estudos sobre o uso de *deep learning* na agricultura.

PALAVRAS-CHAVE: Agronegócio. CNN. Processamento de imagens. Agricultura inteligente. Pestes. Imagem.

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RESUMEN
La inteligencia artificial y sus herramientas se están utilizando ampliamente en todo el mundo. Su uso en la agricultura está siendo ampliamente estudiado y ampliado, desde la precosecha hasta la poscosecha. El aumento de la población mundial ha desencadenado la necesidad de incrementar la producción de alimentos. Esta demanda desencadenó una búsqueda de soluciones que promuevan una mayor producción y calidad de los alimentos. Una forma de lograr este objetivo es el control de plagas. La inteligencia artificial y sus herramientas han demostrado ser una solución cada vez mayor para controlar y combatir las plagas. Esta investigación se centra en revisar y demostrar avances en el combate y control de plagas, utilizando herramientas e imágenes de inteligencia artificial. Se destacan actividades como clasificación de plagas, identificación de insectos, uso y captura de imágenes por UAV, además del uso de aprendizaje profundo y red neuronal convolucional. El estudio presenta el uso actual de la inteligencia artificial, el aprendizaje automático y el aprendizaje profundo, identificando las herramientas en uso y las soluciones propuestas o desarrolladas para combatir y controlar las plagas. Esta investigación sirve como base para abordar los desafíos futuros relacionados con el uso de la inteligencia artificial y sus herramientas en la identificación de plagas en imágenes reales, brindando conocimientos a los investigadores interesados en desarrollar estudios sobre el uso del aprendizaje profundo en la agricultura.

PALABRAS CLAVE: Agronegocios. CNN. Procesamiento de imágenes. Agricultura inteligente. Plagas. Imagen.

1. INTRODUCTION

Population growth in the world brings challenges, such as increasing food production. The increase in production must occur without increasing the planting areas and simultaneously guarantee the preservation of the environment and improving the quality of life (Issad; Aoudjit; Rodrigues, 2019). Large-scale productivity is critical for the world to meet the demand caused by world population growth. For many countries, agriculture is the leading economic resource. The United Nations Report released in June 2017 points to significant growth in the world population. The population is estimated to reach 9.8 billion in 2050 and 11.2 billion in 2100[1] (Un, 2017). In 2019, the 2017 report was revised, projecting small changes in the world population estimates. For 2050 the forecast is 9.7 billion and for 2100, 10.875 billion (Un, 2019. However, this small reduction does not change the need to increase food production. Due to the estimated increase in world population, increasing food production by 50% is necessary to meet the projected world population demand UN, 2019).

The lack of pest control is one of the severe production problems, posing a serious threat to agricultural production (Peng; Wang, 2022). It can lead to economic losses in terms of quality and quantity of production, harming the world's food supply (Das *et al.,* 2018). The existence of pests is an ongoing problem Pereira *et al.*, (2022). Traditional control often causes damage to the environment due to excessive use of pesticides or use in places that do not need agricultural applications Pradeep *et al.*, 2019). The use of pesticides and pest control, in most operations, is still done by land or area agricultural spraying in places where pests were manually identified (Junior *et al.*, 2017). Computational technologies, mainly Artificial Intelligence (AI), have shown potential in controlling and combating pests, diseases and weeds.

[1] This link has spreadsheets with detailed numbers on the world population. (population.un.org/wpp/Download/Probabilistic/Population).

The forms of pest identification are still, for the most part, manual (Silva *et al.*, 2019). Existing pest detection and control systems are time-consuming as they depend on human intervention. Human interventions include receiving the batch of images to submit to the classification process, using a beat cloth that takes time to execute, and traps that demand installation and capture time and the human eye. All these alternatives are local and punctual. More rigorous, permanent and early control and combat promote the reduction in pesticide use, environmental preservation, and production quality.

Computational technologies, mainly AI and its tools, have broad applicability in several areas. Agriculture is one of these areas and is extremely important for the world. Approximately 30.7% of the world's population is directly involved in food production and 2781 million hectares of land are in agricultural activity (Das *et al.,* 2018). AI has proven to be essential in identifying, controlling, and combating pests, diseases and weeds. However, they are still costly and often difficult to be accepted or use by farmers. Several challenges are faced, from planting to post-harvest, such as control and infestation of pests, diseases and weeds, inadequate e application of chemical products, resource management, production prediction, etc Das *et al.,* (2018).

The identification and control of pests (insects, diseases, and weeds) using AI, Machine Learning (ML), Deep Learning (DL), and Convolutional Neural Network (CNN) is gaining ground and new systems are being developed (Xu *et al.*, 2022). DL has introduced an important role in intelligent agriculture and has aroused great interest in pest detection/recognition actions through images (Tassis; Souza; Krohling, 2021). Acts in controlling pests, diseases, weeds, information control, decision making, pattern recognition, and knowledge acquisition (Voutos; Katheniotis; Sofou, 2019). Perform control and monitoring of devices and pest infestations with precision (Pradeep *et al.*; 2019). CNN architectures are being studied and demonstrated to dominate several actions, mainly in image and pattern recognition (Wang *et al.*; 2019). CNN has been standing out in image classification, presenting itself as an excellent tool for the automatic detection/classification of pests (Tassis; Souza; Krohling, 2021). It has demonstrated a superior ability to learn different pattern categories on objects and large amounts of training data (Liu *et al.;* 2019a). Farmers or technicians in charge have already heard of the terms AI and their techniques in combating and controlling pests in agriculture. However, many farmers or technical managers do not know the benefits, technologies, and how to use them.

The following stand out in this study: the classification of pests; insect identification; use and capture of images from Unmanned Aerial Vehicle (UAV) and other forms; use of ML, DL and CNN. As for AI, ML and DL, the tools used in proposed or developed solutions for combating and controlling pests in smart agriculture are reported. For this research, emphasis was given to studies that used insect pests. This study serves as a basis for future problems to be explored in the identification of pests in real images and for researchers who want to develop research on the use of DL in agriculture. The systematic review is organized as follows.

The systematic review is organized as follows, in section I, there is a brief introduction to the subjects that guide the research. Section II is about related work recounting basic and stimulating subjects for carrying out the research. Section III describes the methodology and resources used in the systematic review, and the study search mechanism results are presented. Section IV presents the results and analyses of the researched articles. In section V, the three research questions underlying the research are answered. Section VI concludes the review. Section VII, presents declarations, and finally the bibliographic references used are listed.

2. RELATED WORK

Intelligence agriculture is the revolution experienced by using Communication and Information Technologies (CIT) in agribusiness. Agriculture has evolved and transformed recently, producing much information and data from different sources and nature (Voutos; Katheniotis; Sofou, 2019). Precision farming is a component of intelligent farming. It takes an agricultural, management, time, and space approach, intending to increase agricultural production efficiently and effectively using CIT (Castillo, Gutierrez, Hadi, 2012). Smart agriculture allows farmers to remotely monitor and control crops without being present in their fields, meeting the necessary needs (Pradeep *et al.,* 2019). Smart agriculture addresses the challenges of increasing food production and protecting the environment without increasing cultivated areas. It brings the possibility of being more sustainable and promoting environmental preservation. Resources such as automation, data capture, decision processing, data transmission, AI, Internet of Things (IoT), sensors, robots, etc., control from pre-planting to post-harvest (Albahar, 2023). For intelligent agriculture, the internet is needed, which enables the integration and control of all equipment and devices on a single platform and sharing of information between the parties (Pradeep *et al.*, 2019).

Pests cause damage and reduce final agricultural production (Peng, Wang, 2022). Uncontrolled pests are serious problems, representing an essential threat to agricultural production (Peng; Wang, 2022). Pests' existence and emergence are permanent problems (Pereira *et al.*, 2022). It leads to economic and food production losses harming world supply (Das et al. 2018). However, traditional control often causes damage to the environment due to the excessive use of pesticides (Pradeep *et al.,* 2019). The excessive use of chemical pesticides to combat pests (insects), diseases, and weeds can damage the soil (Pradeep *et al.,* 2019), which may cause a reduction in production. The use of pesticides and pest control (insects), in most cases, is still done by aerial or terrestrial agricultural spraying (Junior *et al.,* 2017) in places where identified pests manually. Manual verification of pests in crops is carried out by sampling; therefore, there is no complete verification of the area. If you confirm the existence of pests in the samples, the product is applied.

Computational technologies such as computer vision and AI are crucial for diagnosing, identifying, and controlling insects (Junior *et al.,* 2017). DL is an ML tool used in proposed solutions for agriculture (Albahar, 2023). DL can carry out pest identification accurately and efficiently. The application of CNNs encompasses a variety of tasks, such as object detection and recognition, image classification, and analysis (Albahar, 2023). Com o uso de DL aplicando a arquitetura CNN, pode-se identificar o tipo de praga que está atacando a cultura e aplicar o agrotóxico específico (Song *et al.,* 2019).

AI technologies: ML, DL, Expert Systems (ES), intelligent sensors, pattern recognition, robotics, neural networks, etc., are used for pest control and combat, among other applications in agriculture. New systems and applications are developed to meet the demands of agriculture (Xu *et al.*, 2022). Using AI and its technologies improves efficiency and effectiveness in pest control, soil, and weather monitoring, increases production, avoids wasting products and biological resources, prevents environmental damage, etc. (Castillo; Gutierrez; Hadi, 2012). DL technology and other ML tools emerge as one of the main items in the agricultural technological scenario (Xu *et al.*, 2022), helping farmers in their actions (Albahar, M. 2023). DL technology plays an essential role in agriculture, arousing great interest in models that detect and recognize pests through images (Tassis; Souza; Krohling, 2021). DL can control pests, diseases, weeds, information control, decision-making, pattern recognition, and knowledge acquisition (Voutos; Katheniotis; Sofou, 2019). The different DL architectures apply in various actions, which can be used alone or in conjunction with other models, forming hybrid architectures.

Reviews on the use of AI technologies show how evolutions and trends in applications and actions etc., in agriculture Domingues, Brandão, Ferreira (2022) reviewed, addressing the use of older ML and CNN techniques used in agriculture to classify, detect, and predict disease. Computer vision and DL using CNN were detected with manual pest trait management. He reported the need for extensive data aids for training and learning transfer to supply small databases (Domingues, Brandão, Ferreira, 2022). He identified pest predictions in his review, but the studies are substantial Albahar (2023) comprehensively report the use of DL in fruit counting, water management, crop and soil management, weed detection, seed sorting, yield forecasting, and disease detection. The ability of DL to learn from large datasets is promising in transforming agriculture, but it faces difficulties such as: compiling large datasets, computational cost, and lack of DL specialists (Albahar, 2023).

