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Deep Learning and Machine Learning for Plant and Fruit Recognition: A Systematic Review

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Abstract. This study conducted a systematic literature review to investigate machine learning techniques for plant and fruit recognition, analyzing 40 research articles from 2016-2022. The articles were searched across 8 databases and screened based on predefined inclusion/exclusion criteria. Data was extracted to identify he techniques, accuracies, metrics, and applications. The results showed convolutional neural networks and support vector machines achieved the highest accuracy of 95-99% for fruits like apple and banana. Accuracy and precision were the predominant metrics used for evaluating model performance. The view concludes that deep learning approaches demonstrate effective capabilities for fruit and plant classification, disease detection, and yield prediction.

Keywords: Machine learning, deep learning, fruits, plants.

1. Introduction

According to current estimates, around 690 million people (8.9% of total of the world) go hungry, representing a number of 10 million in just one year (UNAMI, 2021), so that 90% of the world's inhabitants depend of the agronomy (Mukti & Biswas, 2019); and approximately than 50% of crops are lost, this for diseases and pests of plants or fruits (Arunnehru, Vidhyasagar & Anwar, 2020). Therefore, the recognition of these diseases is urgent and necessary.

In this review, we focus mainly on studying different methods of machine learning (ML) and deep learning (DL), in order to carry out a more exhaustive investigation, so that this information makes known which are the most used methods, as well as their main characteristics in the recognition of plants and fruits, and with all this show how efficient and effective is the use of technology in the food sector, by detecting diseases and problems in both fruits and plants and offering a quality product.

Different diseases of plants and fruits have a great effect on the cultivation of food. A particular case is the Irish potato famine of 1845-1849, where it occasioned in 1.2 million deaths (Hughes & Salathe, 2015). With what has been said before, artificial intelligence methods in the food sector have important advantages, since it helps in the transformation of manual activities when selecting fruits and plants, as well as reducing labor costs for inspections (INFAIMON, 2022), providing quality products, according to the requirements of consumers.

Therefore, the recognition of diseases of fruits and plants, as to classify them, and estimate the yield, within the sector have been gaining importance in recent times (Liang et al.,2019), which is undoubtedly an important criterion to develop studies on this topic. In fact (Khune et al., 2016), used a convolutional neural network (CNN) for the identification of 971 fruit images (strawberry, lemon, watermelon and apple), being the learning rate 0.01, decay rate 0.005, impulse 0.9, and early detection in 50, highlighting that the maximum number was 1000. Likewise, (Lu et al., 2016), they proposed a softwares to classify fruits (apples, bananas, green plantains, tangerines, hass avocados, pineapples, etc.) efficiently and accurately, and then compare it with the advance of a hidden layer (SLFN), with the yield accuracy of the proposed methodology of 89.5%. On the other hand, (Marimuthu & Roomi, 2017), made a model to classify the degree of maturation of 3,108 samples of bananas, so the optimization of swarm of particles was used, which obtained an accuracy of 93.11%.

To solve this problem, machine learning techniques are used for activities to detect and classify fruits and plants, based on characteristics taken from the images, including: Texture, color and shape, where it should be noted that the application of machine learning is transcendental, this because it helps identify people (Iqbal et al., 2018; Sharif et al., 2018), Objects and places based on images and with a precision as a person does, so machine learning is applied in different areas such as: education (Daza et al., 2022; Daza et al., 2022; El Mrabet & Ait Moussa, 2022), security (Jenga, Catal & Kar, 2023), health (Abdullah et al., 2023; Goyal & Singh, 2021). At the same time, if we talk about predicting defects, diseases, pests or knowing the ripening of a fruit, it detects 97% future damage and helps farmers, providing a better quality of the fruits (Lu et al., 2018), where different algorithms are used, such as: Neural network, Support vector machine, Decision tree, logistic regression, neural network, convolutional, etc. (Gill et al., 2022; Amin et al., 2022).

Therefore, farmers and food specialists can leverage machine learning to overcome the limitations of statistical approaches and employ more reliable and efficient prediction models, thus, the lack of reviews that focus on the consolidation of evidence about techniques, metrics, applications and machine learning tools that substantiate the need and importance of using technology to predict diseases, and classify plants and fruits correctly is highlighted.

Thus, this article aims to carry out a systematic review of the research works that deal with the topic of machine learning for the identification of fruits and plants. To achieve this objective, a systematic review of the last eight years of publications in several of the indexed databases was established, in order to answer the following research questions:

RQ1: What type of fruits or plants (leaves) have they been applied to?

RR2: *What were the techniques that had the best precision results?*

RQ3: Which softwares are the most concurrent for the development and testing of the predictive model?

RQ4: What metrics are used to determine the effectiveness of machine learning techniques?

RQ5: What were the most used techniques?

This literature review is composed as follows: Section 2 presents the literature review, Section 3 shows the methodology used within the study. In section 4, the results and discussion are presented with their respective analyses based on the questions posed. Finally, section 5 shows the conclusions, as well as the limitations and recommendations of the study.

