MACHINE LEARNING AND DEEP LEARNING FOR FRUIT IDENTIFICATION: SYSTEMATIC REVIEW

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ABSTRACT

Machine learning and deep learning applications are becoming increasingly popular in the agricultural industry, especially in the fruit sector, using techniques that provide the necessary advantages to transform manual practices; the objective of this study was to carry out a systematic review of the literature on Machine Learning and deep learning techniques, tools and metrics to identify fruit characteristics, using Kitchenham's methodology, which yielded 18 articles. Among the results obtained, the most used techniques, tools and metrics were: Convolutional Neural Network (CNN) and Artificial Neural Network (ANN); Python and TensorFlow, and the most used metrics to determine the effectiveness were found to be Accuracy and precision, so it can be concluded that the described techniques are considered efficient to predict certain fruit characteristics. In addition, difficulties encountered in the literature to obtain good results are mentioned. Finally, we propose some ideas for future work in the development of fruit identification.

Keywords: *Machine Learning, Identification of Fruits, Techniques, Convolutional Neural Network, Python*.

1. INTRODUCTION

Artificial intelligence methods are used more frequently in the food sector, in order to perform quality inspections that provide the necessary advantages to transform manual practices when selecting fruits and eliminate high labor costs in inspecting [1], offering quality products, according to what consumers require.

Thus, fruit screening for yield estimation, grading, disease control and other applications in the sector have been gaining notoriety lately [2]-[6], being undoubtedly the primary parameter when considering conducting research on the topic. So, several authors have developed over time algorithms to detect fruits efficiently [7], [8].

Based on this, there are many technologies based on machine learning for detection tasks that have been applied to identify fruits, focusing on characteristics of each of the images, such as: color, shape and texture [9,10], extracting discriminative features from images, which provide a high prediction [11].

It should be emphasized that, applying machine learning is important, since it allows the identification of places, people and objects in images and always with an accuracy almost similar as a person would do, whether it is prediction of ripe, unripe, failed or spoiled fruits, automatic detection of diseases, etc. ; predicting 97% future crop yield, mitigating effects, this with the purpose of being of help to small producers and efficiently determine the products, offering quality fruits [12], where several algorithms are used, among them: Decision Tree, Neural Network, Support Vector Machine, logistic regression, Convolutional Neural Network, etc.[13,14].

With the aforementioned, what is wanted is to perfect the various solutions proposed by several authors about machine learning in order to identify fruits properly, and achieve cost and time savings, by performing it in an automated way, as well as achieving to have more closeness with consumers, providing a qualified product, with the help of safe and dynamic algorithms.

The objective of this article is to perform a systematic review of the research works that deal with the topic of machine learning and deep learning for fruit identification.

This article is divided as follows: in section 2, the methodology of the systematic literature review will be presented. In section 3, the respective analysis of the results will be presented according to the questions formulated, and finally, in section 4, information about the discussion and conclusions reached in this review will be shown.

2. METHODS

In this systematic review, the guide proposed by Kitchenham and Charters [15] will be used, consisting of three important stages: planning the review, conducting the review and review results.

Planning the review: In this phase, the need for the study is defined, considering the research questions.

Conducting the review: Here the primary studies are selected, based on the inclusion and exclusion criteria.

Review results: In this last phase, the statistics are detailed and an analysis of the articles is performed.

2.1 Review Planning

To have an idea about machine learning for fruit identification, as well as their experiences using algorithms has been positive, this is why it is essential to have research that helps in the use of this. With the aforementioned, the process of planning in the review helps the analysis of the study.

Thus, we proceeded to consult different databases of scientific articles, being the following: Springer Link, ScienceDirect, IEEE Xplore, Dialnet, MDPI, ResearchGate, Portal of the Technological University of Panama and Pirhua Institutional Repository. A review protocol was also carried out to identify the needs of the search and define the area of study on the theories that support machine learning techniques for fruit identification, whose research questions are shown in Table 1:

Table 1. Literature Search Questions.

Id	Search Question	Motivation
Q1	What were the techniques used and which had the best accuracy results?	Reveal the various machine learning techniques that are implemented for fruit identification.
Q2	Which tools are the most concurrent for predictive model development and testing?	Recognize machine learning tools for the identification of fruits.
Q3	What metrics are used to determine the effectiveness of machine learning techniques?	Identify the most common machine learning metrics for fruit identification.