Kumar, Laxmi (2022) reviewed some image processing techniques with artificial neural networks for automatically detecting pests, focusing on diseases. DL technology has enabled advances in image processing for pest classification. Mekha, Parthasarathy (2022) reported on work on detecting and identifying pest infestations using DL. Examined and reported various ML and DL techniques and focused on diseases identified in leaf images through the symptoms visible on the leaves (Mekha; Parthasarathy, 2022).

3. RESEARCH METHODOLOGY

The research process carried out in this work is based on the Systematic Review (SR) method. The SR is a rigorous review of the results of research, identifying, evaluating and interpreting the works already published (Kitchenham, 2004). SR is intended to aggregate existing evidence and support researchers and the development of new research (Kitchenham *et al.* 2009). This articles elaboration was based on the RS proposal by Kitchenham *et al.* (2004), with the following steps: 1 - Defined the research questions: the questions guided the search for articles relevant to the researched subject; 2 - Article search process: reports how carried out the search for articles and what the chosen sources; 3 - Selection of relevant studies: creation and definition of the criteria used in the choices of studies considered suitable; 4 - Evaluation of the quality of the studies: analysis of the quality, quantitatively, of the studies, already selected.

3.1 Question underlying the research.

The elaboration of research questions is one of the main parts of SR, providing the means to understand and conduct SR on the researched topic (Kitchenham *et al.* 2009). In this research, the questions seek to know how AI is applied and used in combating and detecting pests in agriculture. A leading question was elaborated, based on previous studies on the subject of the work, aiming to find the solutions and existing studies. The main question defined was: Identify the use of AI in combating and controlling pests in food production in intelligent agriculture?

Three specific research questions were designed to fill in potential gaps and identify existing and possible new solutions. It was based on the central question to elaborate on the specifications. The research questions seek to answer the main question.

- QP1 - What are computational technologies used to combat and control pests in agricultural production?
- QP2 - How Artificial Intelligence have been used for pest control and combat?
- QP3 - Which machine learning tools are used to combat and control pests in agricultural production?

3.2 Selection criteria and search strategies

The realization process of researching the topic of interest was defined by reading numerous articles, reports, and experiences on the specified subject. Next, define the terms to be searched and the selection of sources for the article searches. Selection criteria and search strategies were created and selected to answer the research questions. We selected the sources for searching articles based on the relevant publications in the area. The electronic databases selected for the article search include many agriculture studies and AI technology applied to combating pests. The databases selected were dl.ACM.org, ieeexplore.ieee.org, ScienceDirect.com, Springer.com, and Scholar.google.com.

The critical words for defining the search string were created based on the research questions, reading of articles, keywords, and synonyms of the topic of interest researched. Several strings were tested to eliminate articles not addressing the research topic. The string was adapted according to the search engine of each source, keeping all the keywords, ("Agriculture" OR "Intelligence Agriculture" OR "Smart Agriculture") AND ("AI" OR "Artificial Intelligence") AND ("Machine Learning" OR "ML") AND ("Reasoning") AND ("Pests).

3.3 Article inclusion and exclusion criteria

Created the article selection criteria to remove studies irrelevant to the research objective selected by the search string. The articles were selected according to this works inclusion and exclusion criteria (Kitchenham *et al.* 2009). The removal of articles was carried out in accordance with the exclusion criteria described in table 1, which presents the inclusion and exclusion criteria for articles. Choose the articles selected in the electronic databases according to the inclusion criteria: I1 - published between 2015 and 2022; I2 - published in English; I3 - with relevance to the theme suggested for the work; I4 - published in Journal, conferences, and scientific magazines, complete; I5 - that demonstrate the results of using AI to combat pests; I6 - open access. The exclusion criteria created to eliminate selected articles from the electronic databases were: E1 - Review and Surveys, studies such as dissertations, theses, books and book chapters, tutorials, reports; E2 - different from the searched topic; E3 - White paper; E4 - Duplicate articles, published in two sources; E5 - without presenting search results.

Studies that addressed other forms of pest control that did not involve AI were discarded as they needed to meet the scope of this study. The search range from 2015 to 2022 provides a sample of 7 years of research, showing a broad scope of studies in pest control and combat. Given the rapid evolution and scope of the subject, a 7-year period covers the most recent research and innovations. Duplicate studies were discarded to avoid any bias in the results. Even when dealing with pest control, studies that did not include the use of AI in the process or did not explain how the process was conducted were excluded. Studies with 3 (three) or fewer pages were discarded because they did not present a broad discussion and clarity in the research development, that is, because they were succinct in their descriptions of what was developed. Studies that were unclear or did not provide sufficient information about the results were excluded, as this could influence the actual usefulness and application of the study.

3.4 Quality assessment

Defined the criteria for evaluating the quality of the articles according to Kitchenham et al. (2009).

- QA1: Did the evaluated article develop any AI solution to combat pests in agriculture?
- QA2: Does the article use machine learning models to combat pests in agriculture?
- QA3: Does the evaluated article demonstrate that AI's use in combating pests contributes to increased production in agriculture?

Still based on Kitchenham's methodology (Kitchenham *et al.* 2009), three possible answers were defined for each question, being: Yes = 1; In parts = 0.5 and No = 0. After applying the quality assessment criteria and analyzing the score, it was decided that articles classified with a score below 1,5 would be removed.

4. SEARCHE RESULTS

At this stage, the results of the article selection process and quality assessment are presented. The article selection process located 1958, of which, after applying the filter, resulted in 71 studies. Figure 01 shows that the search string and inclusion criteria of item 1 selected a total of 1958 works. The number of works selected by the electronic bases are ScienceDirect, 103; ACM, 160; Springer, 256; IEEE, 285; and google. scholar,1277, as shown in Figure 01. Google.Scholar had the

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
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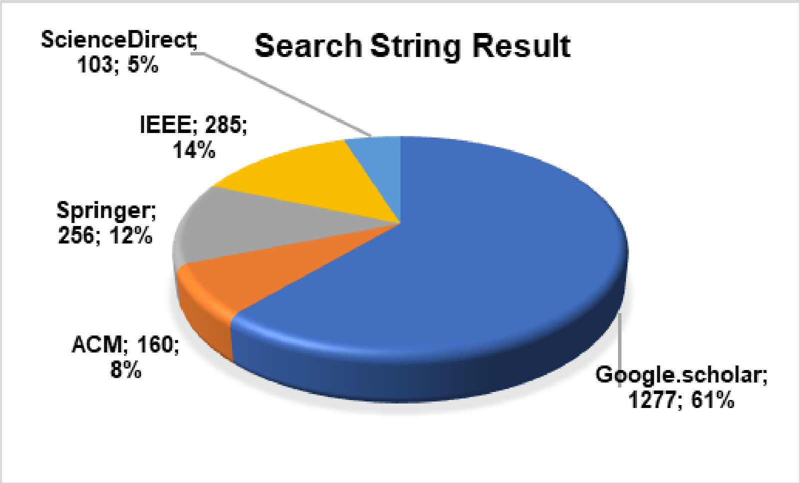
highest percentage of results, with 61%. With the selection of 1958 works, the process of cutting stages began. The cutting steps were performed using the exclusion criteria mentioned in item 3.3, shown below in item 4.1.

Figure 01: Search results in electronic database



Author: prepared by the authors

4.1 Exclusion of selected works in electronic databases

Select the 71 works and apply the exclusion criteria of topic 3.3. In the first stage, exclusion criteria, including reviews, surveys, dissertations, theses, books, and tutorials, resulted in 314 articles. In the second stage, exclusion criteria were used for articles that did not cover the researched topic and whiter papers, resulting in 139 articles. In the third stage, the exclusion criteria included duplicate articles and those without practical demonstration of results, resulting in 71 articles considered relevant to SR. The articles eliminated in the stages met the exclusion criteria, but this did not mean they were unattractive. However, they were not included in this review.

4.2 Evaluation of the quality of articles

To apply the quality assessment, the questions mentioned in item 3.4 were used. The values attributed to each question answer are presented in Table 02. The answers attributed to the quality questions represent yes, when the answer covers one hundred percent of the question; in parts, when it partially contemplates; and no, for the questions it does not answer, as described in Table 01. Answered the evaluation questions according to Kitchenham *et al.,* (2009).

Table 01: Score assigned to questions in the quality assessment of article

Answer	Description	Score
Yes	Answered the question	1
In parts	partially answered the question	0,5
No	don't mention the topic in the article	0

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RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
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The questions used to evaluate the 71 selected works are described in item 3.4. Table 02 presents the answers for each quality assessment question and the total grade for each work. With the application of quality questions, articles that received total scores between 1.5 and 3 were considered relevant and suitable for analysis and SR.

Table 02: Article quality assessment table

N	Autor	Ano	PQ1	PQ2	PQ3	PQ4	PQ5	Nota
1	Alves, Sousa, Borges	2020	Yes	Yes	Yes	Yes	Yes	5
2	Karar *et al.*	2021	Yes	Yes	Yes	Yes	Yes	5
3	Abid, Nida, Irtaza	2022	Yes	Yes	Yes	Yes	En parts	4,5
4	Segalla *et al.*	2020	Yes	Yes	Yes	Yes	No	4
5	Yu et al.	2022	Yes	No	Yes	Yes	Yes	4
6	Junior et al.	2017	Yes	Yes	Yes	No	Yes	4
7	Shankar et al.	2018	Yes	En Parts	Yes	En Parts	Yes	4
8	Rimal, Shah, Jha	2022	Yes	En parts	Yes	Yes	En parts	4
9	Li *et al.*	2020	Yes	Yes	Yes	En parts	No	3,5
10	Sobreiro *et al.*	2019	Yes	Yes	Yes	En Parts	No	3,5
11	Awuor *et al.*	2019	Yes	Yes	Yes	En Parts	No	3,5
12	Wani e Ashtankar	2017	Yes	En Parts	Yes	En Parts	No	3
13	Brunelli *et al.*	2019	Yes	Yes	Yes	No	No	3
14	Martini *et al.*	2019	Yes	No	Yes	Yes	No	3
15	Hossain *et al.*	2019	Yes	En Parts	En Parts	En Parts	En Parts	3
16	Banerjee, Sarkar, Ghosh	2017	Yes	Yes	No	Yes	No	3
17	Agnihotri, V.	2019	Yes	No	Yes	En Parts	En Parts	3
18	Fiehn *et al.*	2018	Yes	En Parts	Yes	No	En Parts	3
19	Ren *et al.*	2018	Yes	En Parts	Yes	En Parts	No	3
20	Ma, Liang, Lyu	2019	Yes	No	Yes	En parts	En Parts	3
21	Wang *et al.*	2021a	Yes	Yes	Yes	No	No	3
22	Peng, Wang	2022	Yes	Yes	Yes	No	No	3
23	Lins *et al.*	2020	Yes	Yes	Yes	No	No	3
24	Wang *et al.*	2021b	Yes	Yes	Yes	No	No	3
25	Wang *et al.*	2022	Yes	Yes	Yes	No	No	3
26	Xu *et al.*	2022	Yes	No	Yes	Yes	No	3
27	Gosaye, Moloo	2022	Yes	Yes	Yes	No	No	3
28	Ozdemir, Kunduraci	2022	Yes	Yes	Yes	No	No	3
29	Chen *et al.*	2021	Yes	No	Yes	Yes	No	3