2. Literature Review

2.1. Machine learning and Deep Learning to predict fruits

With regard to plant prediction using Machine and Deep Learning techniques, many authors have developed algorithms to identify fruits efficiently. (Le & Lin, 2019) in their study they made use of a dataset of 194 images of bananas, as well as the Mask-RCNN technique, whose accuracy was 96.49%. (Al-Shawwa, 2020) used a dataset of 8,554 images of apples along with the CNN technique, which obtained 100% accuracy. (Figueredo & Ballesteros, 2016) in their study they used 255 fruit values, as well as the ANN technique that obtained an accuracy of 96.66%. (Ponce, Aquino & Andújar, 2019) made use of the CNN algorithm to predict 1,050 olive trees, whose accuracy was 95.91%.(Mota, Juárez & Olguín, 2018) in their study they predicted 25 images of Golden apples by means of 1 real-time video of the fruits, making use of the ANN technique that achieved an accuracy of 95.36%. (Villalba et al., 2022) predicted 650 photographs of bananas using the AGR-DL technique with 96.00% accuracy. (Hossain, Al-Hammadi & Muhammad, 2019) in their article they also used the AGR-DL technique to predict 32 samples of orange, sweet lemon, onion and watermelon, whose accuracy was 96.75%. (Behera et al., 2020) classified fruits, for which they took into account articles from 2010 to 2019, along with 7 machine learning and Deep learning techniques, where SVM achieved the best accuracy, this being 99.00%.(Zhang et al., 2019) in their study used the MCCN technique to detect 28 images of apples. (Abbaspour et al., 2020) made use of 2 Machine Learning and Deep Learning techniques (ANN and ABC) to predict 56 Red Delicious apples, where ABC achieved the best accuracy of 92.30%. (Jiang et al., 2019) managed to detect the diseases of 26,377 apples using the CNN algorithm, which reached an accuracy of 78.80%. (Oraño, Maravillas & Aliac, 2019) in their article they detected 516 images of Jackfruit using the CNN algorithm, which obtained an accuracy of 97.93%. (Calle et al., 2021) measured the Quality of 83 grapes, where of the 2 algorithms used (CNN and SVM), CNN reached an accuracy of 90.36%. (Rodriguez, Pastor & Ugarte, 2021) made use of 15 databases to classify oranges, red and green apples, strawberries and bananas, for this the CNN algorithm was used, achieving an accuracy of 96.34%.(Wuang et al., 2022) in their research they took into account 96 jujube fruits together with the CNN algorithm, where it reached an accuracy of 39.00%. (Wu, Zhu & Ren, 2020) detected 50 images of apples using 4 Machine learning and Deep learning algorithms, however, CNN achieved the best accuracy of 92.50%. (Cecotti et al., 2020) used 50 grapes and apples along with the CNN algorithm, which achieved 99.00% accuracy. (Khan et al., 2020) classified 176,312 fruits, these being: pears, bananas, grapes and apples, whose Bayesian Regularization (BR) algorithm achieved an accuracy of 76.30%.(Khan et al., 2020) identified 11,990.5 pears, citrus, grapes and bananas using 6 algorithms, including AGR-DL which reached the best accuracy of 95.56%. (Aherwadi et al., 2022) predicted the ripening and quality of 2 kinds of bananas, where the first set was composed of 700 images and the second set by 1,312 images, for which they made use of two Deep learning techniques (CNN and AlexNet), where CNN reached the best accuracy of 81.96%. (Agarwal & Sagar, 2019) conducted a study with the intention of predicting different fruits from 2 datasets, the first of 8,846 images and the second of 48,905 photos, for which 5 algorithms were used, where SVM reached the best accuracy of 91.18%.(Ati et al., 2022) developed a study to identify the size of 90 orange trees and tree tomatoes, with the CNN algorithm, which reached an accuracy of 95.00%. (Jiang, Li & Safara, 2021) managed to predict 3,279 infected and healthy apples, making use of the DNN algorithm that reached an accuracy of 88.00%. (Bai et al., 2021) predicted the yield of 47 apples of the year 2019 and 57 apples of the year 2020, using the Random Forest and Channels Matching algorithms, obtaining the best accuracy of 71.00% when making use of Random Forest. (Vaishnav & Rao, 2018) classified 49 fruits (pineapple, apple, mango, orange and cherry) using 6 machine learning techniques, where logistic regression reached the best accuracy of 92.40%.(Saranya et al., 2020) identified four kinds of fruits, these being banana, pomegranate, orange and apple, using the KNN and SVM algorithms, where the latter reached the highest accuracy of 66.00%. (Chung & Van Tai, 2019) recognized 77,917 images of fruits of 19 classes, including: apricot, banana, cherry, mango, apple, kiwi, grapes, etc., for which they used the CNN algorithm, which reached an accuracy of 95.67%. (Arévalo, Ruiz & Ayala, 2021) classified 360 peaches using the CNN algorithm, which reached an accuracy of 95.31%.(Risdin, Mondal & Hassan, 2020) detected information from 565 images of 4 fruits, these being: grape, lychee, apple and tangerine, using 5 machine learning algorithms, whose algorithm that reached the best accuracy was CNN with 99.89%. (Hussain et al., 2022) recognized 10,000 images of vegetables and fruits, using the DCNN algorithm that reached an accuracy of 96.00%.(Mohapatra, Choudhury & Sabat, 2021) detected 849 images of rotten and healthy apples, oranges and bananas, using two deep learning algorithms (R-CNN and CNN), the latter reaching a better accuracy of 99.00%. (Behera, Rath & Sethy, 2021) conducted a study to detect the ripening state of 300 papayas, where it could be observed that both CNN, VGG-19, VGG-16 and Google Net reached 100% accuracy unlike AlexNet. (Yu et al., 2019) detected 1,900 strawberry images using the Mask-RCNN algorithm, which achieved an accuracy of 95.78%. (Aguilar & Campoverde, 2019) classified 13 kinds of fruits, for which they used the CNN algorithm, which reached an accuracy of 87.00%.

2.2. Machine learning and Deep Learning to predict plants

Studies have been carried out focused on the classification of plants using Machine and Deep Learning techniques. (Koirala et al., 2019) in their research they used 1,515 images of mango tree crowns, for which the YOLO v3 technique obtained an accuracy of 98.3%. (Lu, Tan & Jiang, 2021) predicted the leaf diseases of plants of legumes, eggplants, pickles, tomatoes, pumpkins, ginger and soybeans, making use of 5 algorithms, so AlexNet reached the best accuracy of 99.35%. (Pratap, Singh & Jain, 2019) in their study 1,070 images of leaves of the mango tree were used to detect diseases in the plant, for which 4 algorithms were used, of which MCNN achieved the best accuracy of 97.13%. (Sujatha et al., 2021) detected 609 citrus plants using six Machine Learning and Deep Learning techniques, within which VGG-16 achieved the best accuracy of 89.60%. (Vijayakumar, Ampatzidis & Costa, 2023), predicted the yield of 48 citrus plants, using the YOLO v3 technique that achieved 96.00% accuracy. (Villanueva & Salenga, 2018) predicted the performance of 293 pumpkin plants using the CNN algorithm, which reached an accuracy of 100.00%.

3. Methods

The present investigation is based on a systematic literature review made up of scientific databases using a PRISMA methodology (Moher at al., 2010), whose search focuses on scientific articles related to the prediction of fruits and plants disease.

3.1. Research Questions

The aim of this article is to compare, synthesize and analyze the studies on the prediction of fruits and plants disease using ML and LBP published from 2016 to 2023. Table 1 shows the 5 research questions (RQ) asked, with their respective motivations:

Table 1: Research questions

ID	Research Question	Motivation
Q1	What type of fruits or plants (leaves) have they been applied to?	Identify the fruits and plants studied with machine learning and deep learning
Q2	What were the techniques that had the best precision results?	Present the machine learning and deep learning techniques that have greater precision for identifying fruits and plants
Q3	Which softwares are the most concurrent for the development and testing of the predictive model?	Recognize machine learning and deep learning softwares for fruit and plant identification
Q4	What metrics are used to determine the effectiveness of machine learning techniques?	Identify the most common machine learning and deep learning metrics for fruit and plant identification
Q5	What were the most commonly used techniques?	Reveal the various machine learning and deep learning techniques that are implemented for the identification of fruits and plants