2.2 Conducting the Review

2.2.1 Initial search

The search process started on July 09, 2022, with the first searches related to the terms 'Convolutional neural networks', identification', 'Deep learning', in the following databases: Springerlink, ScienceDirect, IEEE Xplore, Dialnet, MDPI, ResearchGate, Portal de la Universidad Tecnológica de Panamá and Pirhua Institutional Repository.

Then, the search was expanded using AND (and) and OR(or) operators, combined with the terms 'machine learning, ' fruits', 'classification'.
These searches yielded several results, even repeated, but they provided a general idea of the context of the words described, i.e., it was of great contribution to the research.

2.2.2 Systematic search

Continuing in the databases Springer Link, ScienceDirect, IEEE Xplore, Dialnet, MDPI, ResearchGate, Portal of the Technological University of Panama and Pirhua Institutional Repository, the results of study was limited to the years 2016 to 2022, where the search string is shown in Table 2. These search strings, combined with the inclusion and exclusion criteria and additional filters, allowed us to obtain the results shown in section 3.

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Table 2. Literature Search Chain.

Question	Search String
Q1	(((MACHINE LEARNING) AND MACHINE LEARNING TECHNIQUES) AND FRUITS)
Q2	(((MACHINE LEARNING) AND TOOLS) AND IDENTIFICATION) AND FRUITS)
Q3	(((MACHINE LEARNING) AND METRICS) AND IDENTIFICATION) AND FRUITS)

2.2.3 Inclusion and exclusion criteria

Table 3 shows the criteria used to filter the articles:

Table 3. Search Criteria.

Inclusion criteria	Exclusion criteria
Only articles published in indexed virtual libraries such as Scopus, Web of Science, Ebsco Host and ProQuest will be considered.	Articles that present duplicity of publication.
Articles related to the research questions	Book reviews, technical reports, newspaper publications, incomplete articles.
Items will be taken into account, from 2016 to 2022.	Items that have any access restriction.
Only articles in English and Spanish will be accepted, with priority given to those in English.	Articles that do not have any concordance or relationship with the subject of study.
Articles that are available in full text are considered.	Research that does not meet the inclusion criteria
Machine learning field research.	Theses, books and offprints.

2.2.4 Additional filter:

To select the studies, filters will be used, constituted as follows: First, a review of the contents of the articles established in the review was made.

3. RESULTS

The 18 selected studies are shown in Table 4, where the different contents related to machine learning for the identification of fruit characteristics are detailed.

4. DISCUSSION

According to the analysis carried out on the studies that deal with the use of machine learning to identify fruits, it was observed that the most used techniques were Convolutional Neural Network (CNN), with 10 articles, and both Artificial Neural Network (ANN) and Support Vector Machine (SVM) with 2 and 3 articles (table 6); also the techniques that obtained a high accuracy were Support Vector Machine (SVM) and Convolutional Neural Network (CNN).

In the same way, in relation to the most popular tools to identify fruits, Python and TensorFlow are found with 11 and 09 studies respectively (table 8), this is due to the fact that these programming languages are considered the best because they have more advantages than others, among them their high level and easy reading in fruit identification. Based on what has been presented, a variety of research on the topic of machine learning to identify fruits can be observed, shown in Table 5 Number of studies by year of publication.

Taking into account the above, the results related to the research questions posed are presented below:

Table 5: Number Of Studies By Year Of Publication.

Year	Number	Related Studies
2016	1	[19]
2018	1	[21]
2019	7	[16], [26], [27], [29], [30], [31], [35]
2020	5	[22], [23], [24], [25], [34]
2021	4	[17], [28], [32], [20]
2022	2	[18], [33],

Q1. Which techniques were used and which had the best accuracy results?

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There are many machine learning techniques to identify fruits, used by different authors, as shown in Table 6, being Convolutional Neural Network (CNN), the most used technique, since as can be seen 11 authors mention it, followed by Artificial Neural Network (ANN) and Support Vector Machine (SVM) with 4 articles, which shows that these are the most efficient for the correct identification of fruit characteristics.

Convolutional Neural Network (CNN) is the most widely used for the field of object identification and classification by feature extraction and clustering, and it is a technique that yields an accuracy higher than 90% according to the reviewed articles [16], [17], [18], [20], [25], [29], [30], [32], [34], [35].

In the same way, Table 7 shows the machine learning techniques with the highest accuracy, highlighting that these are related to the size of the information used in the studies, being Support Vector Machine (SVM) and Convolutional Neural Network (CNN) the algorithms with the highest accuracy in fruit identification.

