



Towards Detecting Crop Diseases and Pest by Supervised Learning¹

Hacia la detección de plagas y enfermedades en cultivos a través de aprendizaje supervisado²

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Abstract

The climate change has caused threats to agricultural production; the extremes of temperature and humidity, and other abiotic stresses are contributing factors to the etiology of disease and pest on crops. About the matter, recent research efforts have focused on predicting disease and pest crops using computer science techniques such as supervised learning algorithms. Therefore in this paper, we present an overview of supervised learning algorithms commonly used in agriculture for the detection of pests and diseases in crops such as corn, rice, coffee, mango, peanut, and tomato, among others, with the aim of selecting the algorithms that give the best performance for the agricultural sector.

Keywords

supervised learning; classifier; crop; disease; pest; agriculture

Resumen

El cambio climático ha generado amenazas a la producción agrícola. Los cambios extremos de temperatura y humedad y otros factores abióticos de estrés contribuyen a la aparición de enfermedades y plagas en los cultivos. Por ello, recientes esfuerzos de investigación se han enfocado en la predicción de plagas y enfermedades en cultivos, haciendo uso de algoritmos de aprendizaje supervisado. En este artículo se presenta una revisión bibliográfica de los algoritmos de aprendizaje supervisado más utilizados para la detección de plagas y enfermedades en cultivos como maíz, arroz, café, mango, maní y tomate, con el objetivo de seleccionar los algoritmos con mejor rendimiento para el sector agrícola.

Palabras clave

aprendizaje supervisado; clasificador; cultivo; enfermedad; peste; agricultura

1. Introduction

Nowadays the agricultural yield is affected by global change factors such as: new varieties in the crops, changes in consumer taste, natural causes, and/or anthropogenic events [1], [2]. In this sense, the agricultural is exposed to global change effects, where its vulnerability depend of factors such as abiotics, biologics, socioeconomics and regionals [3]-[5], thus different land areas on earth are potentially vulnerable to climate change and direct and indirect productivity loses, contributing also to the occurrence of diseases and pest [6].

On the other hand exist an area of machine learning, which builds models for regression and classification named supervised learning. These algorithms learn through examples (data training), with the goal of predict or detect a new input data [7]. The outcome of learning process (training) of the algorithm (Bayesian networks, Decision tree, Support vector machine, Artificial neural networks, K-nearest neighbors, etc) is to create a classifier (hypothesis or model) for data set training.

The idea of using information as examples, has inspired researchers in apply supervised learning algorithms for predicting future diseases and pest in agricultural crops [8]. For example, data collected about weather conditions, soil fertility properties, and physical properties and management of a coffee crop, can be used to predict the rust infection rate still in the early days of the harvest [9]. In the same way, weather conditions such as the minimum and maximum levels of temperature, humidity and rainy days can help estimating the behavior of rice blast [10].

This article focuses on presenting a review of supervised learning algorithms commonly used in agriculture for the detection of pests and diseases in crops such as corn, rice, coffee, mango, tomato, wheat, peanut, grape, kiwi and fungal. The remainder of this paper is organized as follows: Section 2 describes the main supervised learning algorithms; Section 3 refers to the most relevant research of this topic; Section 4 reviews algorithms used in the agricultural sector; and Section 5 presents the conclusions.

2. Background and basic definitions of Supervised Learning

Supervised learning is characterized by learning from a set of examples, commonly called training data (data sets), which are used to define the behavior of the algorithm employed. Training data consist of a set of attributes. For example in Table 1, there are three attributes, the number of days of precipitation (NDP), average daily nighttime relative humidity (DNH), and average daily minimum temperatures (DMT), which can take different values (discrete or continuous) called instances; and are associated with a target variable, rust infection rate (RIR), which also can take continuous or discrete variables, commonly called classes [7].

Table 1. Training data for rust detection

Attribute			Target Variable
NDP	DNH	DMT	RIR
2	96.1	14	65.23%
3	93.8	16	62.54%
4	95.7	15	57.32%
1	98.2	14	61.12%

Source: authors' own elaboration

A formal notation of supervised learning [11], begins with a case represented by a set of instances in a vector $x_{(i)}$ and a class symbolized by $y_{(i)}$, forming a pair $(x_{(i)}, y_{(i)})$ denominated example, and m example data $\{ (x_{(i)}, y_{(i)}); i = 1, \dots, m \}$ called training data. Therefore, when the value of class $y_{(i)}$ is continuous it is referred to as a regression problem, otherwise when $y_{(i)}$ is discrete it becomes a classification problem.

Thus, the goal of this family of algorithms, once the learning process is successfully completed, is to assign the value of the class that best represents the set of instances that belongs to a new case $x_{(i)}$.

It is important to note that the result of the learning process (or training) of the algorithm employed generates a classifier (hypothesis or model) for a set of specific training data. Thus, if there are n training data sets, an algorithm can generate n classifiers.