3.2. Literature Search

The search for the information began on August 24, 2022, in 8 databases: MDPI, Portal de la Universidad Tecnologica de Panamá, IEEE Xplore, Pirhua Institutional Repository, Springer Link, Dialnet, ResearchGate and ScienceDirect, where the following keywords were taken into account: 'Deep learning', 'Convolutional neural networks' and 'Identification', to then expand the search with AND and OR connectors, adding the terms 'classification', 'machine learning' and 'fruits' ,which finally established the following search strings: ((((MACHINE LEARNING) AND TYPES) AND IDENTIFICATION) PLANTS OR FRUITS)))); (((MACHINE LEARNING) AND MACHINE LEARNING TECHNIQUES) PLANTS OR FRUITS))); ((((MACHINE LEARNING) AND SOFTWARES) PLANTS OR FRUITS))); ((((MACHINE LEARNING) AND METRICS) AND IDENTIFICATION) PLANTS OR FRUITS)))); y (((MACHINE LEARNING) AND TYPES) AND IDENTIFICATION) PLANTS OR FRUITS))); However, many of the articles were repeated, and that is where the inclusion criteria applied only to the years 2016 to 2023; as shown in Figure 1 and Figure 2.

Table 2: Literature search string

Question	Research Question
Q1	((((MACHINE LEARNING) AND TYPES) AND IDENTIFICATION) PLANTS OR FRUITS))))
Q2	(((MACHINE LEARNING) AND MACHINE LEARNING TECHNIQUES) PLANTS OR FRUITS)))
Q3	((((MACHINE LEARNING) AND SOFTWARES) PLANTS OR FRUITS)))
Q4	((((MACHINE LEARNING) AND METRICS) AND IDENTIFICATION) PLANTS OR FRUITS))))
Q5	(((MACHINE LEARNING) AND TYPES) AND IDENTIFICATION) PLANTS OR FRUITS)))

It should be noted that the study had several limitations, including the search for related information in different databases, regarding the years of publication during the search, since there were still some that were before 2016, the same ones that had to be eliminated along with books, at the same time of those that were not of the English language.

3.3. Inclusion and exclusion criteria

IC1: Only articles published in indexed information sources, such as: Web of Science, ProQuest, Scopus, etc., will be taken into consideration; IC2: Articles related to the study questions; IC3: Articles after 2016 to the present; IC4: Articles in English and Spanish; IC5: Studies with full texts; IC6: Machine Learning Studies.
EC1: Duplicate articles; EC2: Incomplete articles, theses and books; EC3: Articles without free access; EC4: Articles that don't talk about machine learning.

Additional Filter

To choose the appropriate articles, a review of each one was made, where filters were applied. Applying the string of words, a total of 170 articles were obtained, which were submitted to the inclusion and exclusion criteria as shown in Figure 1, then some articles were available in more than one database, so these duplicate files were removed. After reading the content of the articles, many found 27 irrelevant, managing to have 67 articles.
Thus, of the 67 articles found, the inclusion and exclusion criteria were applied, going through more detailed filters attaching articles in the review process, reducing to 40 primary studies.

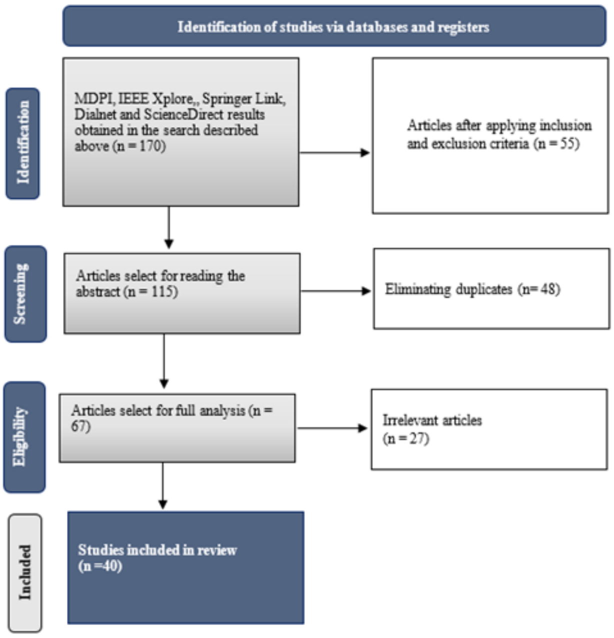

Fig. 1: PRISMA methodology for selected articles

3.4. Quality Assessment

Below are the criteria based on 5 evaluation criteria (EC):
EC1: Are the articles clearly organized, described, and properly developed?; EC2: Does the bibliographic search include search strategies and was mention made of all journals, addressing the topic of interest?; EC3: Was the methodology used for the study documented according to the relevant regulations?; EC4: Do the articles reviewed answer the questions asked clearly?; EC5: Were the objectives of the investigation declared correctly?
Likewise, the quality evaluation indicators are established, which are structured as follows: If it meets (S) = 1, Partially complies (P) = 0.5 and Does not meet (N) = 0, so the evaluation criteria are shown in Table 3:

Table 3: Quality assessment of the systematic literature review on machine learning methods for plant and fruit recognition