Support Vector Machine (SVM) is also another widely used technique, but it is more oriented to data classification, email, parameters, it also shows very high accuracies but in object identification we have few results according to the reviewed articles [20], [31], [34].

Q2. Which tools are the most concurrent for predictive model development and testing?

When talking about machine learning techniques, there are different tools to use for fruit identification. Therefore, Table 8 presents the most used tools based on the 18 studies conducted, showing that Python is considered the best, i.e. 11 authors mention it in their research, followed by TensorFlow with 09 articles that talk about it, these results are due to the fact that both tools have advantages, including their high-level and easy to read languages, in addition to containing open source platforms, being useful for correct identification of fruits.

Table 8. Machine Learning Tools.

Ref.	Tool	Related studies
H01	Matlab	[16], [20], [23], [24], [25], [30],
H02	Image batch Processor	[20]
H03	REV	[20]
H04	Keras	[21], [28], [29], [32]
H05	Pytorch	[28]
H06	Paint 3D	[32]
H07	Python	[16], [18], [21], [22], [25], [27], [28], [31], [32], [34], [35]
H08	TensorFlow	[16], [18], [21], [22], [28], [29], [31], [32], [35]
H09	OpenCV	[18], [21], [22]

As it is already known Python has become in recent years the most used tool for data science and machine learning because it uses a syntax easy to learn and write and above all is compatible with many frameworks and libraries that help worldwide to create applications on different platforms such as Web, desktop, video games, neural networks, among others, that is why researchers have mentioned Python as the most used tool in the field of Machine learning [16], [18], [21], [22], [25], [27], [28], [31], [32], [34], [35].

Q3. What metrics are used to determine the effectiveness of machine learning techniques?

As shown in Table 9 there are a variety of metrics used for fruit identification, whose values obtained in each metric define whether the method used has good results in relation to the environment. Based on that there are quite a few metrics that most researchers use, standing out among all Accurance with 14 articles [17], [20], [23], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35] and precision with 12 articles [16], [17], [18], [20], [21], [22], [27], [28], [29], [31], [32], [35], showing that these 2 metrics are the best as they are more reliable. Similarly, the following are also used: F1 score, Recall, ROC curve, Specificity, etc.

Previous systematic literature review studies reveal the existence of applications of artificial neural networks and machine vision to the classification, inspection and prediction of physical changes in fruits and vegetables [19], as well as different techniques applied to the identification, classification and varieties of fruits [24].

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Our motivation is to know the most used machine learning and deep learning technique in the last 6 years. The findings indicate that CNN is the most used technique for fruit identification (table 6) and it is the one to be used in our next project.

5. OPEN RESEARCH ISSUES AND PROBLEMS

The manuscript summarizes several studies to know the machine learning techniques (and their best accuracy), the metrics used and the most concurrent tools for predictive model testing and development. The followed research points can contribute to enhance the current state of the art.

5.1. Open Research Issues

The codes or algorithms developed for a CNN could be included in different automated fruit picking robots, other mobile applications and publicly available websites could also be implemented for this purpose.

5.2. Problems

From the literature review, the following difficulties have been found, among them: The choice of a bad machine learning technique can lead us to obtain poor accuracy; Obtaining a correct output depends nor only on the input data set, but also the architecture in which the neural network is conformed; the minimum number of images that we should use for training a neural network is unknown; the neural network can be retrained to recognize new characteristics of fruits, losing what has been learning in past training, which demands new resource consumption (memory , disk storage, processing, among others) and possibly new creation of algorithms.

6. CRITICAL JOB EVALUATION

we would like to point out that this paper reviews almost all peer-reviewed quality articles of the last 6 years, we also include information from research groups and university theses, among others. This paper does not include conceptualizations of machine learning and deep learning techniques, widely used in the articles consulted. The research questions were very clearly defined, and we tried to avoid bias. We believe that the results obtained are applicable, especially in our field, where we are working on future fruit-oriented research articles.

7. CONCLUSIONS

It can be concluded that the techniques described above are considered efficient in correctly predicting fruit defects, in other words, using reliable algorithms is indispensable and beneficial for easy and effective identification.

Finally, the most effective metrics used in the study were Accurance by 15 authors and precision with 14 articles, concluding on the basis of the above that these metrics are the best, due to their reliability in demonstrating good results at the time of their use.