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
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30	Albattah *et al.*	2022	Yes	No	Yes	Yes	No	3

Table continuation

N	Autor	Ano	PQ1	PQ2	PQ3	PQ4	PQ5	Nota
31	Chudzik *et al.*	2022	Yes	Yes	Yes	No	No	3
32	Sourav, Wang	2022	Yes	Yes	Yes	No	No	3
33	Tetila *et al.*	2020b	Yes	No	Yes	Yes	No	3
34	Qinsi *et al.*	2021	Yes	Yes	Yes	No	No	3
35	Dong *et al.*	2021	Yes	No	Yes	Yes	No	3
36	Pereira *et al.*	2022	Yes	No	Yes	En parts	No	2,5
37	Jiao *et al.*	2020	Yes	No	Yes	En parts	No	2,5
38	Arvind *et al.*	2017	Yes	No	Yes	En Parts	No	2,5
39	Chougule *et al.*	2016	Yes	En Parts	En Parts	En Parts	No	2,5
40	Wu *et al.*	2019	Yes	No	Yes	En Parts	No	2,5
41	Khalifa *et al.*	2020	Yes	En Parts	En parts	En parts	No	2,5
42	Shahzadi *et al.*	2016	Yes	En parts	No	Yes	No	2,5
43	Jia *et al.*	2019	Yes	En Parts	Yes	No	No	2,5
44	Rajan *et al.*	2016	Yes	No	Yes	No	En Parts	2,5
45	Liu *et al.*	2019b	Yes	No	Yes	En Parts	No	2,5
46	Mique *et al.*	2018	Yes	No	Yes	En Parts	No	2,5
47	Patel *et al.*	2019	Yes	No	Yes	En Parts	No	2,5
48	Truong *et al.*	2018	Yes	En Parts	Yes	No	No	2,5
49	Tetila *et al.*	2020	Yes	En parts	Yes	No	No	2,5
50	Song *et al.*	2019	Yes	No	Yes	No	No	2
51	Liu *et al.*	2019a	Yes	Yes	No	No	No	2
52	Ravisanka *et al.*	2019	Yes	En Parts	No	En Parts	No	2
53	Li *et al.*	2019	Yes	No	Yes	No	No	2
54	Espinoza *et al.*	2016	Yes	No	Yes	No	No	2
55	Xie *et al.*	2015	Yes	No	Yes	No	No	2
56	Nam *et al.*	2018	Yes	No	Yes	No	No	2
57	Gan *et al.*	2022	Yes	No	Yes	No	No	2
58	Yang *et al.*	2021	Yes	No	Yes	No	No	2
59	Du *et al.*	2020	Yes	No	Yes	No	No	2
60	Liu *et al.*	2022	Yes	No	Yes	No	No	2
61	Qian *et al.*	2022	Yes	No	Yes	No	No	2
62	He *et al.*	2020	Yes	No	Yes	No	No	2

N	Autor	Ano	PQ1	PQ2	PQ3	PQ4	PQ5	Nota
63	Ma *et al.*	2021	Yes	No	Yes	No	No	2
64	Li *et al.*	2018	Yes	No	No	En parts	No	1,5
65	Zhai *et al.*	2019	Yes	En Parts	No	No	No	1,5
66	Albore *et al.*	2015	Yes	En Parts	No	No	No	1,5
67	Dharini *et al.*	2018	Yes	En Parts	No	No	No	1,5
68	Coulibalya *et al.*	2019	Yes	No	No	No	No	1
69	Khattab *et al.*	2019	Yes	No	No	No	No	1
70	Chougule *et al.*	2019	Yes	No	No	No	No	1
71	Xu *et al.*	2019	Yes	No	No	No	No	1

Table continuation

Author: prepared by the authors

5. DISCUSSION

This section discusses the three research questions listed in subsection 3.1 in the section 3. The questions are answered through the contributions of each work analyzed. It is reported what each work presents regarding development, the tools used, and the solution proposed for combating and controlling pests. Them transformed the three questions into a subsection of section 5.

5.1 QP1 - What are computational technologies used to combat and control pests in agricultural production

Computer technology is currently present in the agribusiness chain, aiming to bring efficiency and effectiveness to agricultural productivity. Acting in control and fighting against pests promotes increased productivity. Several technologies have gained ground, such as the use of UAVs, smartphones, images, sensors, robots, AI, and ML, to monitor the development of agriculture. Some examples of uses of these technologies are UAVs to capture images, film, and for the application of pesticides; smartphones to analyze images and run systems; robots to capture images and videos; ML and DL for image classification; sensors to capture movement sounds and humidity. Smart agriculture uses AI and its tools for various actions such as diagnosis, classification, identification/recognition, pest, disease, and weed control. The use of AI in agriculture grows every day, and its application occurs from pre-harvest to post-harvest. ML technology and its tools are used in models to carry out pest control actions in crops. Most model training and testing are performed using database images and or images captured in real-time.

This section will report the articles that meet the first research question, which presents which computational technologies are used to combat and control pests in agricultural production. The computational technologies used in pest control are vast and applied in different actions, such as classification; detection; elimination; estimation of the severity of the infestation; identification and recognition; location; and monitoring. The works that use computational technologies to control and combat pests in agricultural production are reported below.

Junior *et al.* (2017) and Shankar *et al.* (2018) used ML to control the spraying of agrochemicals in agriculture. Used ML to compare, classify and identify crop pests and demonstrate the results (Brunelli *et al.* 2019; Hossain; Tareq; Uddin, 2019; Liu *et al.* 2019b; Sobreiro *et al.* 2019; Wani; Ashtankar, 2017). The system created by Hossain, Tareq, Uddin (2019) has two categories. In the first, trained the system with the collected information, and in the second came the classification process. Comparing the images returns whether or not it is a harmful insect. With this new data, the system is retrained, thus always being up to date (Hossain; Tareq; Uddin, 2019). The Digicult system uses ML to surveillance and identifies pests, suggest stores specializing in agriculture, and contact field agents and specialists (Awuor *et al.,* 2019). The observation system Martini *et al.* (2019) created uses ML to map, monitor and count pests in agriculture and forestry. Liu *et al.* (2019b) and Bruneli *et al.* (2019) use ML for classification by performing pest identification/recognition. Sobreiro *et al.* (2019) uses a module with ML, allocated in the cloud, to process images to classify and identify pests. Lins *et al.* (Lins *et al.* 2020) used software to automate the counting and classification of pests using ML. Authors have tested ML in various actions to combat and control pests, surveillance, observation, guidance systems, etc.

In the works analyzed, applied the DL tool in several proposals for solutions for combating and controlling pests in agriculture. Models that use DL were proposed for actions to map regions and perform classification for the identification and diagnosis of pests (Albattah *et al.* 2022; Fiehn *et al.* 2018; Liu *et al.* 2019b; Patel; Vaghela, 2019; Tetila *et al.* 2020a; Truon *et al.* 2018). Liu *et al.* (2019b) used DL in the model to estimate the severity of pest infections. An autonomous system uses DL to detect pests and assist farmers in locating pests (Abid, Nida, Irtaza, 2022). Yu *et al.* (2022) present a combination of DL and optimization algorithms for fruit fly diagnosis.

The DL tool, CNN architecture, is used in models to recognize pests, diseases, and weeds, achieving greater accuracy in results than other tools (Jia; Gao; Hang, 2019; Li *et al.* 2020; Ren *et al.* 2018; Tetila *et al.* 2020b; Truong *et al.* 2018; Wu; Li; Wu, 2019). Developed applications with CNN to detect pests and inform the farmer which procedures should be adopted (Liu *et al.* 219b); Mique, Palaoag, 2018. CNN is used to diagnose pests and diseases in images captured in a natural environment (Patel; Vaghela, 2019; Tetila *et al.* 2020b). The systems proposed by Liu et al. (2019b) and Wang *et al.* (2021b) use CNN to classify, identify, detect, and estimate the severity of pest infestation. The CNN is used in classification models for pest identification/recognition, diagnosis, and detection (Alves *et al.* 2020; Dong *et al.* 2021; Gasaye; Mollo, 2022; Jia; Gao; Hang, 2019; Karar *et al.* 2021; Ozdemir; Kunduraci, 2022; Patel; Vaghela, 2019; Ren *et al.* 2019; Rimal; Shah; Jha, 2022; Tetila *et al.* 2020a; Wu; Li; Wu, 2019; Yu *et al.* 2022. Xu *et al.* (2022) use CNN and multiscale CNN for the recognition and identification of different pests and different sizes. The location of the region affected by pests is essential for control, as it determines the exact location of pesticide application. This issue was addressed by authors who used the CNN architecture to identify contaminated regions and diagnose and detect pests using images (Liu *et al.* 2019b; Jia; Gao; Hang, 2019). A model was proposed by Sourav, Wang (2022) using DCNN and transfer learning to identify pests.

The Vector Machine Support (SVM) tool is used in models to perform image processing to identify and classify crop pests. Vivek A. (2019) and Truong *et al.*, (2018) used SVM to perform classification and identify pests. Ma, Liang, Lyu (2019) used Neural network (NN) and D-S Evidence Theory to predict pest outbreaks based on climatic and pest outbreak factors. Arvind *et al.* (2017) used ML and IoT to automate crop irrigation. Banerjee, Sarkar, Ghosh (2017) analyzed and tested the use of an Artificial Neural Network (ANN) based solution that employs Radial Basis Function (RBF) model for classification to detect and identify pests in agriculture. Shankar *et al.* (2018) proposed a multitasking system to detect pests, diseases, and weeds, locate the affected regions and determine the specific locations of pests in the crop. The YOLO architecture is also used in studies to detect and classify pests (insects). Pereira *et al.* (2022) proposed using a YOLO4 based backbone to detect and classify pest stages.

The use of hybrid architecture is another option in the task of controlling and combating pests. Peng and Wang (2022) used the attention mechanism and CNN to create a hybrid architecture. This hybrid architecture is being used for pest recognition, and the tests performed tend to outperform the CNN architecture (Peng and Wang, 2022). Chen et al. (2021) used CNN and attention mechanism to detect pest information. Wang *et al.* (2021b) added RPN and attention mechanism, creating the S-RPN model to improve pest detection accuracy. The S-RPN model highlights details of pests, especially when these details are small, favoring pest detection. Wang *et al.* (2022) went beyond detection and focused on identifying locations and contours of pests.