Ref.	Type of article	CE1	CE2	CE3	CE4	CE5	Total score

(Le & Lin, 2019)	AC	0.5	1	1	0.5	1	4
(Koirala et al.,2019)	AC	0.5	1	1	1	1	4.5
(Al-Shawwa,2020)	AC	1	1	1	1	1	5
(Figueredo & Ballesteros, 2016)	AR	1	0.5	0.5	1	1	4
(Ponce, Aquino & Andújar, 2019)	---	1	1	1	0.5	1	4.5
(Mota, Juárez & Olguín,2018)	AC	1	0.5	1	0.5	1	4
(Villalba et al., 2022)	AC	1	1	1	0.5	1	4.5
(Hossain, Al-Hammadi & Muhammad, 2019)	AC	1	1	1	1	1	5
(Behera et al.,2020)	AR	0.5	1	1	0.5	1	4
(Zhang et al.,2019)	AC	1	1	1	0.5	1	4.5
(Abbaspour et al., 2020)	AC	1	1	0.5	0.5	0.5	3.5
(Jiang et al.,2019)	AC	1	1	1	1	0.5	4.5
(Lu, Tan & Jiang, 2021)	AR	0.5	1	0.5	0.5	1	3.5
(Oraño, Maravillas & Aliac, 2019)	AC	1	1	1	1	0.5	4.5
(Calle et al., 2021)	AC	1	1	1	0.5	1	4.5
(Pratap, Singh & Jain,2019)	AC	1	0.5	0.5	1	1	4
(Rodriguez, Pastor & Ugarte, 2021)	AC	0.5	1	0.5	0.5	0.5	3
(Wuang et al., 2022)	AC	1	0.5	0.5	1	0.5	3.5
(Wu, Zhu & Ren, 2020)	AC	1	0.5	1	1	0.5	4
(Cecotti et al., 2020)	AC	1	0.5	0.5	1	1	4
(Khan et al., 2020)	AC	1	0.5	1	1	1	4.5
(Khan et al., 2020)	AC	1	1	1	1	1	5
(Aherwadi et al., 2022)	AC	1	0.5	1	1	1	4.5
(Agarwal & Sagar, 2019)	AC	1	0.5	1	1	0.5	4
(Ati et al., 2022)	AC	0.5	0.5	1	1	1	4
(Jiang, Li & Safara, 2021)	AC	1	1	1	1	0.5	4.5
(Bai et al., 2021)	AC	1	0.5	1	1	0.5	4
(Vaishnav & Rao, 2018)	AC	0.5	1	0.5	1	1	4
(Saranya et al., 2020)	AC	0.5	0.5	0.5	1	1	3.5
(Sujatha et al., 2021)	AC	1	1	1	1	0.5	4.5
(Chung & Van Tai, 2019)	AC	0.5	0.5	0	1	1	3
(Vijayakumar, Ampatzidis & Costa, 2023)	AC	1	0.5	0.5	1	1	4
(Arévalo, Ruiz & Ayala, 2021)	AC	1	1	1	1	1	5
(Risdin, Mondal & Hassan, 2020)	AC	1	0.5	1	1	1	4.5
(Villanueva & Salenga, 2018)	AC	1	1	1	1	1	5
(Hussain et al., 2022)	AR	1	0.5	1	1	1	4.5
(Mohapatra,	AC	0.5	0	0.5	1	1	3

Choudhury & Sabat, 2021)							
(Behera, Rath & Sethy, 2021)	AC	1	1	1	1	1	5
(Yu et al., 2019)	AC	1	0.5	1	1	1	4.5
(Aguilar & Campoverde, 2019)	AC	1	1	1	1	1	5

Of the 40 articles selected, when applying 5 criteria for quality evaluation, the highest score will be 5, according to the scale presented above (S, P and N), which was rated with 1, 0.5 and 0 respectively. As shown in Table 3, all articles obtained scores that exceeded 50% of the total score, that is, it was a good indicator of quality.

4. Results and Discussion

4.1. Quantity of studies

Based on the above, it can be seen that there are several investigations on machine learning to detect both plants and fruits, which is presented in Fig. 2.

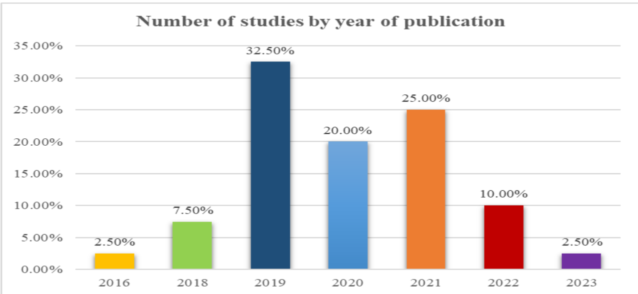

Fig. 2: Number of studies per year of publication

4.2. Type of Fruits and Plants applied with Machine Learning and Deep Learning (RQ1)

As shown in Fig. 3, the fruits that have been applied using machine learning and deep learning are: apple (16.10%) and banana (8.90%). Also, as shown in Fig. 4, with respect to the type of plants are: citrus with 2 items (16.7%) as well as apple, beans, eggplants, cucumber, tomato, pumpkin, ginger, soy, mango and bitter melon, all with 1 article (8.3%).

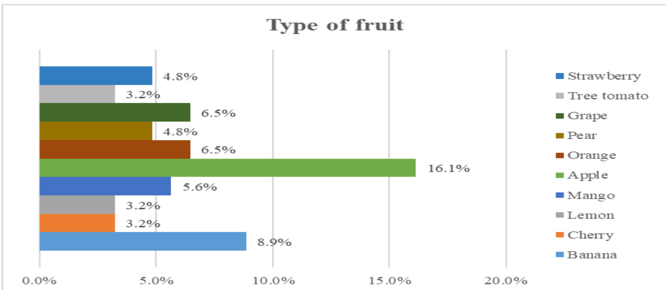

Fig. 3: Type of fruits predicted with ML and DL

With respect to the type of fruits studied with Machine learning and Deep learning, many researchers have studied different fruits. As is the case of (Wu, Zhu & Ren, 2020), who used 50 apple images. The authors demonstrated that the method is able to efficiently and accurately identify the defective areas from which they are healthy, the stem and calyx regions of apples. In the same way, (Jiang, Li & Safara, 2021) in their study they made use of 3,279 images of healthy and infected apples. So the authors showed that the use of machine learning techniques helps identify key features in the images of apples and how they used to classify them, improving early detection. However, also in the study (Aherwadi et al., 2022), the authors used 2 dataset of 2 classes of bananas: Set 1: 700 images of raw, ripe and overripe bananas, and Set 2: 1,312 images of 81 types of fruits: banana and red banana. There are apple and banana, where it was observed that of these studies for both fruits they used mostly Deep learning, these being 70% and 81.81% respectively. According to (Khan, Quadri & Banday, 2020; Ganguli et al., 2022) this is because both fruits are the ones that have the most manual classification problems and this causes an economic loss of 70% each year in the apple industry, and at the same time that a loss of between 3% and 30% of losses in post-harvest banana is evident, which makes it difficult to observe them effectively (Khan, Quadri & Banday, 2020; Ganguli et al., 2022); in the case of (Xiao apples, Nguyen & Yan, 2021) points out that the techniques used in deep learning have proven to help classify this type of fruit correctly, since using images taken by a camera allows to identify the state in which the apple is located automatically.