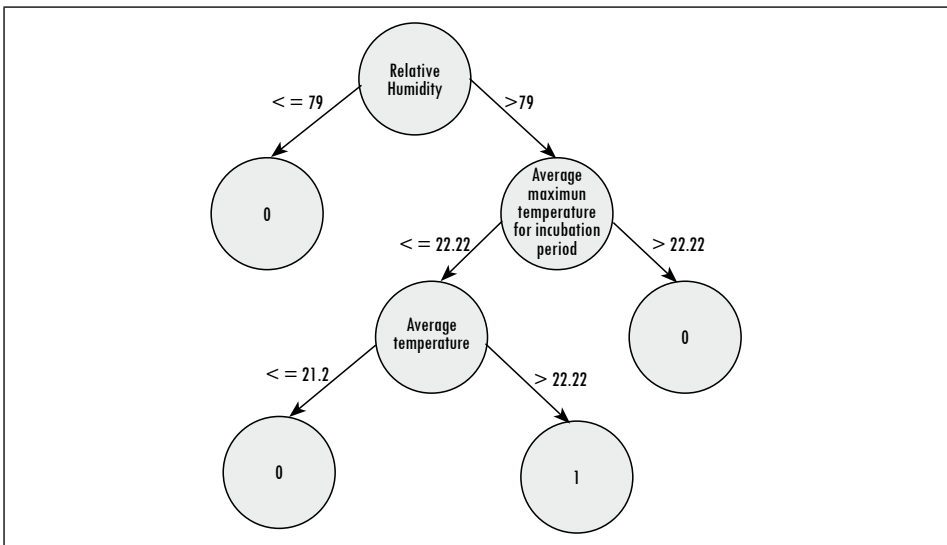
A variety of techniques exist within supervised learning. In the next sections first we present the theory concepts followed by examples. For ease and uniformity of paper the examples for each classifier are focused on coffee rust disease, which are yellow spores that infect to the coffee leaves [12].

2.1. Decision Trees (DT):

Decision trees are algorithms that allow the approximation of functions of discrete and continuous values, beginning with the generation of a set of rules. DTs classify the values that attributes (called instances) can take in a tree, where each node represents an instance of an attribute, and each branch descending from the node corresponds to one of the possible values that the attribute can take [13]. In other words the DTs seek the instance that has the closest relationship with the target variable, dividing the dataset into subsets according to attribute. The procedure is repeated until the established criterion is satisfactorily met [14]. Among the most popular algorithms for building DTs include: ID3 [15], C4.5 [16], CART [17], CHAID [18], and QUEST [19].

Figure 1 shows a case study carried out in [20] to detect the appearance of rust in coffee, making use of a decision tree and taking into account the attributes of relative humidity, average maximum temperature for the rust incubation period, and average temperature.

Figure 1. Detection of rust using a decision tree



Source: authors' own elaboration

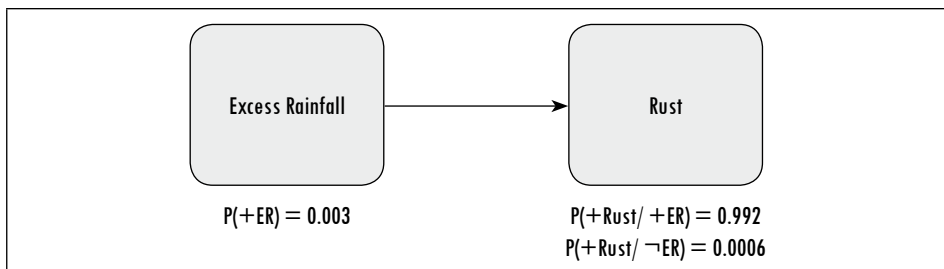
Each attribute is represented by an intermediate node depending on its value. It will take different paths to reach a leaf node. The leaf nodes of the tree correspond to a particular category of the target variable (class), in this case 0 (when there is no rust) and 1 (when rust is detected).

2.2. Bayesian networks (BN):

Bayesian networks model a set of variables and the dependency relations between them, making use of Bayes theorem. Through this model, the *a posteriori* probability of unknown variables can be estimated, based on known variables. These models can have diverse applications: classification, prediction, diagnosis, and so on [7]. Bayesian networks have two essential components: a directed acyclic graph showing the dependence and independence between variables, and a set of probability distribution tables. According to [14], two specific classes of Bayesian networks are popular in the supervised learning context - Naive Bayes (NB) and Tree-Augmented Naive Bayes (TAN). In NB, a relation only exists between the parent and the offspring nodes, while TAN allows relations between peer nodes.

In this domain of application (i.e. rust) the most simple Bayesian network consists of two variables - excess rainfall (ER) and rust - with a edge from the first to the second, as shown in Figure 2.

Figure 2. Appearance of rust using a single Bayesian network



Source: authors' own elaboration

Thus, excess rainfall is a binary variable denoted by presence (+) and absence (-), and similarly with rust. Thus, for this example the following values are calculated using Bayes' Theorem:

- $P(+ER) = 0.003$; indicates that the excess rainfall was present in 0.3%.
- $P(+Rust/+ER) = 0.992$; indicates that when there is excess rainfall there is a 99.2% probability of the occurrence of rust.
- $P(+Rust/\neg ER) = 0.0006$; indicates that in the absence of excess rainfall there is a 0.06 % probability of the occurrence of rust.

2.3. Artificial neural networks (ANN):

Artificial neural networks emulate the computational structure of animal nervous systems to solve tasks that traditional algorithmic computing has not been un-

able to solve satisfactorily [21]. Among the main advantages of neural networks are: adaptive learning, self-organizing capacity, failover, and the integration of diverse technologies [22].