This systematic review article has covered the most recent research on machine learning and deep learning techniques, tools and metrics for fruit identification. As a result of this research, we can highlight that, regarding the technique, the most used were CNN and SVM; regarding the tools, we see python and TensorFlow; and regarding the metrics, accuracy and precision. Also, we can mention that the identification of a fruit not only depends on the resolution of the image, but also on the architecture of the technique and lighting present at the time of image capture (especially when the fruit is on the plant), as indicated in the literature, but what has not been found much is the identification of fruits based on their physicochemical characteristics, so this would be a proposal of great interest to researchers in this field.

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Table 4. Results Found.

Ref.	Title	Description
[16]	Fruit classification based on convolutional neural networks	The study works with 13 categories of fruits, where the training process is shown, using a proposed system (convolutional neural network).
[17]	Sorting of peach fruit into ripe, unripe and damaged fruit for automated harvesting.	The aim is to use the CNN algorithm to recognize ripe peach fruit and identify damaged fruit, helping to improve the quality necessary to market it.
[18]	Device that allows identification by type and size of naranjilla and tree tomato through artificial vision to improve production in SMEs.	Design models that help to classify by type and size of oranges and tree tomatoes; a computer vision system based on a neural network algorithm was used for this purpose.
[19]	Identification of fruit ripeness stage with artificial neural networks, a review.	Applies Artificial Neural Networks to classify, recognize patterns and predict product yields, helping in the food sector.
[20]	Implementation of machine learning algorithms for the measurement of grape quality parameters.	Develop a system with the help of machine learning classifiers for grape quality measurement to select the most suitable classifier.
[21]	Apple sorting using computer vision and artificial neural networks	The study suggests classifying apples using an intelligent algorithm, in this case a convolutional neural network (CNN).
[22]	Prototype of a system to determine the ripeness of a banana using Deep Learning and Computer Vision.	To propose the creation of an intelligent classification model with robotic assistance, oriented to distinguish the ripening stage of banana, for which convolutional neural networks were used.
[23]	Estimation of the Constituent Properties of Red Delicious Apples Using a Hybrid of Artificial Neural Networks and Artificial Bee Colony Algorithm	Study that uses a Hybrid system based on Artificial Neural Networks to estimate the properties that make up vegetables and fruits, classifying them efficiently and accurately.
[24]	Identification, classification & grading of fruits using machine learning & computer intelligence: a review	Compare different techniques for identification, classification and grading of fruits.
[25]	Grape detection with convolutional neural networks	Investigate features such as: color images, grayscale images and color histograms using convolutional neural networks.
[26]	Automatic Fruit Classification Using Deep Learning for Industrial Applications	The research suggests using a fruit classification system to assist the supermarket cashier in identifying prices and types of fruit.
[27]	Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks	Propose a deep learning approach based on enhanced convolutional networks (CNN) for real-time detection of apple leaf diseases
[28]	Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification	An analysis of various research using the CNN networks algorithm was conducted to help classify plant leaf diseases.
[29]	Jackfruit Fruit Damage Classification using Convolutional Neural Network	A convolutional neural network was implemented in an Android compatible mobile app to detect and diagnose damage to jackfruit caused by pests and diseases.
[30]	Olive-Fruit Variety Classification by Means of Image Processing and Convolutional Neural Networks	Study that seeks to implement 6 different convolutional neural network architectures to compute classifiers and categorize fruits.

[31]	Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease	Seeks to propose a multilayer convolutional neural network (MCNN) to classify mango leaves infected by the fungal disease anthracnose.
[32]	Classification of Fruit Ripeness Grades using a Convolutional Neural Network and Data Augmentation	It seeks to describe the use of a convolutional neural network to classify the degree of ripeness of 5 fruits: red apple, green apple, banana, orange and strawberry.
[33]	Convolutional Neural Networks of Whole Jujube Fruits Prediction Model Based on Multi-Spectral Imaging Method	Analyze the feasibility of multispectral imaging combined with deep learning to perform a rapid non-destructive test of internal fruit quality.
[34]	Detection of apple defect using laser-induced light backscattering imaging and convolutional neural network	The study proposes a technique to automatically detect apple defects based on laser-induced light backscattering images and convolutional neural network (CNN) algorithm.
[35]	Multi-Task Cascaded Convolutional Networks Based Intelligent Fruit Detection for Designing Automated Robot	Proposing an improved method of detecting fruits through a multitask cascade convolutional neural network

Table 6. Techniques For Predicting The Identification Of Fruit Features.