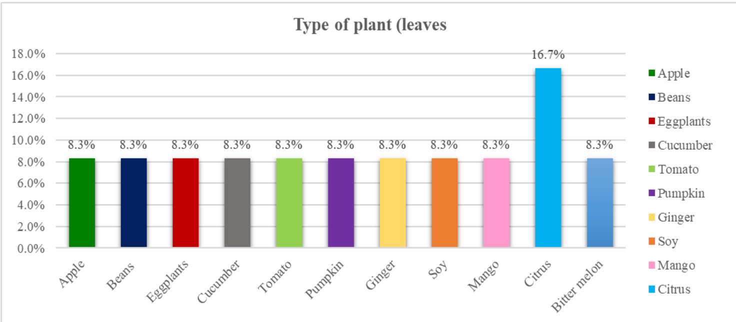

Fig. 4: Plants type predicted with ML and DL

On the other hand, with respect to the type of plants used, (Vijayakumar, Ampatzidis & Costa, 2023), they took into account images of the harvest of 48 citrus fruits (collected in the first quarter of 2020), so the use of machine learning techniques includes information collected by UAV and data about the citrus count that help reduce the global error in the traditional yield estimation procedure, reducing economic losses. At the same time, (Sujatha et al., 2021), they used 609 images of citrus plants, where the images captured and sent to the system can be of help so that farmers can decide which pesticide to use to avoid damage. Contrary to most studies, there is a smaller group of authors (3.3%) who also took into account tree tomato (Behera et al.,2020; Ati et al., 2022; Chung & Van Tai, 2019; Hussain et al., 2022) and lemon (Behera et al.,2020; Chung & Van Tai, 2019; Risdin, Mondal & Hassan, 2020; Aguilar & Campoverde, 2019), both with 4 articles (3.3%); Similarly, regarding the type of plant, it was observed that citrus was the one that obtained the largest number of studies, however, it was contrasted with the authors (Jiang et al.,2019; Lu, Tan & Jiang, 2021; Villalba et al., 2022; Pratap, Singh & Jain,2019; Villanueva & Salenga, 2018), who took into account only one plant.

4.3. Machine Learning and Deep Learning Techniques with greater precision for identification of Fruits and Plants (RQ2)

Table 4 presents the machine learning techniques used in the study, where Support Vector Machine (SVM) and Convolutional Neural Network (CNN) were the algorithms that achieved greater precision of plants and fruits, this due to the size of the data, that is, the greater the amount of data, the greater the precision.

Table 4: Precision of techniques to predict fruit and plant identification

Ref.	Data size	Technique	Precision (%)
(Le & Lin, 2019)	194 images of bananas	Mask-RCNN	96.49 %
(Koirala et al.,2019)	1,515 images of mango tree canopies	YOLO v3	98.3 %
(Al-Shawwa,2020)	Dataset of 8,554 apple images	CNN	100.00%
(Figueredo & Ballesteros, 2016)	255 values	ANN	96.66%
(Ponce, Aquino & Andújar, 2019)	1,050 images of olives	CNN	95.91%
(Mota, Juárez & Olguín,2018)	25 images of Gold apples; 1 video with Gala apples in real-time	ANN	95.36%
(Villalba et al., 2022)	650 photographs of bananas	AGR-DL	96.00%
(Hossain, Al-Hammadi & Muhammad, 2019)	32 samples of orange, sweet lemon, onion and watermelon	AGR-DL	96.75%
(Behera et al.,2020)	Articles from 2010 to 2019	CNN	94.00%
		ANN	94.00%
		PNN	90.00%
		SVM	99.00%
		RF	96.97%
		PNN	89.10%
		SLFN	89.50%
(Zhang et al.,2019)	28 images of apple fruits	MCCN	------
(Abbaspour et al., 2020)	56 Red Delicious apples	ANN	90.00%
		ABC	92.30%
(Jiang et al.,2019)	26,377 images	CNN	78.80%
(Lu, Tan & Jiang, 2021)	BIFROST and Kaggle websites of plant leaves (beans, eggplant, cucumber, tomato, pumpkin, ginger and soy)	AlexNet	99.35%
		ResNet	83.00%
		VGGNet	92.00%
		DCNN	88.46%
		MCT	------
(Oraño, Maravillas & Aliac, 2019)	516 images of Jackfruit	CNN	97.93%
(Calle et al., 2021)	83 data for each class	CNN	90.36%
		SVM	78.10%
(Pratap, Singh & Jain,2019)	1,070 images of the leaves of the Mango tree	PSO	88.39%
		SVM	92.75%
		RBFNN	94.20%
		MCNN	97.13%
(Rodriguez, Pastor & Ugarte, 2021)	15 datasets of 5 classes of fruits: Orange, red and green apple, strawberry and banana	CNN	96.34%
(Wuang et al., 2022)	96 Chinese jujube fruits	CNN	39.0%
(Wu, Zhu & Ren, 2020)	50 images of apples	PSO	86.7%
		SVM	87.8%
		BP	90.3%
		CNN	92.5%
(Cecotti et al., 2020)	50 grapes and apples	CNN	99.00%
(Khan et al., 2020)	176,312 fruit data (bananas, pears, apples and grapes), taken from the Pakistan Economic Survey and the Federal Bureau of Statistics	LM	65.6%
		SCG	70.2%
		BR	76.3%
(Khan et al., 2020)	Production dataset of 11,990.5 fruits (bananas, pears, citrus fruits, apples and grapes)	SVM	90.37%
		SP	87.65%
		LR	88.96%
		AB	91.23%
		MLP	94.12%
		AGR-DL	95.56%
	Two banana image datasets: Set 1:		81.96%

(Aherwadi et al., 2022)	700 images of raw, ripe and overripe bananas. 2nd Set: 1,312 images of 81 types of fruits: banana and red banana.	CNN	
		AlexNet	81.75%
(Agarwal & Sagar, 2019)	Smallest dataset (MP): 18 fruits with 8,846 images Largest dataset (MG):95 fruits with 48,905 photos	SVM	MS: 91.18% ML: 93.28%
		RF	MS: 85.41% ML: 87.77%
		S	MS: 75.88% ML: 61.87%
		NB	MS: 70.98% ML: 62.42%
		KNN	MS: 89.09% ML: 91.74%
(Ati et al., 2022)	90 tests	CNN	95.00%
(Jiang, Li & Safara, 2021)	3279 images of infected and healthy apples	DNN	88.00%
(Bai et al., 2021)	47 apples from 2019 and 57 apples from 2020	RF	71.00%
		CM	56.00%
(Vaishnav & Rao, 2018)	49 fruit images taken from Google, classified in category: Orange, Mango, Pineapple, Cherry and Apple.	RF	1° set: 78.90 % 2° set: 74.2%
		LR	1° set: 86.30 % 2° set: 92.4 %
		NB	1° set: 70.80 % 2° set: 70.8 %
		KNN	1° set: 83. 60% 2° set: 32.7%
		NN	1° set: 85.40 % 2° set: 88.2%
		DT	1° set: 39.90 % 2° set: 39.9 %
(Saranya et al., 2020)	4 fruit categories (apple, banana, orange and pomegranate)	SVM	66.00 %
		KNN	50.00 %
(Sujatha et al., 2021)	609 images of citrus plants	SVM	87.30 %
		RF	78.00 %
		SGD	86.90 %
		VGG-19	87.70 %
		I-V3	89.20 %
		VGG-16	89.60 %
(Chung & Van Tai, 2019)	77917 different fruit images from 19 categories (banana, cherry, lemon, tangerine, mango, apple, orange, pear, pineapple, grape, tree tomato, sweet lemon, strawberry, apricot, avocado, coconut, dwarf orange, pepper and kiwi)	CNN	95.67 %.
(Vijayakumar, Ampatzidis & Costa, 2023)	Harvest images of 48 citrus trees (collected in the first quarter of 2020)	YOLO v3	96.00 %
(Arévalo, Ruiz & Ayala, 2021)	360 ripe and unripe peaches	CNN	95.31%
(Risdin, Mondal & Hassan, 2020)	565 images of 4 fruit categories (tangerine, apple, grape and lychee)	CNN	99.89 %
		ANN	89.00 %
		SVM	87.00 %
		R-CNN	81.00 %
		BW	74.20 %
(Villanueva & Salenga, 2018)	293 images of bitter melon leaves	CNN	100.00 %
(Hussain et al., 2022)	10,000 images of vegetables (onion and pepper) as fruits (cherry, apple, blackberry, pear, grape, peach, tree	DCNN	96.00 %