In the same vein, the authors in [14], [23] define an ANN as a collection of simple processing units called neurons (or nodes) that receives a series of entries ($X_1, X_2, X_3, \dots, X_n$) aimed at producing an output (Y). The output consists of a set of propagation, activation and transfer functions.

The neurons can be interconnected to each other and a weight fixed on each interconnection ($W_1, W_2, W_3, \dots, W_n$). This procedure is called Feed Forward. It should be noted that the weights can be adjusted until the desired output for a set of training data is obtained. This mechanism is implemented by calculating error, which is defined as the difference of the desired value less the value obtained by the neuron. It is thus possible that the errors obtained are propagated backward such that the weights can be adjusted. This technique is called backpropagation [24].

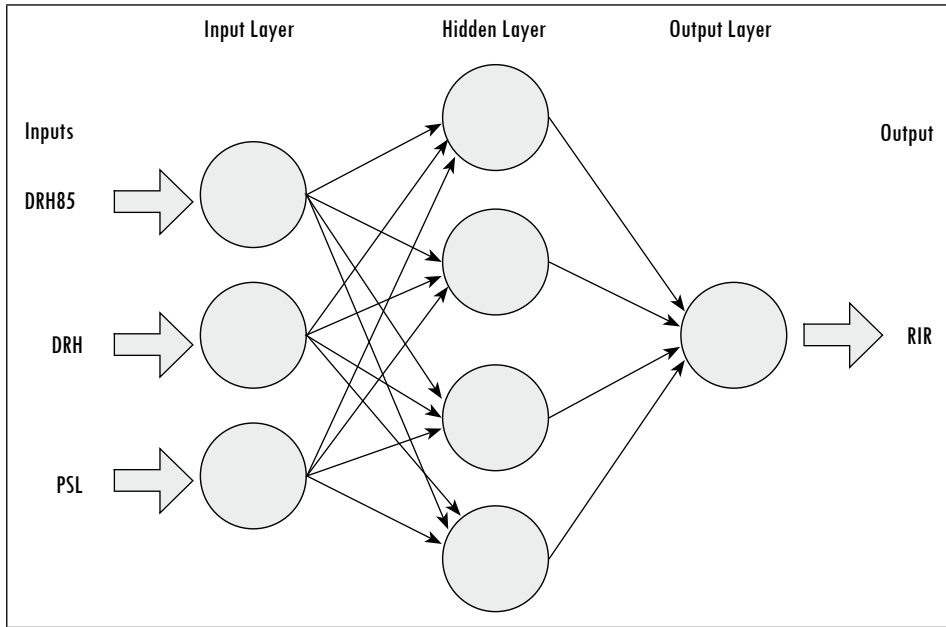
Similarly the neural networks have the capability to organize themselves, forming layers with their neurons. In this regard, there are input layers, hidden layers (intermediate) and output layers [25].

Figure 3 shows an ANN that calculates the rust infection rate (RIR) in coffee one month beforehand. This ANN is comprised of input, hidden and output layers. The input layer receives the number of consecutive days with relative humidity above 85 % (DRH85), number of consecutive days with rain at night (DRN), and the percentage of shade in the lot (PSL). The hidden layer further solves problems when the data are not linearly separable, this way different hidden layers can be used depending on the organization of the data. Finally the output layer calculates the rust incidence rate.

2.4. Support vector machines (SVM):

Support vector machine is a method proposed by Vladimir Vapnik [26] for solving classification and regression problems. The basic operation begins with a set of points, which in turn contains two subsets of points, in which each one belongs to one of two possible classes. Based on this, the support vector machine searches for the greatest distance (maximum margin) that separates the classes by way of a hyperplane, in order to build a model that is able to predict whether a new point (of unknown class) belongs to one class or the other [27]. This method is applied as long as the set of points are linearly separable. Otherwise the input data must first be transformed to a new space, usually to a higher dimension where classes are linearly separable [28].

Figure 3. Rust infection rate using artificial neural networks



Source: authors' own elaboration

The process of transformation of spaces is performed implicitly by a kernel function which allows all the calculations to be performed in the input space. This process is called kernel trick [29].

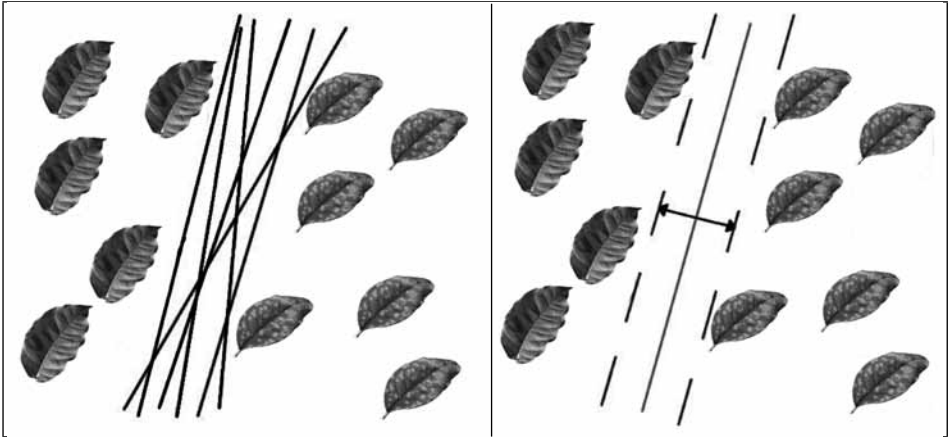
The following is an example of linearly separable binary SVM for the classification of leaves infected with rust. Figure 4 presents the possible hyperplanes that separate healthy leaves and infected leaves. In this context, SVM is searching for the hyperplane that optimally separates the two leaf types.