Expert Systems (ES) used in agriculture generally identify and provide information about pests. Another technology under study for agriculture is the IoT. Its use is associated with combating and controlling pests, automating pest detection actions, sending information, and connecting equipment. ES can provide information on weather forecasts, types of pests, and disease control for the farmer (Chougule; Jha; Mukhopadhyay, 2016). Shahzadi *et al.* (2016) developed an ES to prevent crop pest infestation. It uses IoT to feed the ES in real-time, and upon receiving the data, process them and automatically inform the farmer (Shahzadi *et al.* 2016). Chougule Jha, Mukhopadhyay (2016) created the ES AgroKanti to combat pests and manage diseases, making infor mation available to the farmer by application, via cell phone, or other devices. ES has an incisive role in helping to manage agriculture with information about pests, weather, etc. Segalla *et al.,* (2020) created a model where images are captured in traps and sent to a DNN algorithm, which analyzes and sends alarms to the farmer if the detection is positive. In this process, insects are attracted to the trap by pheromones.

The physical and logical technologies used together allow the combat and control of pests to become more efficient. UAVs capture images for identification, classification, pest quantity counting, diagnosis, detection, etc. (Martini *et al.,* 2019; Vivek, 2019). Martini *et al.* (2019) use the remote sensing technique with the UAV and photogrammetry to capture the images. Vivek (2019) uses a thermal and high-resolution camera to capture images.

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
ISSN 2675-6218

The use of mobile devices such as smartphones, notebooks, etc. in crops, it ranges from a simple connection to the use of a system. The use of smartphones in crops is gaining more space with the development of smart agriculture. Smartphones are used to run systems, capture images, send to a model to identify pests in real time (Sourav; Wang, 2022). A pest identification/recognition and detection system using DL can run on both desktop and mobile devices (Chudzik *et al.*, 2020; Gasaye; Mollo, 2022; Rimal; Shah; Jha, 2022). A decision support model uses DL and runs on a mobile device to detect and classify insects (Karar *et al.* 2021; Ozdemir; Kunduraci, 2022). In addition to detecting, the system proposed by Wang *et al.* (2021a) monitors and counts pests using a smartphone.

Smart sensors are used in agriculture applications such as soil, temperature, humidity, pest detection, irrigation, etc. Arvind *et al.* (2017) use humidity and water level sensors associated with ML and IoT for pest control and irrigation. Sensors and IoT were associated with transmitting, in real-time, data on pests, weeds, and diseases Shahzadi *et al.* (2016). Sobreiro *et al.* (2019) used infrared sensors to trigger cameras and collect images of pests. Martini et al. (2019) use remote sensing to capture images with UAVs. A wireless sensor network (RSSF) was used to perform the processing and comparison between system data and data collected in real-time in the field (Wani; Ashtankar; 2017).

Computer networks, especially wireless networks, can make a difference in pest control actions. Wireless networks in the field are practically non-existent; most properties only have Wi-Fi at the farmhouse. Bruneli *et al.* (2019) uses the LoRa network to send the images for analysis by the person in charge. A mobile application to automatically classify pests using DL runs on the Cloud (Karar *et al.* 2021). Cameras are essential to make so many actions to combat pests possible. Practically all the studied authors use cameras to collect images. We can mention the authors (Arvind *et al.* 2017; Chougule; Jha; Mukhopadhyay, 2016; Junior *et al.* 2017) who did not use images or cameras for their proposals.

Table 03: Physical technologies used in agriculture

Table of application of physical technologies to combat pests		
Reference	Application	Smart Farming Technologies
Albattah et al. (2022)	Identification and categorization of insects	UAVs
Agnihotri, V. (2019)	Classification of pests through images	UAVs and cameras
Arvind et al. (2017)	A system that automates the irrigation process and promotes pest control	Sensores and transmitter
Awuor et al. (2019)	Pest surveillance. Use a smartphone to control and identify pest invasion. It connects to extension services and also uses voice assistants for the illiterate	Sensors and smartphone
Chen et al. (2021)	pest identification	Smartphone
Chudzik et al. (2022)	pest detection	Smartphone
Dong et al. (2021)	Recognition of pests and diseases	Smartphone
Fiehn et al. (2018)	System for diagnosing and recognizing pests,	Cameras

	including birds	
Hossain, Tareq, Uddin (2019)	System for pest detection, ecognizing whether it isharmful or beneficial, through images. Pest classification	Cameras
Hahzadi et al. (2016)	ES to identify different types of pests, weeds, and insects. Returns information to farmers	Sensors and Xbee802.15.4
Karar et al. (2021)	Automatic pest classification	Smartphone

Table continuation

Reference	Application	Smart Farming technologies
Liu et al. (2019b)	Capture images, classify for large-scale pest detection, and provide possible affected regions	Cameras
Li et al. (2020)	Pest recognition mobile app	Smartphone
Martini et al. (2019)	Solution for detecting and classifying diseases and pests. Get the location and record the geographic coordinates	Cameras
Mique, Palaoag (2018)	An application that helps farmers detect rice pests and diseases in images	Cameras and sensors
Ma, Liang, Lyu (2019)	Capture images, run the system to identify pests, and transmit the result	Cameras, UAVs, IoT, robots and smartphone
Pereira et al. (2022)	Capture images to detect and classify whiteflies	Cameras
Rimal, Shah, Jha (2022)	Pest recognition and detection	Cameras
Segalla et al. (2020)	Detect insects in images	Raspberry-Pi, cameras
Shankar et al. (2018)	System to locate regions affected by diseases and pests. Control the use of agrochemicals	UAVs and cameras
Sobreiro et al. (2019)	Early pest detection system. Use a trap to attract insects, take pictures, process and send to the cloud for processing	Raspberry-Pi, camera and sensor
Tetila et al. (2020a)	Pest detection in soybean images captured with UAV	UAVs and smartphone
Tetila et al. (2020b)	Identify and classify pests	Cameras
Wang et al. (2021a)	Mobile pest monitoring system	Smartphone
Wani, Ashtankar (2017)	Identify and quantify if you have pests	Raspberry Pi, sensors, zigbee and modem

Author: prepared by the authors

Table III presents the leading physical technologies used in the analyzed works. Cameras are the most used, followed by smartphones and UAVs. As for logic tools, they are all linked to AI, and the vast majority use ML and DL. Very few papers use other technologies, such as ES and Ontologies.

5.2 QP2 - How Artificial Intelligence have been used for pest control and combat

AI is growing, and its application occurs in all fields of intelligent agriculture. The need for pest control is increasing every day, enabling food production growth without increasing the already planted areas. Pest control has been gaining special attention because it reduces the risk of production losses for the farmer and provides a productivity forecast for the Government. The research question is, how has AI been used for pest control and combat? demonstrate how AI has been used in this context. The behavior patterns of pests, diseases, and weeds and the identification of mineral failures or soil correction failures can be identified by image processing or using sensors. These diagnostics allow the manager to intervene quickly. All these features generate a vast amount of data for various purposes, including training ML models.

Pest control in crops has been a challenge for farmers. Climatic variations and the appearance of new species of pests and diseases make control more difficult, causing damage to various sectors of agriculture. Some problems caused by pests are decreased production; ground contamination; excessive use of pesticides; economic loss; human health. AI and its tools brought services and tools that help control pests, promoting efficiency and effectiveness in reducing costs and increasing productivity from pre-harvest to post-harvest. AI tools are used in pest control in actions such as classification; detection; estimation of the severity of the infestation; identification; location; monitoring; and recognition. AI is applied to preparing models that perform the actions mentioned above. AI, ML, and DL tools are used in the models to train and test them. These actions use databases, sentic images or are captured in real-time. Figure 02 demonstrates the actions to control and combat pests. These actions are reported in the analyzed works. Classification, identification, and detection actions are the ones that appear most in the works.

The elimination of pests in crops can be carried out using techniques such as high frequency sound waves, spraying of chemical or natural products, etc. Combating with agricultural, land, or aerial spraying can generate waste products because it is applied in places that do not need it or by excess in the exact location (Junior *et al.* 2017). ML and DL are being studied for pest control, irrigation, and spraying systems (Arvind *et al.* 2017; Junior *et al.* 2017). In spraying, a deposition model predicts the volume of products that are deposited at the place of cultivation (Junior *et al.* 2017). Arvind *et al.* (2017) created pest control along with the irrigation system, which emits ultrasonic sound through emitting sensors placed around the field.

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
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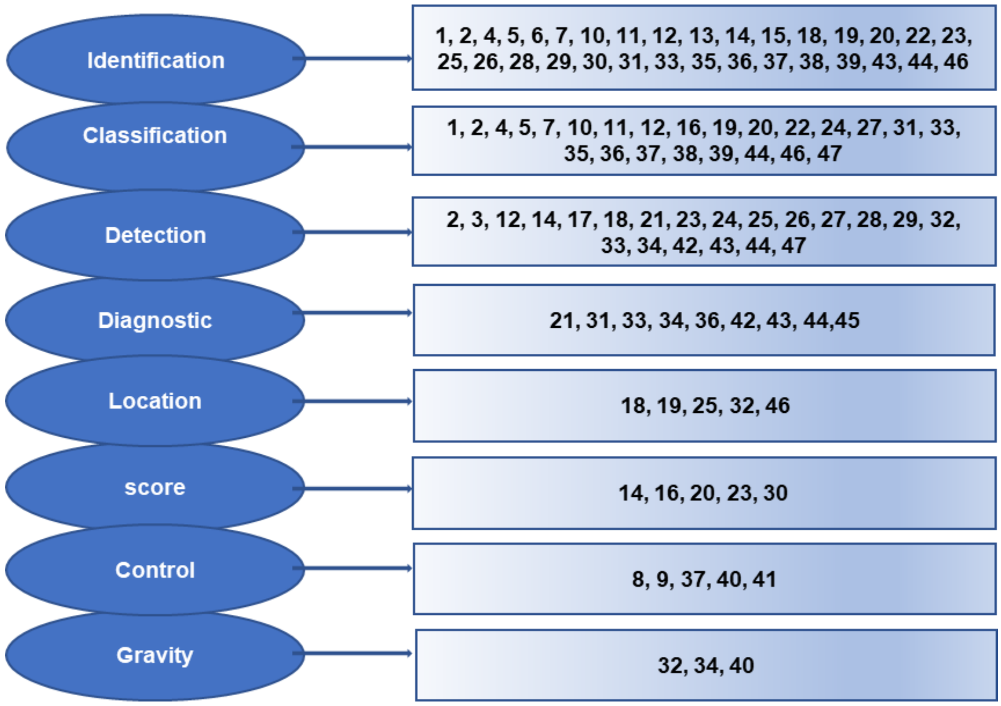
Figure 02: Actions to combat and control pests reported in the researched works



Author: prepared by the authors

The ML and DL tools are widely used in pest combat and control processes, with DL being the most used, according to the works analyzed in this study. The Digicult system performs electronic pest surveillance, image, and information processing using ML on smartphones (Awuor *et al.,* 2019). Lins *et al.,* (2020) created a method and software to automate the counting and classification of pests using image processing, computer vision, and ML. Liu *et al.,* (2019b) used CNN to estimate the severity of pest infestation in the field and used CNN to classify, create location maps, and improve accuracy respectively. Identifying places infested with pests favors the fight and control of pests, allowing the application of agrochemicals only where they are infected.