	tomato, strawberry, persimmon, fig, hazelnut, nectarine, cucumber and walnut) taken over two months		
(Mohapatra, Choudhury & Sabat, 2021)	849 data from images of healthy and diseased fruits (banana, apple and orange)	CNN	99.00 %
		R-CNN	97.86 %
(Behera, Rath & Sethy, 2021)	300 samples with 100 from each category of papaya	CNN	100.00 %
		AN	96.67 %
		VGG-19	100.00 %
		VGG-16	100.00 %
		GN	100.00 %
(Yu et al., 2019)	1,900 images of strawberries	Mask-RCNN	95.78 %
(Aguilar & Campoverde, 2019)	13 categories of fruits	CNN	87.00%

The research included in this review shows that the machine learning and deep learning techniques that achieved greater precision were CNN and SVM, which obtained between 66.00% to 100%, as observed in the studies (Le & Lin, 2019; Hossain, Al-Hammadi & Muhammad, 2019; Jiang et al.,2019; Ponce, Aquino & Andújar, 2019; Rodriguez, Pastor & Ugarte, 2021; Cecotti et al., 2020; Aherwadi et al., 2022; Ati et al., 2022; Saranya et al., 2020; Chung & Van Tai, 2019; Villanueva & Salenga, 2018; Hussain et al., 2022; Mohapatra, Choudhury & Sabat, 2021; Aguilar & Campoverde, 2019). These values are related to the size of the data taken into account in the articles, that is, the greater the amount of data, the greater the accuracy, so using more specific data for the variable studied helps predict with greater reliability and improve accuracy (Reilly, 2022; Bourilkov, 2019). The evidence demonstrates is the importance of the techniques presented to identify plants and fruits.

4.4. Machine Learning and Deep Learning Software for Fruit and Plant identification (RQ3)

When talking about machine learning techniques, there is a variety that have been used to detect plants and fruits. Table 5 shows the software in the 40 investigations, so it is observed that Python is the most used tool by most authors (29.6%), in the same way, TensorFlow is followed with 12 studies (22.2%). These percentages is because both tools have advantages, in which they highlight that it is open source, free, ease of use, simple language, among others, being indispensable for the identification of plants and fruits.

Table 5: ML and DL Software

Ref.	Software	Related studies
H01	Matlab	(Ponce, Aquino & Andújar, 2019), (Hossain, Al-Hammadi & Muhammad, 2022), (Behera et al., 2020), (Zhang et al., 2019), (Calle et al., 2021), (Khan et al., 2020), (Bai et al., 2021), (Villanueva & Salenga, 2018), (Behera, Rath & Sethy, 2021), (Sujatha et al., 2021)
H02	Image batch Processor	(Ponce, Aquino & Andújar, 2019)
H03	REV	(Ponce, Aquino & Andújar, 2019)
H04	Keras	(Mota, Juárez & Olguín, 2018), (Lu,Tan & Jiang, 2021), (Oraño, Maravillas & Aliac, 2019), (Rodriguez, Pastor & Ugarte,2021), (Aherwadi et al., 2022), (Villanueva & Salenga, 2018), (Yu et al., 2019)
H05	Pytorch	(Lu,Tan & Jiang, 2021)
H06	Paint 3D	(Rodriguez, Pastor & Ugarte,2021)
H07	Python	(Le & Lin, 2019), (Koirala et al., 2019), (Al-Shawwa, 2020), (Mota, Juárez & Olguín, 2018), (Villalba et al., 2022),(Zhang et al., 2019), (Jiang et al.,2019), (Lu,Tan & Jiang, 2021), (Pratap, Singh & Jain,2019), (Rodriguez, Pastor &

		Ugarte,2021), (Wu, Zhu & Ren, 2020), (Cecotti et al., 2020), (Vaishnav & Rao, 2018), (Chung & Van Tai, 2019), (Villanueva & Salenga, 2018), (Aguilar & Campoverde, 2019)
H08	TensorFlow	(Al-Shawwa, 2020), (Mota, Juárez & Olguín, 2018), (Mota, Juárez & Olguín, 2018), (Villalba et al., 2022), (Lu,Tan & Jiang, 2021), (Oraño, Maravillas & Aliac, 2019), (Pratap, Singh & Jain,2019), (Rodriguez, Pastor & Ugarte,2021), (Cecotti et al., 2020), (Aherwadi et al., 2022), (Villanueva & Salenga, 2018), (Yu et al., 2019), (Aguilar & Campoverde, 2019)
H09	OpenCV	(Al-Shawwa, 2020), (Mota, Juárez & Olguín, 2018), (Mota, Juárez & Olguín, 2018), (Villalba et al., 2022)
H10	Orange 3	(Vaishnav & Rao, 2018), (Sujatha et al., 2021)

As expected, the most commonly used Software to identify plants and fruits were Python (29.6%) and TensorFlow (22.2%). This is because both have advantages such as their high-level and easy-to-read language, plus they contain open source platforms (Aurora, 2021; Raja, Kanagaraj & Galety, 2022), as well as ease of use on different devices (Liu & Grana, 2019; Smilkov et al., 2019). However, there are also some software that were not widely used such as Image batch processor and REV (Ponce, Aquino & Andújar, 2019), OpenCV (Al-Shawwa,2020; Mota, Juárez & Olguín,2018; Villalba et al., 2022) and Orange 3 (Vaishnav & Rao, 2018; Sujatha et al., 2021), which seems that the use of machine learning tools are beneficial in this area of agriculture and is widely used for its efficiency, but more detailed studies are still needed about many others that can be helpful.