2.5. Nearest neighbor (K-NN):

This algorithm proposed by Fix and Hodges [30], classify a new input data , according to the k training data closest to those around them, where k is an integer defined by the user. As such, the class assigned to the new input data will be the most voted class among the k nearest neighbors from the training dataset. However, a tie among the most voted classes is a possibility. In this case, to select the class to be assigned, it is necessary to use a method for resolving ties. Among the functions of methods for ties are assigning the class with the first nearest neighbor among those tied on votes; and selecting the class among those tied that has the lowest average distance to its neighbors [7].

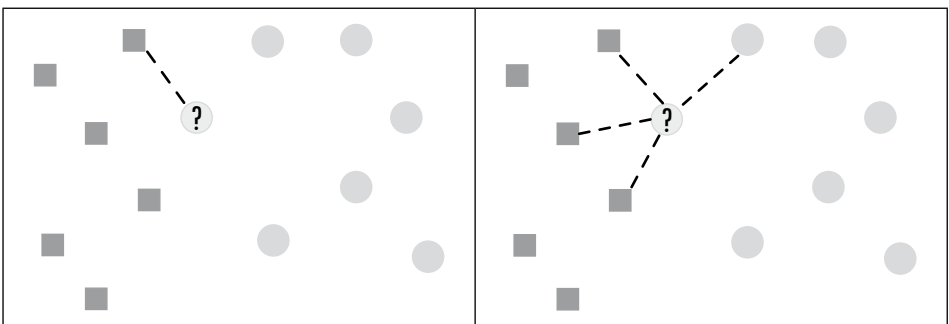
Taking the example of classification of rust-infected leaves presented above, the K-NN algorithm classifies the new input data by the value of k . When $k = 1$ the new input data is classified as a healthy leaf (Figure 5a). Similarly, when $k = 4$, the k nearest neighbors are three healthy leaves and one infected leaf. As a result, the new input data is classified as a healthy leaf (Figure 5b).

Figure 4. (a) possible hyperplanes (b) optimal hyperplane using SVM.



Source: authors' own elaboration

Figure 5. (a) $k = 1$ is classified as a healthy leaf, just as in (b) $k = 4$ is classified as healthy leaf



Source: authors' own elaboration

3. Related Work

In this section, several existing approaches related to the stated research problem are considered. The proposals of these research works are oriented to the use of classifiers in diverse applications for the agricultural sector.

The first of the approaches included in this category is documented in [31]. This work consists of evaluating the risks posed by gray spot on corn leaves. The authors make use of logistic regression (LR) and classification and regression tree (CART) algorithms to predict the severity of the disease according to sowing date, amount of corn residue on the soil surface, maturity of the genotype, and resistance to gray leaf spot. The training data used were collected between 1998 and 2001, for a total of 332 cases. The results of the LR algorithm show that 70% of the examples were classified correctly, 77% for CART.

A second paper [10] proposes predicting the severity (percentage affected in each plant in a given area) of the fungus *Pericularia oryzae*, also called rice blast, which attacks rice crops. The training data used were collected between 2000 and 2004, involving data meteorological and pathology of plant. The authors use the SVM algorithm to solve this problem. However, they compare SVM with such other approaches as Conventional Multiple Regression (REG), Generalized Regression Neural Network (GRNN), and Back-Propagation Neural Network (BPNN). The results obtained for the algorithms mentioned in calculating the absolute percentage error (APE) indicate that SVM is the most accurate in predicting the severity of rice blast with $\%APE = 36.66$. The other algorithms presented the following results: GRNN with $\%APE = 46.30$, BPNN with $\%APE = 52.24$ and REG with $\%APE = 65.42$. Similarly [32] predicted the rice blast in Hulin County of the Heilongjiang province from 2002 to 2011 with Radial Basis Function Neural Network where prediction model accuracy was 97.84%.

Jain [33] proposes techniques to generate warnings of the occurrence of powdery mildew in mango crops. For this, four supervised learning algorithms are used: Inductive Decision Trees C4.5 (IDT), Rough Set (RS), Logistic Regression (LR), and a variant of the inductive decision tree and rough set algorithms (VAR). The results obtained in this investigation indicate that the IDT and VAR algorithms generate alerts at the onset of powdery mildew with a precision percentage of 84% and 83 % respectively, outperforming the RS (75%) and LR (74%) algorithms.

Recent research efforts have focused on predicting the incidence of rust in coffee using supervised learning algorithms. The base training data used for these efforts was collected by [34] on the experimental farm of the Pro-Coffee

Foundation in Varginha, Minas Gerais, Brazil over eight years (from October 1998 to October 2006). The final dataset includes 182 examples. This work is presented below.