DL technology appeared in most studies on combating and controlling pests and diseases in agriculture, either directly or associated with other technologies. An autonomous DL system detects and locates pests (Abid; Nida; Irtaza, 2022). Fiehn *et al.*; (2018) used LD to identify pests. DL's CNN architecture is being used to make a diagnosis, measure the severity and identify pests in crops, according to Liu *et al.* (2019b), Patel, Vaghela (2019) and Truong *et al.* (2018). They evaluated CNN architectures for their performance in classifying and identifying pests (Ozdemir; Kunduraci, 2022; Tetila *et al.* 2020b). A combination of CNN and optimization algorithms were built for pest diagnosis (Yu *et al.* 2022).

Classification, diagnosis, detection, identification, and recognition of pests are actions carried out by CNNs reported by Alves *et al.* (2020), Dong *et al.* (2021), Jia, Gao, Hang (2019), Khalifa, Loey, Taha (2020), Li *et al.* (2020), Mique, Palaoag (2018), Patel, Vaghela (2019), Sourav, Wang (2020), Ren *et al.* (2018), Tetila *et al.* (2020a), Truong *et al.* (2018), Wu, Li, Wu, (2019). The strategies used by the cited authors were fine-tuning, learning transfer, and segmented images with superpixel simple linear interactive clustering (SLIC). The DanseNet-201 model showed the best result using images collected at 1m altitude (Tetila *et al.* 2020a). Wang *et al.* (2021a) used CNN on an automatic system to detect and count pests on a smartphone. Used the CNN architecture to develop identification and detection systems running on applications (Albattah *et al.* 2022; Chudzik *et al.* 2020; Gasaye; Mollo, 2022; Ozdemir, Kunduraci, 2022; Rimal; Shah; Jha, 2022). The use of CapsNet and multiscale CNN to recognize and identify various types of pests was proposed by Xu *et al.* (2022). An application to run on a mobile device was created by Karar *et al.* (2021) to classify pests automatically using DL (Faster R-CNN) and cloud computing. Jiao *et al.* (2020) designed a network for pest recognition, classification, and location using Faster R-CNN. New pest control and combat models were developed, using attention mechanisms and CNN to create hybrid architectures. To carry out the classification and recognition of pests, an attention mechanism and associated CNN were used (Chen *et al.* 2021; Peng; Wang, 2022). The association of the attention mechanism and ML gave rise to a network for detecting little pests and generating the selection of the affected region (Wang *et al.* 2021; Wang *et al.* 2022).

Tools such as SVM, ANN, YOLO, and IoT are in use to combat and control pests, but on a smaller scale, as seen in this study. Segalla *et al.* (2020) developed an intelligent device with DNN and IoT to detect pests. To identify and classify pests, Agnihotri, (2019) used a model that performs pre-processing and segmentation of images. Banerjee, Sarkar, Ghosh (2017) used ANN and RBF to detect three pests. Shankar *et al.,* (2018) created a multitasking system to detect pests, diseases, and weeds, through treated images that are compared with the database. To predict possible pest attacks, Ma, Liang, Lyu (2019) related climatic factors and outbreaks using AI and ANN. The YOLOv4 architecture was used as a backbone to classify, identify and detect the life stage of the whitefly pest (Pereira *et al.,* 2022).

ES is used in combating and controlling, in actions, generally, identification, and providing information; it can even supply specialized human knowledge. Models provide information about predictions and types of pests and disease control for the farmer, helping in agriculture management (Chougule; Jha; Mukhopadhyay, 2016). The ESs developed for pest prevention use images, texts, and information from experts in the field to carry out the determined action (Shahzadi *et al.* 2016). Shahzadi *et al.* (2016) used IOT and sensors in the field to transmit data on pests, diseases, and weeds collected in real-time to the server, which processes and returns the result to the farmer. The ES by Shahzadi *et al.* (2016) informs the farmer about the agricultural situation when receiving and processing data in real time. These ESs use ML algorithms to give the farmer access to information. This information is stored, forming the ES knowledge base (Shahzadi *et al.* 2016). AgroKanti is an ES for the management of pests and diseases in grapes. The AgroKanti knowledge base was developed as an ontology and can be shared with other systems (Chougule; Jha; Mukhopadhyay, 2016). AgroKanti runs on mobile devices, in which the farmer needs to register. When starting ES use, its location is detected, and all information about pests and diseases is provided to farmers (Chougule; Jha; Mukhopadhyay, 2016).

Most studies analyzed in this work use image processing to extract information about pests. There are several ways to work with images, such as segmentation, enlargement, cropping, and

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ISSN 2675-6218

grouping. These techniques are necessary for ML and DL models and their tools to present better results. Of the DL tools, the ones that appear the most are the CNN architectures Inceptio-V3, Inception-V4, Resnet-50, DenseNet-201, VGG 16, VGG 19, GoogleNet, etc. Other tools like SEs, ANN, SVM, DNN, attention mechanisms, and YOLO appear less frequently. The use of attention mechanisms and YOLO appear in more recent works.

5.3 QP3 - Which machine learning tools are used to combat and control pests in agricultural production

Smart agriculture uses ML and its tools to control and combat pests. In the works analyzed, the ML tool that appears the most is the DL. DL's CNN architecture appears in most of the analyzed works pest control models, as seen in Figure 03. The use of CNN architecture in models occurs alone, associated with other ML tools, and in hybrid models with other DL tools. Figure 03 shows the AI, ML and DL tools and which references used them. The most used tool in pest control and combat proposals was CNN. The use of ML tools to combat and control pests includes actions of classification, identification, diagnosis, detection, spray control, etc., as reported below. Junior *et al.* (2017) developed an ML-based spraying system with a main module composed of RN and Regression Tree techniques. He has chosen these two techniques because they are from different paradigms. The same system that irrigates also emits short, high-frequency sound waves, affecting the brain and nervous system of pests (Junior *et al.* 2017). ML was associated with IoT to receive and send data to a database, process them, and emit sounds (Arvind *et al.* 2017). Images are captured in traps, processed using ML, and used to classify and identify pests (Arvind *et al.* 2017). A smart device with AI and IoT was developed for pest detection by Segala *et al.* (2020). The PestNet system used CNN, together with the Region Proposal Network (RPN) and the Position Sensitive Score Map (PSSM), for image data extraction to generate a map of the contaminated region (Liu *et al.* 2019b). They have enlarged the images in four different resolutions, using the test time increase (TTA) and the multiscale training model, detecting the pest separately in each image. Subsequently, the four images were merged, generating the final processing of recognition and accuracy in location (Liu *et al.* 2019b).

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
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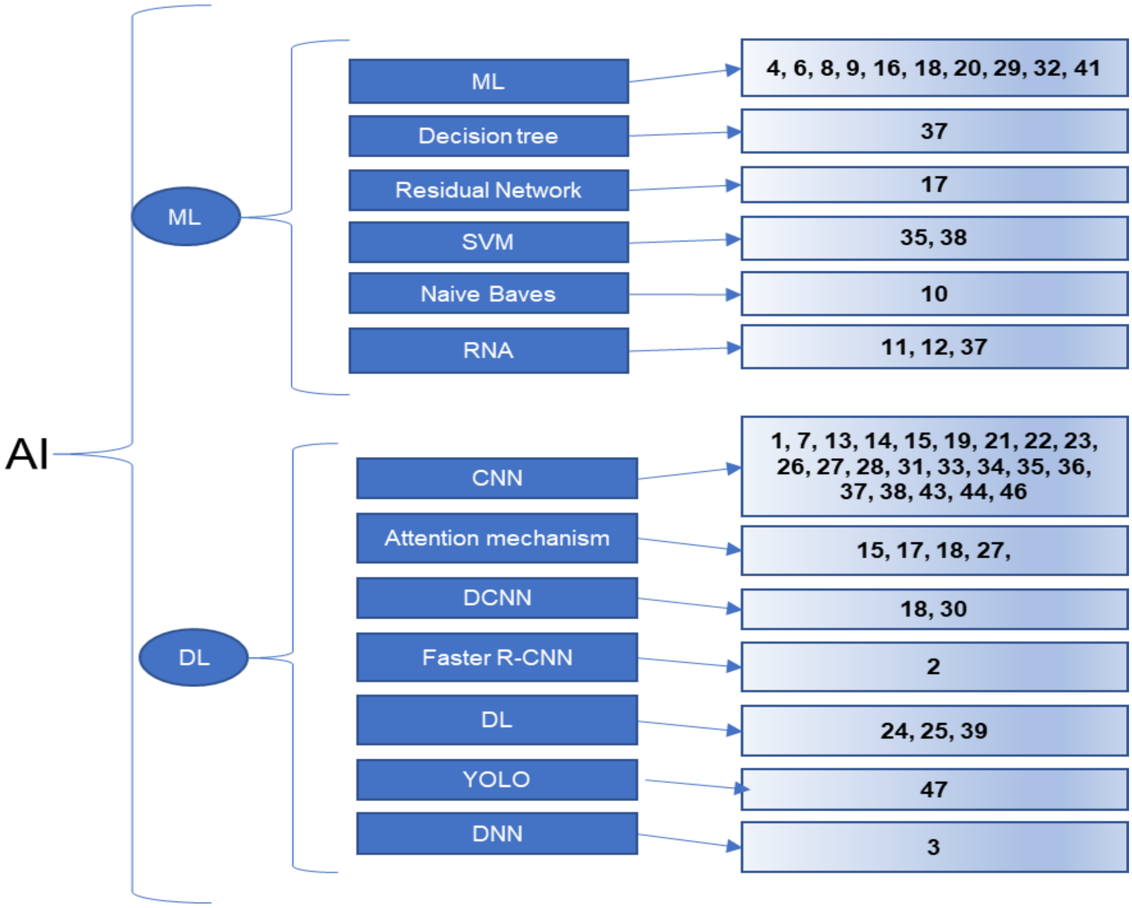
Figure 03: The AI tools (ML and DL) and which references used them



Author: prepared by the authors

Martini *et al.* (2019) used ML, remote sensing, photogrammetry techniques, and images captured with UAVs to identify pests. The images are processed using an ML classifier and Visual Computing. Pre-processed images and segmentation count pests and species (Martini *et al.* 2019). Digicult is an electronic pest surveillance system that runs on a smartphone, processing images and information using ML and returning possible pest outbreaks (Awuor *et al.* 2019). The AphidCv application uses computer vision and ML for pest classification and counting (Lins *et al.* 2020). Bruneli *et al.* (2019) process the images in loco, applying ML and DNN. If the result is positive for the plague, the report is forwarded to the responsible person in charge (Bruneli *et al.* 2019). Sobreiro *et al.* (2019) developed the I2MS system, which applies ML in image processing in a Cloud module. The system proposed by Shankar *et al.* (2018) uses ANN, which involves two types of support, Vector machine, and K-means. Used the K-means Cluster because it is efficient in image segmentation, and the vector machine provides the best results in extracting color and texture from images. Wani and Ashtankar (2017 use the Naïve Bayes algorithm to compare the images and return the results using a WSN. Khalifa, Loey, Taha (2020) present a model that uses AlexNet, GoogleNet, and SqueezNet that enlarges the images four times to facilitate their analysis. Ren *et al.* (2018) used VGGNet and the

RMSProp algorithm to process images, make cuts, apply distortion methods, make color adjustments, and change the background, generating new images.