4.5. Metrics used from Machine Learning and Deep Learning for the identification of Fruits and Plants (RQ4)

As shown in Fig. 5 there are a variety of metrics used to identify fruits and plants, where the results obtained from the metrics, demonstrate if the algorithm being used is the best. With what has been said above, it is observed that accuracy was the most used by most of the authors (18.5%); at the same time accuracy, representing 15.9%. So both metrics are the most common due to their reliability. However, there are also other important metrics, such as: ROC curve, Recall, sensitivity, among others.

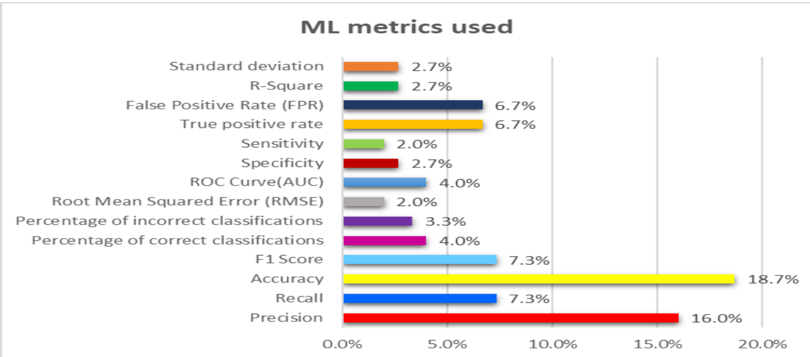

Fig. 5: ML and DL metrics for fruit and plant identification

The metrics for plant and fruit identification in this review were Accuracy (Le & Lin, 2019; Al-Shawwa,2020; Ponce, Aquino & Andújar, 2019; Hossain, Al-Hammadi & Muhammad, 2019; Behera et al.,2020; Zhang et al.,2019; Abbaspour et al., 2020; Jiang et al.,2019; Lu, Tan & Jiang, 2021; Oraño, Maravillas & Aliac, 2019; Calle et al., 2021; Pratap, Singh & Jain,2019; Rodriguez, Pastor & Ugarte, 2021; Wuang et al., 2022; Wu, Zhu & Ren, 2020; Cecotti et al., 2020; Khan et al., 2020; Khan et al., 2020; Aherwadi et al., 2022; Agarwal & Sagar, 2019; Bai et al., 2021; Saranya et al., 2020; Chung & Van Tai, 2019; Villanueva & Salenga, 2018; Mohapatra, Choudhury & Sabat, 2021; Behera, Rath & Sethy, 2021) and precision (Le & Lin, 2019; Koirala et al.,2019; Figueredo & Ballesteros, 2016; Calle et al., 2021; Mota, Juárez & Olguín,2018; Villalba et al., 2022; Behera et al.,2020; Zhang et al.,2019;

Jiang et al.,2019; Lu, Tan & Jiang, 2021; Oraño, Maravillas & Aliac, 2019; Pratap, Singh & Jain,2019; Rodriguez, Pastor & Ugarte, 2021; Khan et al., 2020; Ati et al., 2022; Vaishnav & Rao, 2018; Saranya et al., 2020; Sujatha et al., 2021; Vijayakumar, Ampatzidis & Costa, 2023; Arévalo, Ruiz & Ayala, 2021; Hussain et al., 2022; Mohapatra, Choudhury & Sabat, 2021; Yu et al., 2019; Aguilar & Campoverde, 2019), where these are essential to evaluate the performance of the model (Zhong et al., 2021), as well as to measure it during training and testing (Bajaj, 2023); using to improve reliability, but it was also observed that they make less use of metrics considered important such as: Sensitivity (Pratap, Singh & Jain,2019; Jiang, Li & Safara, 2021; Arévalo, Ruiz & Ayala, 2021), Root Mean Squared Error (RMSE) (Wuang et al., 2022) and specificity (Oraño, Maravillas & Aliac, 2019; Calle et al., 2021; Jiang, Li & Safara, 2021; Arévalo, Ruiz & Ayala, 2021), and therefore could be useful for the food sector, especially the issue we are dealing with such as the identification of fruits and plants.

4.6. Machine learning and Deep Learning Techniques most commonly for the identification of Fruits and Plants (RQ5)

Of the 40 articles studied, it is evident that there are different techniques of ML and DL to detect plants and fruits, used by several authors; Table 6 shows that CNN was the most frequent algorithm, represented by 18 studies (20.00%), as well as Support Vector Machine (SVM) with 9 authors (10.0%) and Artificial Neural Network (ANN) with 5 articles (5.6%), demonstrating in this way that these are the most effective when detecting fruits.

Table 6: Techniques of Machine Learning and Deep Learning

Ref.	Technique	Related studies	Quantity
T01	Convolutional neural network	(Al-Shawwa,2020), (Ponce, Aquino & Andújar, 2019), (Behera et al.,2020), (Oraño, Maravillas & Aliac, 2019), (Calle et al., 2021), (Rodriguez, Pastor & Ugarte, 2021), (Wuang et al., 2022), (Wu, Zhu & Ren, 2020), (Cecotti et al., 2020), (Aherwadi et al., 2022), (Ati et al., 2022), (Chung & Van Tai, 2019), (Arévalo, Ruiz & Ayala, 2021), (Risdin, Mondal & Hassan, 2020), (Villanueva & Salenga, 2018), (Mohapatra, Choudhury & Sabat, 2021), (Behera, Rath & Sethy, 2021), (Aguilar & Campoverde, 2019)	18
T02	Artificial neural network	(Figueredo & Ballesteros, 2016), (Mota, Juárez & Olguín,2018), (Abbaspour et al., 2020), (Behera et al.,2020), (Risdin, Mondal & Hassan, 2020)	5
T03	Agricultural Deep Learning	(Villalba et al., 2022), (Hossain, Al-Hammadi & Muhammad, 2019), (Jiang et al.,2019), (Vaishnav & Rao, 2018)	4
T04	Artificial bee colony algorithm	(Abbaspour et al., 2020)	1
T05	Prefed neural network	(Behera et al.,2020)	1
T06	Vector Support Machine	(Behera et al.,2020), (Calle et al., 2021), (Pratap, Singh & Jain,2019), (Wu, Zhu & Ren, 2020), (Khan et al., 2020), (Agarwal & Sagar, 2019), (Saranya et al., 2020), (Sujatha et al., 2021), (Risdin, Mondal & Hassan, 2020)	9
T07	Random Forest	(Behera et al.,2020), (Agarwal & Sagar, 2019), (Bai et al., 2021), (Vaishnav & Rao, 2018), (Sujatha et al., 2021)	4
T08	Prefed neural network	(Behera et al.,2020)	1
T09	Single hidden Layer Feed-forward Neural Network	(Behera et al.,2020)	1
T10	AlexNet	(Lu, Tan & Jiang, 2021), (Aherwadi et al., 2022), (Behera, Rath & Sethy, 2021)	3
T11	Residual Network	(Lu, Tan & Jiang, 2021)	1