In [35] the authors develop a decision tree (DT) for cultivation areas with a high fruit load, in which the target variable (class), is determined by the rust infection rate (RIR), defined by the percentage of leaves infected monthly. In this respect the target variable is defined by three classes. The first class is given the name of reduction or allocation and occurs when RIR is less than or equal to 0%, while the second, named moderate growth, occurs when RIR is greater than 0% and less than or equal to 5%. Finally a class called accelerated growth occurs when RIR is greater than 5%. The precision results obtained for the three classes were 88%, 75% and 79% respectively.

The authors of [36], [37] similarly developed decision trees, but unlike the approach proposed in [35], various classifiers are generated depending on the plant fruit load. The reason for the generation of different classifiers is due to the characteristics presented in biannual coffee crops (Brazil), indicating that crops in years with a high fruit load are more likely to be attacked by rust than those in years with low fruit load.

In this connection, recent research involving the same authors [38] presents an approach for predicting the percentage of coffee leaves infected by rust, to develop a warning system, using the support vector machine algorithm (SVM) for regression (discrete target variable). The results express a 94% correlation between SVM predictions and actual results obtained in the field.

Similarly, in [39] the research presented above is extended, using non-deterministic classifiers (carrying out modifications on the SVM regression algorithm) in order to predict if the percentage of coffee leaves infected by rust is above a threshold defined by an expert on the subject. The research in this way contributes to reducing the use of chemical fungicides, investment costs, environmental impact, and thus increases the quality of coffee production.

Elsewhere in [20] the use of fuzzy decision trees (FDT) is proposed for generating coffee rust alerts. The target variable representing the monthly infection rate consists of two levels (5% and 10%). The first level allows the application of preventive actions, while the latter requires remedial action. With this in mind, the FDT were compared with the classic DT algorithm, the FDT obtaining better results in terms of accuracy and interpretability.

In [40] the authors use a portion of the training data from the experimental farm of the Pro Coffee Foundation in Brazil. These data contain evaluations for

rust on 100 leaves per coffee bush planted. The aim of the research was to obtain the percentage of leaves infected by rust, using Bayesian networks and an algorithm called Causal Minimum Message Length (CaMML). Unfortunately this research approach offers no improvement on the approaches presented above, especially when the rate of infection of leaves is below 5%.

On the other hand, in [9], [41] also predict the incidence of rust in coffee using supervised learning algorithms (Support Vector Regression, Backpropagation Neural Network, Regression Tree M5) on the experimental farm of Supracafé in Cajibío, Cauca, Colombia, over three years (2011-2013) with 147 examples. Support Vector Regression presents the best performance evaluation regarding Backpropagation Neural Network and Regression Tree M5 with a Pearson Correlation Coefficient of 0.47.

Elsewhere, in tomato crops [42] is detected the powdery mildew (*Oidium lycopersicum*) and spider mite (from 2008 to 2009) through Multilayer Perceptron (MLP), Learning Vector Quantization (LVQ) and Radial Basis Function (RBF), achieving 94%, 96% and 98% classification accuracy. Equally [43] predicted tomato spotted wilt virus using random forest a specification of decision trees obtaining a minimum prediction error rate of 12.25%.

A Indo-Japan initiative [44], [45] used Bayesian Networks (BN) in peanut crops of India for monitoring of pest and disease. First BN is utilized to assume the presence (or absence) of a particular feature in dataset that describe the thrip pest. Second BN found the ideal conditions of the Leaf Spot (LS) for a semi-arid tropic region. The results show that LS disease infection is strongly influenced by minimum temperature (18 - 20 °C), prolonged duration of leaf wetness (7–10 h), high humidity (75% or more) and age of the crop.

In fungal crops [46] predicted the distribution of diseases (*T. tritici*, *A. pisi*, *U. hordei*, *P. halstedii*, *P. tritici-repentis*, *L. taurica*) with combination biotic variables and climate factors using multilayer perceptrons (MLP). The distribution of *P. tritici-repentis* obtains the best validation Kappa of 0.38 - all other species had a validation Kappa of at least 0.46 which indicates a model that gives a good prediction.

With the same objective in mind, research such as [47] utilized SVM in wheat crops for predict the Stripe Rust in China. The results provide prediction accuracy of 77.27% compared with regression algorithm 40.91%. [48] work with Feed Forward Neural Network for forecast the weather for prevent Downy Mildew, Powdery Mildew and Anthracnose in grapes crops, obtaining a correlation coefficient of 0.64 and 0.66 for rainfall and mean temperature respectively.

Finally, [49] discover the apparition of Leafroller in kiwi crops through Bayesian Networks. The evaluation denoted a 0.65 for recall measure with 888 true positives and 35 false negatives.

4. Discussion

We selected 119 papers (from 2004 - 2014) based on methodology [50], which comprising 20 evaluated and 99 rejected papers in our review (Figure 6a), drawn from 4 information sources: IEEE Xplore, ScienceDirect, Springer Link and Google, taking into account 4 search queries: crop disease detection, crop disease prediction, crop disease forecasting and supervised learning crop disease (Figure 6b). As noted, the information source with more papers is Google (10 evaluated papers), but the articles found in IEEE Xplore (6 evaluated papers), ScienceDirect (6 evaluated papers) and Springer Link (4 evaluated papers) have quality major, insomuch as its journals are evaluated with Journal Impact Factor (JIF).