Patel and Vaghela (2019) developed a DL model using CNN to extract information from images. Processed these images and then created a dataset. Jia, Gao, Hang (2019) developed an Inception-v3 model to identify and classify five classes of pests and diseases in tomatoes. They have used regularization-based CNN and a mobile model to adjust the parameters in the model and increase the robustness of the test data model Jia, Gao, Hang (2019). Mique and Palaoag (2018) used Inception-v3 to detect pests and diseases in rice fields. Tetila *et al.* (2020a) evaluated three CNN models, Inception-Resnet-V2, ResNet-50, and DenseNet-201, for classifying and identifying soybean pests. The combination of AlexNet and GoogleNetV1 generated a new algorithm that eliminates bad images for training a model detection of pests and diseases (Wu; Li; Wu, 2019). Tetila *et al.* (2020b) used CNN to diagnose pests and diseases in images captured in a real environment.

The combination of CNN and optimization algorithms generated a model for pest diagnosis (Yu *et al.* 2022). They have used the CNN architecture in models for pest recognition and classification (Alves *et al.* 2020; Dong *et al.* 2021; Li *et al.* 2020; Xu *et al.* 2022). CNN has been used in mobile systems to monitor, detect, identify, and count pests (Gasaye; Mollo, 2022; Wang *et al.* 2021b). Used CNN and attention mechanisms to create a simplified pest recognition network (Peng; Wang, 2022). Ozdemir, Kunduraci (2022) developed a decision support system, comparing models that use CNN to classify and identify pests. YOLOv4 and Faster R-CNN were also used in their model (Ozdemir; Kunduraci, 2022). Liu *et al.* (2019b) developed a two-step system: global hybrid resource (GaFPN) and local resource-enabled resource (LaRPN). Integrated both steps into one solution, using connected CNN to estimate the severity of pest infestations (Liu *et al.* 2019b). Fiehn *et al.* (2018) used DL in a model which performed well in pest identification. The Pest Inspector system used a decision support system, combining a decision tree and RN to define differences between beetles (Hossain; Tareq; Uddin, 2019). CNN and Faster R-CNN were used in the mobile app to classify pests (Karar *et al.* 2021). Jiao *et al.* (2020) designed the AF-RCNN for accurately recognizing, classifying, and locating pests. Agnihotri (2019) developed an SVM system for image processing to identify and classify crop pests. Pereira *et al.* (2022) created a backbone model with the YOLOv4 architecture to detect and classify pests at various stages on crop leaves. He used attention mechanisms and residual networks to improve the details of little pests in images (Wang *et al.* 2022). CNN, attention mechanism, and activation map were integrated to train a model for pest classification (Chen *et al.* 2021). An intelligent mobile model used DCNN for pest identification (Sourav; Wang, 2022).

6. CONCLUSION

The employability of AI occurs in practically all areas. In agriculture, its use is growing, transforming traditional agriculture into intelligent agriculture. This RS investigated and presented the results of scientific articles that deal with the use of AI, ML, and DL in the control and combat of pests in agriculture. The focus was on searching for works demonstrating the solutions and updates in the control and combat using ML and DL. The use of AI, ML, and Dl in combating and controlling pests

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
ISSN 2675-6218

has limitations and factors such as high cost, scarce labor, large regions, lack of knowledge and skills of farmers, the precision of applications, knowledge held by few, complexity, and mobility, among others. These technologies have taken place in areas such as the application of agricultural products, control and combat of pest infestation, inadequate soil treatment, irrigation, climate, generating information for the farmer, and suggesting solutions, among others. In the fight against pests, ML acts in the classification, detection, identification, monitoring, pest counting, irrigation, and application of agrochemicals and products, among others. The applicability of ML in agriculture can bring economic and time gains; accuracy in decision-making; precision in combating and controlling pests, diseases, and weeds; market information.

The high cost, long distances, and difficulties in operationalizing technologies have impacted and limited the use of AI and its tools in agriculture. Small farmers do not have the knowledge or economic power to use technologies. Medium-sized and large farmers, in addition to the cost, have long distances, making the use of technologies difficult. An example is the networks that do not reach farming locations. These sites have large extensions, which makes the points far from each other; the number of necessary sensors becomes impracticable, due to the size of the area, for example. Farmers' difficulties in accepting and using new intelligent technologies have also been a limiting factor. They believe Cannot replace human labor with equal efficiency and effectiveness. The difficulty of dealing with technology makes them give up using it.

The research in the five databases showed many existing works in this context. With the application of the inclusion and exclusion filters, 71 works remained. After applying the quality assessment, 47 articles remained, which were analyzed. Of the 47 works examined, practically all use an ML tool, with DL being the most constant. Including the use of two or more ML tools in a single model, providing the capacity to learn, flexibility, and more accurate and faster training of processes. Another constant is the use of images in the models, whether captured in real life or from a database, to carry out pest control and combat actions. Among the ML tools found in the works, the most used is DL, with the CNN architecture being the most prominent, as seen in Figure 03. The tools SVM, DNN, SE, attention mechanism, and YOLO, among other solutions, are also being used to combat and control pests. These ML technologies help increase productivity and production quality and preserve the environment.

RS demonstrated that AI, ML, and DL technologies contribute to combating and controlling pests. It can generate increased production, food quality, and preservation of the environment (Das *et al.,* 2018). Despite all the difficulties, research has shown the advancement, growth, and benefits of using intelligence technologies in agriculture. But it also showed that there is much to be researched in this area, such as: identifying insects, weeds, and diseases simultaneously, using pest behavior to identify them, and using leaf damage to identify insects. Deepen the study of the use of attention mechanisms and ViT in identifying pests in real images and natural images captured by low-cost drones to identify pests. The benefits of using ML in agriculture are increasing; new opportunities are emerging, and new forms of use and actions to control and combat pests.

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REFERENCES

ABID, H.; NIDA, N.; IRTAZA, A. PestinaNet- A real-time crop pest detection system. *In:* **2nd International Conference on Computing and Machine Intelligence (ICMI)**, p. 1–4, 2022. doi:10.1109/ICMI55296.2022.9873654

AGNIHOTRI, V. Machine learning based pest identification in paddy plants. **International conference on Electronics, Communication and Aerospace Technology – ICECA**, v. 3, p. 246-250, 2019. doi:10.1109/ICECA.2019.8822047

ALBAHAR, M. A survey on deep learning and its impact on agriculture: Challenges and opportunities. **Agriculture**, v. 13, p. 540, 2023. doi:10.3390/agriculture13030540

ALBATTAH, W.; MASOOD, M.; JAVED, A.; NAWAZ, M.; ALBAHLI, s. Custom cornernet: a drone based improved deep learning technique for large-scale multiclass pest localization and classification. **Complex Intelligent Systems**, v. 2198-6053. 2022. doi.org/10.1007/s40747-022-00847-x

ALBORE, A. V. Z.; PEYRARD, N.; SABBADIN, R.; TEICHTEIL-KONIGSBUCH, F. An online replanning approach for crop fields mapping with autonomous UAVs. **Proceedings of the Twenty-Fifth International Conference on International Conference on Automated Planning and Scheduling – ICAPS 25**, p. 259-2677, 2015. doi.org/10.1609/icaps.v25i1.13692

ALVES, A. N.; WITENBERG. S. R. S.; BORGES, D. L. Cotton pests classification in field-based image using deep residual networks. **Computers and Electronics in Agriculture**, v. 174 p. 105488, 2020. doi.org/10.1016/j.compag.2020.105488

ARVIND, G.; ATHIRA, V.; HARIPRIYA, H.; RANY, R. A.; ARAVIND, S. Automated irrigation with advanced seed germination and pest control. **Technological Innovations in ICT for Agriculture and Rural Development – TIAR**, 2017. doi:10.1109/TIAR.2017.8273687

AWUOR, F.; OTANGA, S.; KIMELI, V.; RAMBIM, D.; ABUYA, T. E-pest: Surveillance large scale crop pest surveillance and control. **Africa Week Conference – IST**, 2019. doi:10.23919/ISTAFRICA.2019.8764824

BANERJEE, G.; SARKAR, U.; GHOSH, I. A radial basis function network-based classifier for detection of selected tea pests. **International Journal of Advanced Research in Computer Science and Software Engineering – IJARCSSE**, v. 7, p. 665–669, 2017. doi:10.23956/IJARCSSE/V7I5/0152

BRUNELLI, D.; ALBANESE, A.; ACUNTO, D.; NORDELLO, M. Energy neutral machine learning based IoT device for pest detection in precision agriculture. **Internet of Things**, v. 2, 2019. doi:10.1109/IOTM.0001.1900037

CASTILLO, E.; GUTIERREZ, J. M.; HADI, A. S. Expert Systems and Probabilistic Network Models. [S. l.]: Springer Link, 2012.