T12	VGGNet	(Lu, Tan & Jiang, 2021)	1
T13	Deep Convolutional Neural Network	(Lu, Tan & Jiang, 2021), (Hussain et al., 2022)	2
T14	Multicondition training	(Lu, Tan & Jiang, 2021)	1
T15	Particle Swarm Optimization	(Pratap, Singh & Jain,2019), (Wu, Zhu & Ren, 2020)	2
T16	Radial Base Function Neural Network	(Pratap, Singh & Jain,2019)	1
T17	Multilayer Convolutional Neural Network	(Pratap, Singh & Jain,2019)	1
T18	Backpropagation	(Wu, Zhu & Ren, 2020)	1
T19	Multitasking cascading convolutional networks	(Zhang et al.,2019)	1
T20	Levenberg-Marquardt optimization	(Khan et al., 2020)	1
T21	Scale conjugate gradient back propagation	(Khan et al., 2020)	1
T22	Bayesian regularization back propagation	(Khan et al., 2020)	1
T23	Spatial Prediction	(Khan et al., 2020)	1
T24	Logistic regression	(Khan et al., 2020), (Vaishnav & Rao, 2018)	2
T25	AdaBoost	(Khan et al., 2020)	1
T26	Multilayer Perceptron	(Khan et al., 2020)	1
T27	Softmax	(Agarwal & Sagar, 2019)	1
T28	Naive Bayes	(Agarwal & Sagar, 2019), (Vaishnav & Rao, 2018)	2
T29	K-Nearest Neighbor	(Agarwal & Sagar, 2019), (Vaishnav & Rao, 2018), (Saranya et al., 2020)	3
T30	Deep neural network	(Jiang, Li & Safara, 2021)	1
T31	CASA Model	(Bai et al., 2021)	1
T32	Neural Network	(Vaishnav & Rao, 2018)	1
T33	Decision Tree	(Vaishnav & Rao, 2018)	1
T34	Stochastic Gradient Descent	(Sujatha et al., 2021)	1
T35	VGG-19	(Sujatha et al., 2021), (Behera, Rath & Sethy, 2021)	2
T36	Inception-V3	(Sujatha et al., 2021)	1
T37	VGG-16	(Sujatha et al., 2021), (Behera, Rath & Sethy, 2021)	2
T38	YOLO v3	(Koirala et al.,2019), (Vijayakumar, Ampatzidis & Costa, 2023)	2
T39	Faster Regionbased CNN	(Risdin, Mondal & Hassan, 2020), (Mohapatra, Choudhury & Sabat, 2021)	2
T40	Bag-of-Words	(Risdin, Mondal & Hassan, 2020)	1
T41	GoogleNet	(Behera, Rath & Sethy, 2021)	1
T42	Mask Region Convolutional Neural Network	(Le & Lin, 2019), (Yu et al., 2019)	2

With respect to the machine learning and deep learning techniques that were implemented to identify plants and fruits, the most used were Convolutional Neural Network (CNN) (Al-Shawwa,2020; Ponce, Aquino & Andújar, 2019; Behera et al.,2020; Oraño, Maravillas & Aliac, 2019; Calle et al., 2021; Rodriguez, Pastor & Ugarte, 2021; Wuang et al., 2022; Wu, Zhu & Ren, 2020; Cecotti et al., 2020; Aherwadi et al., 2022; Ati et al., 2022; Chung & Van Tai, 2019; Arévalo, Ruiz & Ayala, 2021; Risdin, Mondal & Hassan, 2020; Villanueva & Salenga, 2018; Mohapatra, Choudhury & Sabat, 2021; Behera, Rath & Sethy, 2021; Aguilar & Campoverde, 2019), Support Vector Machine (SVM) (Behera et al.,2020; Calle et al., 2021; Pratap, Singh & Jain,2019; Wu, Zhu & Ren, 2020; Khan et al., 2020; Agarwal & Sagar, 2019; Saranya et al., 2020; Sujatha et al., 2021; Risdin, Mondal & Hassan, 2020) and Artificial Neural Network (ANN) (Figueredo & Ballesteros, 2016; Mota, Juárez & Olguín,2018; Abbaspour et al., 2020; Behera et al.,2020; Risdin, Mondal & Hassan, 2020), demonstrating that these were considered the most efficient.

5. Conclusion

The systematic review shows the current context of the study with respect to the identification of plants and fruits, for which 40 articles were taken into account. Therefore, by making a general approach to all studies, the authors provide an overview in the use of DL and ML techniques for the correct identification of crops over time. What was shown that the apple and banana were the most applied fruits, along with the citrus plant, which shows that these are the most common and the one of greatest interest by researchers, also the techniques that had better precisions were CNN and SVM, while the most used softwares were Python and TensorFlow, this due to the advantages that both have. On the other hand, Accuracy and Precision were the metrics that proved to be the best due to their use and reliability that they demonstrate in their results. Finally, the most used techniques were Convolutional Neural Network (CNN), Support Vector Machine (SVM) and Artificial Neural Network (RNA), which shows that these techniques described are efficient in correctly identifying plants and fruits.

5.1. Research challenges, limitations and Future research directions

The present systematic review of literature constitutes an in-depth study of machine learning techniques applied to the recognition of plants and fruits, which took into account 40 articles from 8 databases. Although it was possible to answer the research questions raised, the research has some limitations. In the first place, although it is true that 7 databases were taken into account, this was because there were few articles in each of them. So it is possible to expand the search to more recognized databases, such as: Scopus, Taylor and Francis, Web of science and EBSCOhost, which should be included. Likewise, it was observed that there are 42 machine learning techniques, where Convolutional neural network was the one that obtained the most studies, however there could also be other algorithms that could be useful such as: Vector Support Machine, Artificial neural network and Random Forest to detect fruits and plants. Therefore, the list of techniques should be constantly updated. Finally, based on the study, most of the articles present comparisons of Machine Learning algorithms to show the performance of each one, however, a novel model has not been proposed such as the combination of machine learning techniques (Ensemble Stacking) to integrate the techniques and achieve greater effectiveness of the results.

For future research it is recommended to propose techniques for the selection of variables such as Information Gain and Recursive feature elimination (RFE) to determine the most appropriate for the study, as well as to propose the most studied methods in different areas of product selection in the industrial sector. e.g.: Convolutional Neural Network (CNN) and Support Vector Machine (SVM). Finally, the research can be focused on the study of new fruits.

5.2. Recommendations

Based on the information related to the detection of plants and fruits, it is recommended to integrate the data, and apply machine learning with big data. In the same way, it is also suggested to build software using machine learning that helps to efficiently predict problems in fruits and plants, and thus improve their quality.

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