The papers considered in our review (20 evaluated papers) use the supervised learning algorithms: DT, SVM, BN and ANN as reported in Figure 7a. The most used algorithm is DT (7 papers), followed by SVM (5 papers), ANN (4 papers) and BN (4 papers). On the other hand the classifiers were applied for disease and pest detection in crops such as: Corn (1 paper), Rice (2 papers), Coffee (8 papers), Mango (1 papers), Tomato (2 papers), Wheat (1 papers), Peanut (2 papers), Grape (1 paper), Kiwi (1 paper), and Fungal (1 paper). The supervised learning algorithms in coffee crops are the most used since 2008, as shown in Figure 7b.

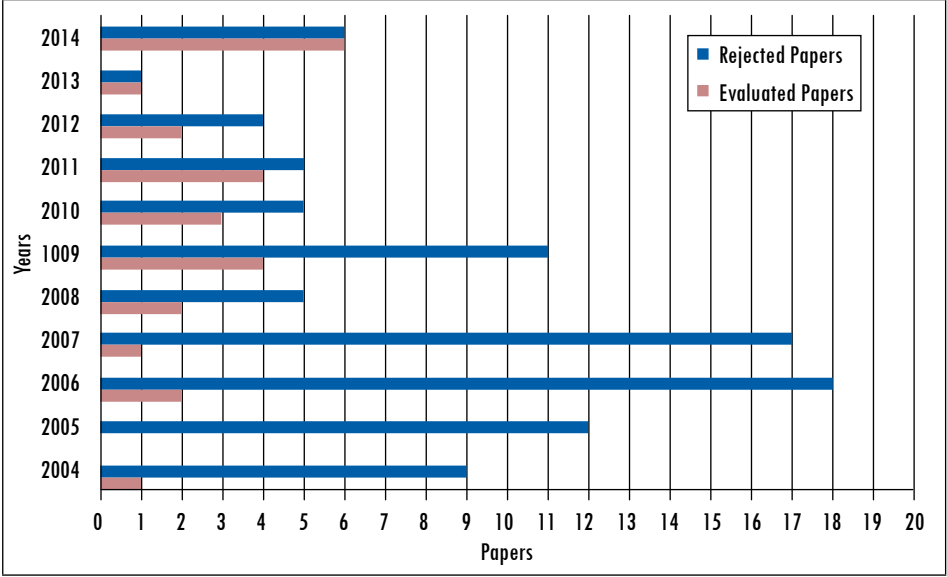
Based on supervised learning algorithms used in the research mentioned above, the following is an assessment conducted in [51] for the DT, ANN, BN, K-NN, and SVM algorithms, taking the following metrics into account:

- **Accuracy (A):** precision of the classifier in predicting a value.
- **Tolerance to noise (TN):** ability of the classifier to handle erroneous data in the training process.
- **Explanation ability (EA):** ease of understanding by a user how the classifier operates.
- **Speed of learning (SL):** speed of learning of the classifier.
- **Speed of classification (SC):** speed of the algorithm in classifying a new instance.

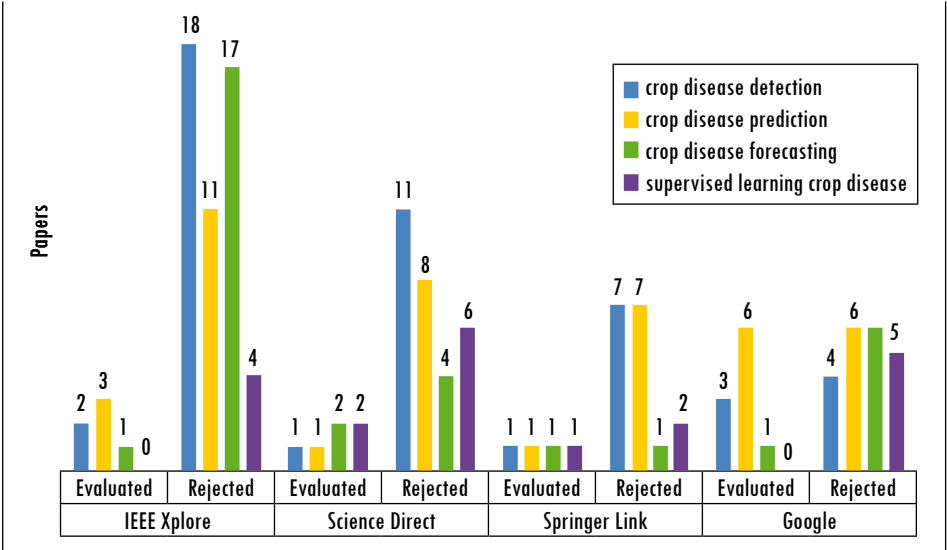
These metrics can have values between 1 and 4, with 4 being Excellent, 3 Good, 2 Average, and 1 Poor.

The results obtained in [51], [52] are presented in Figure 8 for the algorithms: DT, ANN, BN, K-NN, and SVM.