CHEN, J.; CHEN, W.; ZEB, A.; ZHANG, D.; NANEHKARAN, Y. A. Crop pest recognition using attention-embedded lightweight network under feld conditions. **Applied Entomology and Zoology**, v. 56, p. 427–442, 2021. doi.org/10.1007/s13355-021-00732-y

CHOUGULE, A.; JHA, V.; MUKHOPADHYAY, D. Ontology based system for pests and disease management of grapes in india. **International Conference on Advanced Computing – IACC**, v. 6, 2016. doi:10.1109/IACC.2016.34

CHOUGULE, A.; JHA, V. K.; Mukhopadhyay, D. Decision support for grape crop protection using ontology. **International Journal of Reasoning-based Intelligent Systems – IJRIS**, v. 11, n. 1, 2019. doi.org/10.1504/IJRIS.2019.098051

CHUDZIK, P.; MITCHELLI, A.; ALKASEEM, M.; WU, Y.; FANG, S.; HUDAIB, T.; PEARSON, S.; ALDIRI, B. Mobile real-time grasshopper detection and data aggregation framework. **Scientific Reports**, v. 10, 2020. doi:10.1038/s41598-020-57674-8

COULIBALYA, S.; KAMSU-FOGUEM, B.; KAMISSOKO, D.; TRAORE, D. Deep neural networks with transfer learning in millet crop images. **Computers in Industry**, v. 108, 2019. doi.org/10.1016/j.compind.2019.02.003

DAS, S.; GHOSH, I.; BANERJEE, G.; SANKAR, U. Artificial Intelligence in Agriculture: A Literature Survey. **International Journal of Scientific Research in Computer Science Applications and Management Studies - Artificial-IJSRCSAMS**, v. 7, 2018.

DHARINI, P. U.; NARRMADHA, K.; SARANYA, k.; MORRISHA, S. Iot based decision support system for agriculture yield enhancements. **International Journal of Recent Technology and Engineering – IJRTE**, v. 7, p. 362–367, 2018. ISSN: 2277-3878

DOMINGUES, T.; BRANDÃO, T.; FERREIRA, J. C. Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey. **Agriculture**, v. 12, n. 9, p. 1350, 2022. doi:10.3390/agriculture12091350

DONG, C.; ZHANG, Z.; YUE, J.; ZHOU, L. Automatic recognition of strawberry diseases and pests using convolutional neural network. **Smart Agricultural Technology**, v. 1, p. 100009, 2021. doi:10.1016/j.atech.2021.100009

DU, Y.; LIU, Y.; LI, N. Insect detection research in natural environment based on Faster-R-CNN model. **Proceedings of the 2020 5th International Conference on Mathematics and Artificial Intelligence**, p. 182–186, 2020. doi:10.1145/3395260.3395265

ESPINOZA, K.; VALERA, D. L.; TORRES, J. A.; LÓPEZ, A.; MOLINA-AIZ, F. D. Combination of image processing and artificial neural networks as a novel approach for the identification of BemisiaTabaci and Frankliniella occidentalis on sticky traps in greenhouse agriculture. **Computers and Electronics in Agriculture**, v. 127, 2016. doi.org/10.1016/j.compag.2016.07.008

FIEHN, H. B.; SCHIEBEL, L.; AVILA, A. F.; MILLER, B.; MICKELSON, A, Smart agriculture system based on deep learning. **International Conference on Smart Digital Environment – ICSDE**, v. 2, 2018. doi.org/10.1145/3289100.3289126

GAN, G.; XIAO, X.; JIANG, C.; YE, Y.; HE, Y.; XU, Y.; LUO, C. Strawberry disease and pest identification and control based on se-resnext50 model. **3rd International Conference on Computer Vision, Image and Deep Learning International Conference on Computer Engineering and Applications (CVIDL & ICCEA)**, p. 237–243, 2022. doi:10.1109/CVIDLICCEA56201.2022.9825283

GASAYE, K.; MOLLO, R. K. A mobile application for fruit fly identification using deep transfer learning: A case study for Mauritius. **International Conference for Advancement in Technology (ICONAT)**, p. 1–5, 2022. doi:10.1109/ICONAT53423.2022.9725945

HE, Y.; ZHOU, Z.; TIAN, L.; LIU, Y.; LUO, X. Brown rice planthopper (nilaparvata lugens stal) detection based on deep learning. **Precision Agriculture**, v. 21, pp. 1385-1402, 2020. doi.org/10.1007/s11119-020-09726-2

HOSSAIN, M. D. A.; TAREQ, A. H. M.; UDDIN, M. Pest-inspector: An insect detection system by learning data representations. **International Conference on Advances in Science, Engineering and Robotics Technology – ICASERT**, p. 1-7, 2019. doi:10.1109/ICASERT.2019.8934578

ISSAD, H. A.; AOUDJIT, R.; RODRIGUES, J. A comprehensive review of data mining techniques in smart agriculture. **Engineering in Agriculture Envivonment and Food**, v. 12, p. 511–525, 2019. doi.org/10.1016/j.eaef.2019.11.003

JIA, S.; GAO, H.; Hang, X. Tomato pests and diseases classification model based on optimized convolutional neural network. **Journal of Physics: Conference Series**, v. 1437 2019. doi.10.1088/1742-6596/1437/1/012052

JIAO, L.; DONG, S.; ZHANG, S.; XIE, C.; WANG, H. AF-RCNN: An anchor-free convolutional neural network for multi-categories agricultural pest detection. **Computers and Electronics in Agriculture**, v. 174, p. 105522, 2020. doi.org/10.1016/j.compag.2020.105522

JUNIOR, C. R. G.; GOMES, P. H.; MANO, L. Y.; OLIVEIRA, R. B. de; CARVALHO, A. C. P. de L. F. de; FAIÇAL B. S. A machine learning-based approach for prediction of plant protection product deposition. **Brazilian Conference on Intelligent Systems**, 2017. doi:10.1109/BRACIS.2017.26

KARAR, M. E.; ALSUNAYDI, F.; ALBUSAYMI, S.; ALOTAIBI, S. A new mobile application of agricultural pests recognition using deep learning in cloud computing system. **Alexandria Engineering Journal**, v. 60 p. 4423–4432, 2021. doi.org/10.1016/j.aej.2021.03.009

KHALIFA, N. E. M.; LOEY, M.; TAHA, M. N. Insect pests recognition based on deep transfer learning models. **Theoretical and Applied Information Technology**, v. 98, p. 60–68, 2020. ISSN: 1992-8645

KHATTABA, A.; HABIB, S. E. D.; ISMAIL, H.; ZAYAN, Y. F. S.; KHAIRY, M. M. An iot-based cognitive monitoring system for early plant disease forecast. **Computers and Electronics in Agriculture**, v. 166, 2019. doi.org/10.1016/j.compag.2019.105028

KITCHENHAM, B. Procedures for undertaking systematic reviews. **Information and Software Technology**, v. 33, p. 1–26. 2004

KITCHENHAM, B.; BRERETON, P.; BUDGEN, D.; TURNER, M.; BAILEY, J.; LINKMAN, S. Systematic literature reviews in software engineering – a systematic literature review. **Information and Software Technology**, v. 51, 2009. doi.org/10.1016/j.infsof.2008.09.009

KUMAR, V.; LAXMI, V. Pests detection using artificial neural network and image processing: A review. **International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)**, p. 462–467, 2022. doi:10.1109/ICSCDS53736.2022.9760976

LI, Y.; YAN, H.; HU, F.; YUAN, K.; QIAN, M.; LIU, P.; CAI, Q.; LI, X.; GUO, J.; YU, J.; QIN, L.; LIU, H.; WU, W.; XIAO, P.; ZHOU, Z. The recognition of rice images by uav based on capsule network. **Cluster Computin**, v. 22, p. 9515–9524, 2018. doi.org/10.1007/s10586-018-2482-7

LI, R.; WANG, R.; ZHANG, J.; XIE, C.; LIU, L.; WANG, F.; CHEN, H.; Chen, T.; HU, H.; JIA, X.; HU, M.; ZHOU, M.; LI, D.; LIU, W. An effective data augmentation strategy for cnn-based pest localization and recognition in the field. **IEEE ACCESS**, v. 7, p. 160274–160283, 2019. doi:10.1109/ACCESS.2019.2949852

LI, Y.; WANG, H.; DANG, L. M.; SADEGHI-NIARAKI, A.; MOON, H. Crop pest recognition in natural scenes using convolutional neural networks. **Computers and Electronics in Agriculture**, v. 169, p. 105174, 2020. doi.org/10.1016/j.compag.2019.105174

LINS, E. A.; RODRIGUEZ, J. P. M.; SCOLOSKI, S. I.; PIVATO, J.; LIMA, M. B.; FERNANDES, J. M. C.; PEREIRA, P. R. V. da.; LAU, D.; RIEDER, R. A method for counting and classifying aphids using computer vision. **Computers and Electronics in Agriculture**, v. 169, p. 105200, 2020. doi.org/10.1016/j.compag.2019.105200

RECIMA21 - REVISTA CIENTÍFICA MULTIDISCIPLINAR
ISSN 2675-6218

LIU, L.; WANG, R.; XIE, C.; YANG, P.; SUDIRMAN, S.; WANG, F.; LIU, W. Deep learning based automatic approach using hybrid global and local activated features towards large-scale multi-class pest monitoring. **International Conference on Industrial Informatics**, v. 17, 2019a. doi:10.1109/INDIN41052.2019.8972026

LIU, L.; WANG, R.; XIE, C.; YANG, P.; WANG, F.; SUDIRMAN, S.; LIU, W. Pestnet: An end-to-end deep learning approach for large-scale multi-class pest detection and classification. **IEEE Access**, v. 7, 2019b. doi.org/10.1109/access.2019.2909522

LIU, L.; WANG, R.; XIE, C.; LI, R.; WANG, F.; QI, L. A global activated feature pyramid network for tiny pest detection in the wild. **Machine Vision and Applications**, v. 33, n. 76, 2022. doi.org/10.1007/s00138-022-01310-0

MA, C.; LIANG, Y.; LYU, X. Weather analysis to predict rice pest using neural network and d-s evidential theory. **International Conference on CyberEnabled Distributed Computing and Knowledge Discovery – CYBERC**, 2019. doi:10.1109/CyberC.2019.00054

MA, K.; NIE, Ming-Jun; LIN, S.; KONG, J.; YANG, C.; LIU, J. Fine-Grained Pests Recognition Based on Truncated Probability Fusion Network via Internet of Things in Forestry and Agricultural Scenes. **Algoritmos**, v. 14, n. 10, p. 290, 2021. doi.org/10.3390/a14100290

MARTINI, D. R. D.; TETILA, E. C.; MARCATO, J. J.; MATSUBARA, E. T.; SIQUEIRA, H.; CASTRO JUNIOR, A. A. de; ARAUJO, M. S.; MONTEIRO, C. H.; PISTORE, H.; LIESENBERG, V. Machine learning applied to UAV imagery in precision agriculture and forest monitoring in brazililian savanah. **International Geoscience and Remote Sensing Symposium – IGARSS**, 2019. doi:10.1109/IGARSS.2019.8900246