Id	Technique	Related studies - references
T01	Convolutional Neural Network (CNN)	[16], [17], [18] [20], [24], [25], [29], [30], [32], [33], [34]
T02	Artificial Neural Network (ANN)	[19], [21], [23], [24]
T03	Deep Learning	[22], [26], [27]
T04	Artificial Bee Colony Algorithm (ABC)	[23]
T05	Probabilistic neural network (PNN)	[24]
T06	Support Vector Machine (SVM)	[20], [24], [31], [34]
T07	Random Forest	[24]
T08	Feed-forward Neural Network (FNN)	[24]
T09	Single hidden Layer Feed-forward Neural Network (SLFN)	[24]
T10	AlexNet	[28]
T11	Residual Network (ResNet)	[28]
T12	VGGNet	[28]
T13	Deep Convolutional Neural Network (DCNN)	[28]
T14	Multicondition training (MCT)	[28]
T15	Particle Swarm Optimization (PSO)	[31], [34]
T16	Radial basis function neural network (RBFNN)	[31]
T17	Multilayer convolutional neural network (MCNN)	[31]
T18	Backpropagation (BP)	[34]
T19	Multi-task cascade convolutional networks	[35]

Table 7. Accuracy Of Techniques To Predict The Identification Of Fruits.

Ref.	Data Base	Technique	Accuracy (%)
[16]	13 fruit categories.	Convolutional neural network (CNN)	87.00%
[17]	Mature and immature peaches.	Convolutional neural network (CNN)	95.31%
[18]	90 trials in total (orange, tomato and unknown object)	Convolutional neural network (CNN)	95.00%
[20]	83 data for each class	Convolutional neural network (CNN)	90.36%
		Support vector machine (SVM)	78.10%
[21]	25 photographs of gold apples; 1 real-time video with Gala apples.	Artificial neural network (ANN)	95.36%
[22]	650 images of each banana state	Deep learning	96.00%
[23]	56 Red delicious apples	Artificial neural network (ANN)	90.00%
		Artificial bee colony algorithm (ABC)	92.32%
[25]	50 berries from each vine	Convolutional neural network (CNN)	99.00%
[26]	32 samples	Deep learning	96.75%
[27]	26377 images	Deep learning	78.80%
[29]	516 images	Convolutional neural network (CNN)	97.93%
[30]	1050 images of olives	Convolutional neural network (CNN)	95.91%
[31]	1070 images of Mango tree leaves	Particle swarm optimization (PSO)	88.39%
		Support vector machine (SVM)	92.75%
		Radial basis function neural network (RBFNN)	94.20%
		Multilayer convolutional neural network (MCNN)	97.13%
[32]	15 data sets	Convolutional neural network (CNN)	96.34%
[33]	96 Chinese jujube fruits	Convolutional neural network (CNN)	39.00%
[34]	50 images	Particle swarm optimization (PSO)	86.7%
		Support vector machine (SVM)	87.8%
		Backpropagation (BP)	90.3%
		Convolutional neural network (CNN)	92.5%
[35]	28 images of fruits	Multi-task cascaded convolutional networks	-------

Table 9. Machine learning metrics for predicting fruit identification.

Ref.	Metrics	Related studies
M01	Precision	[16], [17], [18], [19], [20], [21], [22], [24], [27], [28], [29], [31], [32], [35]
M02	Recall	[20], [28], [29], [32]
M03	Accuracy	[17], [20], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35]
M04	F1 Score	[20], [28], [29], [32]
M05	Percentage of correct classifications	[28], [29], [32] [35]
M06	percentage of incorrect classifications	[28], [29], [32]
M07	Mean square error (MSE)	[23]
M08	Root Mean Squared Error (RMSE)	[23]
M09	Error rate	[25]
M10	ROC Curve (AUC)	[20],[25], [27]
M11	Precision media (mAP)	[27]
M12	Specificity	[17], [20], [29]
M13	Sensitivity	[17], [20]
M14	Mean Absolute Error (MAE)	[23]
M15	Log loss	[32]
M16	Hit rate	[30]
M17	Missing report rate	[31]
M18	False report rate	[31]
M19	Ratio of true positives	[20], [25], [28], [29], [32], [35]
M20	False positive rate (FPR)	[20], [25], [28], [29], [32], [35]
M21	Media	[19], [23]
M22	Arithmetic mean	[19]
M23	Weighted average	[19]
M24	Gaussian Mean	[19]
M25	R-Square	[23], [33]
M26	Root mean square prediction error (RMSPE)	[33]
M27	Recognition rate	[34]
M28	Standard deviation	[23], [24], [25]