Figure 6. (a) Number of papers per year (b) Number of papers per information sources



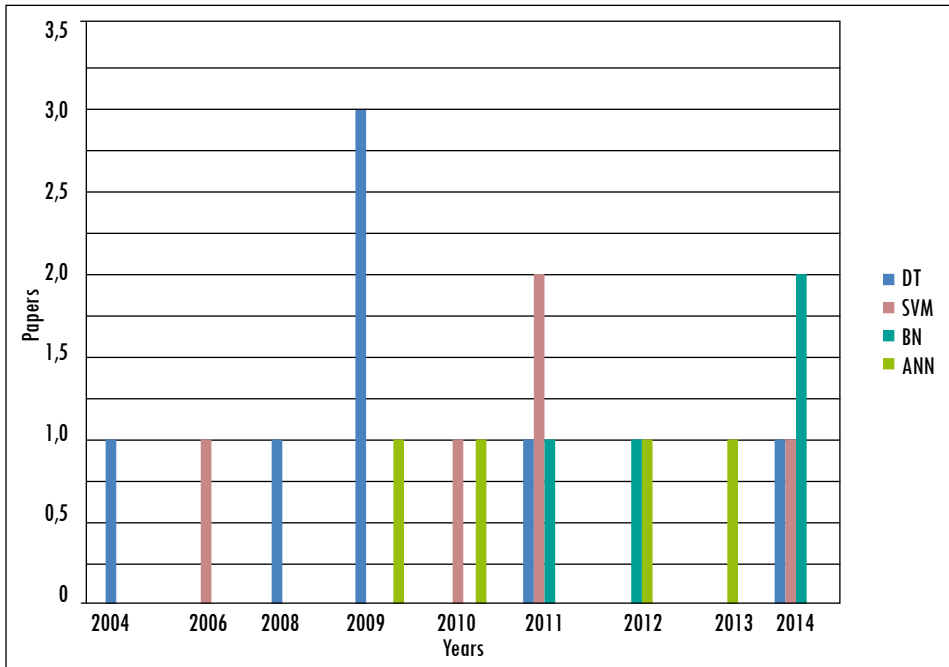
a)



b)

Source: authors' own elaboration

Figure 7. (a) supervised learning algorithms used in papers per year (b) disease and pest detection in crops using supervised learning algorithms per year

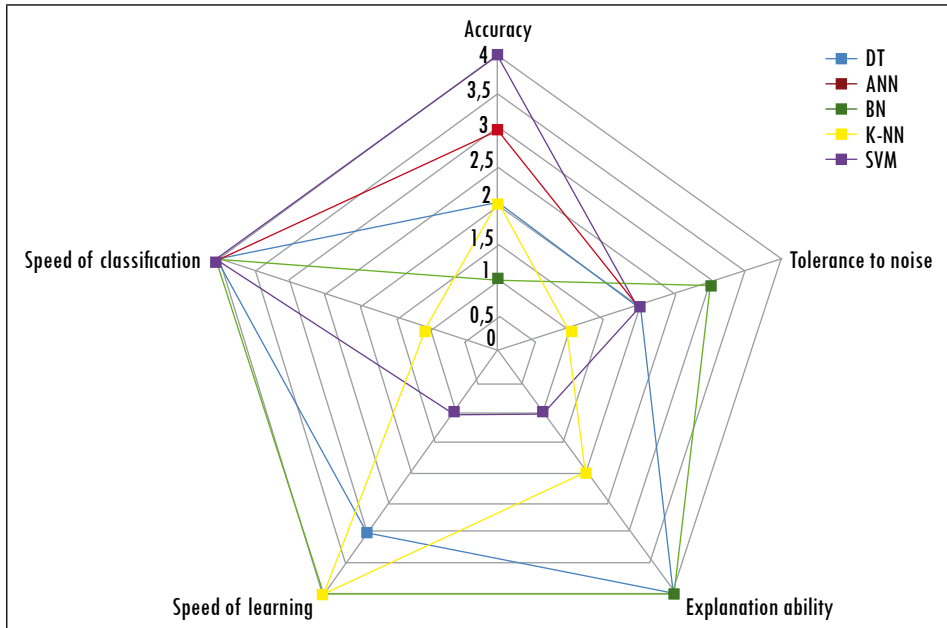


Source: authors' own elaboration

In relation to Figure 8, it can be deduced that the SVM and ANN algorithms are the most accurate. However, they show deficiencies in their interpretation, since the classifiers generated by these algorithms are difficult to understand, unlike with the DT and BN algorithms, which though not being sufficiently accurate, allow the user to observe the classifier using a graph-based representation. The K-NN and BN algorithms stand out for their speed of learning (training), but K-NN is slow in classifying new input data compared to the other algorithms. Finally, BN is the only one of the algorithms presented in Figure 8 that displays an acceptable behaviour to support erroneous data in the training process (tolerance to noise).

Using as a starting point the studies in [51], [52], for the present research, the supervised learning algorithms (SVM, DT, BN, ANN) used in the work presented in the previous section were evaluated, taking into account the crops on which they were used (corn, rice, coffee, mango, tomato, wheat, peanut, grape, kiwi, fungal). Equation 1 thus calculates the percentage of evaluation of the chosen metric M (A, TN, EA, SL, SC), on each crop C , taking into account the number of algorithms used, A .