MEKHA, V.; PARTHASARATHY, V. An automated pest identification and classification in crops using artificial intelligence—a state-of-art-review. **Automatic Control and Computer Sciences,** v. 56, 3, p. 283–290, 2022. doi:10.3103/S0146411622030038

MIQUE, E. L.; PALAOAG, T. D. Rice pest and disease detection using convolutional neural network. **Proceedings of the 2018 International Conference on Information Science and System – ICISS**, p. 147–151, 2018. doi.org/10.1145/3209914.3209945

NAM, N. T.; P. D. HUNG. Pest detection on traps using deep convolutional neural networks, **Proceedings of the 2018 International Conference on Control and Computer Vision – ICCCV**, p. 33–38, 2018. doi.org/10.1145/3232651.3232661

OZDEMIR, D.; KUNDURACI, M. S. Comparison of deep learning techniques for classification of the insects in order level with mobile software application. **IEEE Access**, v. 10, p. 35675–35684, 2022. doi:10.1109/ACCESS.2022.3163380

PATEL, P. P.; VAGHELA, D. B. Crop diseases and pests detection using convolutional neural network. **IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)**, p. 1–4, 2019, 10.1109/ICECCT.2019.8869510

PENG, Y.; WANG, Y. Cnn and transformer framework for insect pest classification. **Ecological Informatics**, v. 72, p. 101846, 2022. doi.org/10.1016/j.ecoinf.2022.101846

PEREIRA, R. de C.; HIROSE, E.; CARVALHO, O. L. F. de; COSTA, R. M. da.; BORGES, D. L. Detection and classification of whiteflies and development stages on soybean leaves images using an improved deep learning strategy. **Computers and Electronics in Agriculture**, v. 199, p. 107132, 2022. doi.org/10.1016/j.compag.2022.107132

PRADEEP, N.; KAUTISH, S.; NIRMALA, C.R.; GOYAL, V.; ABDELLATIF S. **Modern Techniques for Agricultural Disease Management and Crop Yield Prediction. IGI Global Books**, 2019. 10.4018/978-1-5225-9632-5

QINSI, W.; XUEYI, J.; XIAOLONG, X.; XUESHUN, W. Research on invasive insect image recognition based on artificial intelligence. **2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)**, p. 744–748, 2021. doi:10.1109/ICBAIE52039.2021.9389971

QIAN, S.; DU, J.; ZHOU, J.; XIE, C.; JIAO, L.; LI, R. An effective pest detection method with automatic data augmentation strategy in the agricultural field. **Signal, Image and Video Processing**, 2022. doi.org/10.1007/s11760-022-02261-9

RAJAN, P.; RADHAKRISHNAN, B.; SURESH, L. P. Detection and classification of pests from crop images using support vector machine. **International Conference on Emerging Technological Trends – IETT**, 2016. doi:10.1109/ICETT.2016.7873750

RAVISANKA, H.; RAO, S.; SREEDHAR, U. A web based expert system for identification and management of insect pests of tobacco. **Journal of Entomology and Zoology Studies**, v. 7, 2019.

REN, L.; HU, M.; FANG, Y.; DU, X.; FENG, H. Recognition of common pests in agriculture and forestry based on convolutional neural networks. **Chinese Automation Congress – CAC**, 2018. doi:10.1109/CAC.2018.8623223

RIMAL, K.; SHANH, K.B.; JHA, A.K. Advanced multi-class deep learning convolution neural network approach for insect pest classifcation using tensorflow. **International Journal of Environmental Science and Technology**, 2022. doi.org/10.1007/s13762-022-04277-7

SEGALLA, A.; FIACCO, G.; TRAMARIN, L.; NARDELLO, M.; BRUNELLI, D. Neural networks for pest detection in precision agriculture. **2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor)**, p. 7-12, 2020. doi:10.1109/MetroAgriFor50201.2020.9277657

SHAHZADI, R.; FERZUND, J.; TAUSIF, M.; ASIF, M. Internet of things based expert system for smart agriculture. **International Journal of Advanced Computer Science and Applications**, v. 7, 2016. doi:10.14569/IJACSA.2016.070947

SHANKAR, R. H.; VEERARAGHAVAN, A. K.; UVAIS; SIVARAMAN, K.; RAMACHANDRAN, S. S. Application of UAV for pest, weeds and disease detection using open computer vision. **International Conference on Smart Systems and Inventive Technology**, 2018. doi:10.1109/ICSSIT.2018.8748404

SILVA, L. A.; BRESSAN, P. O.; NUNES, D. G.; FREITAS, D. M.; MACHADO, B. B.; GONÇALVES, W. Estimating soybean leaf defoliation using convolutional neural networks and synthetic images. **Computers and Electronics in Agriculture**, v. 156, p. 360-368, 2019. doi.org/10.1016/j.compag.2018.11.040

SOBREIRO, L.; BRANCO, S.; CABRAL, J.; MOURA, L. Intelligent insect monitoring system -i²ms- using internet of things technologies and cloud-based services for early detection of pests of field crops. **Industrial Electronics Society – IECON**, 2019. p. 3080–3084. doi:10.1109/IECON.2019.8927085

SONG, Y.; DUAN, X.; REN, Y.; XU, J.; LUO, L.; LI, D. Identification of the agricultural pests based on deep learning models. International Conference on Machine Learning, **Big Data and Business Intelligence – MLBDBI**, 2019. doi:10.1109/MLBDBI48998.2019.00044

SOURAV, M.S.U.; WANG, H. Intelligent identification of jute pests based on transfer learning and deep convolutional neural networks. **Neural Processing Letters**, 2022. doi.org/10.1007/s11063-022-10978-4

TASSIS, L. M.; SOUZA, J. E. T. de; KROHLING, R. A. A deep learning approach combining instance and semantic segmentation to identify diseases and pests of coffee leaves from in-field images. **Computers and Electronics in Agriculture**, v. 186, p. 106191, 2021. doi.org/10.1016/j.compag.2021.106191

TETILA, E.C.; MACHADO, B.B.; MENEZES, G.V.; BELETE, N.A.S.; ASTOLFI, G.; PISTORE, H. A deep-learning approach for automatic counting of soybean insect pests. **IEEE Geoscience and Remote Sensing Letters**, v. 17, n. 10, p. 1837–1841, 2020a. doi:10.1109/LGRS.2019.2954735

TETILA, E. C.; MACHADO, B. B.; ASTOLFI, G.; BELETE, N.A.S; AMORIM, W. P.; ROEL, A. R.; PISTORI, H. Detection and classification of soybean pests using deep learning with uav images. **Computers and Electronics in Agriculture**, v. 179, p. 105836, 2020b. doi.org/10.1016/j.compag.2020.105836

TRUONG, Q. B.; THANH, T.K.N.; NGUYEN, M. T.; TRUONG, Q. D.; HUYNH, H. X. Shallow and deep learning architecture for pests identification on pomelo leaf. **International Conference on Knowledge and Systems Engineering KSE**, v. 10, 2018. doi:10.1109/KSE.2018.8573422

UN. **World Population prospectos**. UN: United nations report, 2017. http://population.un.org/wpp/Publications/Files/WPP2017_KeyFindings.pdf. Acesso em: 30 abr. 2020

VOUTOS, P. M.; KATHENIOTIS, J.; SOFOU, A. A survey on intelligent agricultural information handling methodologies. **Sustentabilidade**, v. 11, n. 12, 2019. doi.org/10.3390/su11123278

WANG, W.; YANG, Y.; WANG, X.; WANG, W.; LI, J. Development of convolutional neural network and its application in image classification: a survey. **Optical Engineering**, v. 58, n. 4, p. 040901, 2019. doi.org/10.1117/1.OE.58.4.040901

WANG, F.; WANG, R; XIE, C.; ZHANG, J.; LI, R.; LIU, L. Convolutional neural network based automatic pest monitoring system using hand-held mobile image analysis towards non-site-specific wild environment. **Computers and Electronics in Agriculture**, v. 187, p. 106268, 2021a. doi.org/10.1016/j.compag.2021.106268

WANG, R.; JIAO, L.; XIE, C.; CHEN, P.; DU, J.; LI, R. S-RPN: Sampling-balanced region proposal network for small crop pest detection. **Computers and Electronics in Agriculture**, v. 187, p. 106290, 2021b. doi.org/10.1016/j.compag.2021.106290

WANG, H.; LI, Y.; DANG, L. M.; MOON, H. An efficient attention module for instance segmentation network in pest monitoring. **Computers and Electronics in Agriculture**, v. 195, p. 106853, 2022. 106853. doi.org/10.1016/j.compag.2022.106853

WANI, H.; ASHTANKAR, N. An appropriate model predicting pest/diseases of crops using machine learning algorithms. **International Conference on Advanced Computing and Communication Systems – ICACCS**, v. 4, 2017. doi:10.1109/ICACCS.2017.8014714

WU, J; LI, B.; WU, Z. Detection of crop pests and diseases based on deep convolutional neural network and improved algorithm. **International Conference Proceeding Series**, p. 20-27, 2019. doi.org/10.1145/3340997.3341010

XIE, C.; ZHANG, J.; LI, R.; LI, J.; HONG, P.; XIA, J.; CHEN, P. C. Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning. **Computers and Electronics in Agriculture**, v. 119 2015. doi.org/10.1016/j.compag.2015.10.015

XU, J.; WEI, H.; YE, M.; WANG, W. Research on recognition method of zanthoxylum armatum rust based on deep learning. **International Conference Proceeding Series**, p. 84-88, 2019. doi.org/10.1145/3365966.3365975

XU, C.; YU, C.; ZHANG, S.; WANG, X. Multi-scale convolution-capsule network for crop insect pest recognition. **Electronics**, v. 11, n. 10, p. 1630, 2022. doi:10.3390/electronics11101630

YANG, F.; LI, F.; XU, J.; SU, G.; LI, J.; JI, M.; XIONG, W.; ZHAO, B. Effective insect recognition based on deep neural network models in complex background. **Proceedings of the 5th International Conference on High Performance Compilation, Computing and Communications**, p. 62–67, 2021. doi:10.1145/3471274.3471285

YU, H.; LIU, J.; CHEN, C.; HEIDARI, A. A.; ZHANG, Q.; CHEN, H. Optimized deep residual network system for diagnosing tomato pests. **Computers and Electronics in Agriculture**, v. 195, p. 106805, 2022. doi.org/10.1016/j.compag.2022.106805

ZHAI, Z.; ORTEGA, J. F. M.; BELTRAN, V.; MARTINEZ, N. L. An Associated Representation Method for Defining Agricultural Cases in a Case-Based Reasoning System for Fast Case Retrieval. **Sensors**, (Basel), v. 19, n. 23, 2019. doi.org/10.3390/s19235118