Figure 8. Evaluation of supervised learning algorithms



Source: authors' own elaboration

$$C(M, A) = \frac{\sum_{i=0}^n A_i x M_i}{\sum_{j=0}^n A_j}; \text{ where: } n = 4, M = \begin{bmatrix} W_{svm} \\ W_{dt} \\ W_{bn} \\ W_{ann} \end{bmatrix}, A = \begin{bmatrix} A_{svm} \\ A_{dt} \\ A_{bn} \\ A_{ann} \end{bmatrix}$$

Eq. 1 Percentage of evaluation of the metric M on a crop C, taking into account the number of algorithms used, A.

Thus the weights $w_{svm}, w_{dt}, w_{bn}, w_{ann}$ were obtained from evaluations in [51], [52], for the SVM, DT, BN, and ANN algorithms, converting them to quantitative values, as can be seen in Table 2.

The results are presented in Figure 9, where the algorithms evaluated are considered weak as regards tolerating erroneous data in the training process (tolerance to noise equal to 35% for classifiers used in crops of: corn, rice, coffee, mango, tomato, wheat, while 70% of TN for algorithms used in peanut and kiwi crops), but fast when classifying a new input data (SC = 100%). Moreover the algorithms used in corn, mango, peanut and kiwi crops (EA = 100%) allow easy interpreta-

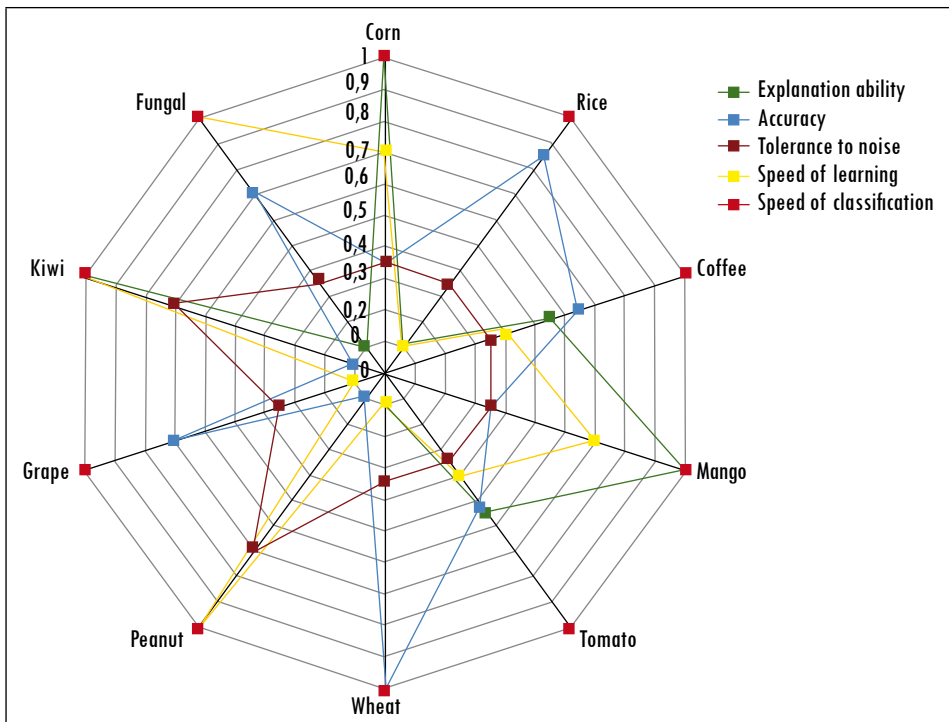
tion of the classifiers generated. They are also fast in the process of learning from the training data (SL of algorithms in crops of: corn and mango 70%, peanut and kiwi 100%). Finally, the algorithms considered in wheat (A = 100%), rice (A = 85%), grape (A = 70%) and fungal (A = 70%) crops are the most accurate.

Table 2. Matrix of weights of the supervised learning algorithms associated with each evaluation metric

	A	TN	EA	SL	SC
SVM	1	0.35	0.1	0.1	1
DT	0.35	0.35	1	0.7	1
BN	0.1	0.7	1	1	1
ANN	0.7	0.35	0.1	0.1	1

Source: authors' own elaboration

Figure 9. Evaluation of algorithms used in different crops



Source: authors' own elaboration

It is thus worth noting that the DT algorithm is the most widely used for the detection of pests and diseases - in corn, coffee, mango, tomato. It is followed by the SVM and ANN algorithms, used for such crops as rice, coffee, tomato, wheat, grape, fungal. Placing an emphasis on these three algorithms, it can be concluded that SVM and ANN are most used in sectors where the priority is to obtain a high degree of accuracy in predictions, while DT is used in areas where it is most important to generate classifiers that are easy for any user to interpret.

5. Conclusions

In this article a review is carried out of research on the detection of diseases and pests in different crops using supervised learning algorithms. The research and algorithms were compared in order to observe performance, DT being regarded as the most widely used and the best to generate easily interpretable classifiers, followed by SVM and ANN algorithms, which are the most accurate algorithms for predicting or classifying diseases and pests. On the other hand, K-NN, and BN are seldom used in an agricultural context. Nevertheless, K-NN and BN stand out for their speed of learning (training).

Regarding future work, it is intended to combine a set of classifiers for the detection of diseases and pest in Colombian crops, to increase the accuracy of prediction results through the use of techniques commonly referred to as ensemble methods [53]-[55].

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