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Review

Detection of Rust Emergence in Coffee Plantations using Data Mining: A Systematic Review

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Abstract: *Hemileia vastatrix* is a fungus that causes coffee rust disease and, depending on the level of severity, reduces the photosynthetic capacity of the plant and of new shoots, leading to low coffee yields and even death; its symptoms are visible on the leaf. Systems based on computer algorithms have been developed to predict diseases and pests in coffee. The objective of the manuscript was to analyse the detection of rust occurrence in coffee plantations, through field determinations of climatological, agronomic and crop management variables using data mining algorithms. A systematic review of studies published from 2001 to 2021 was carried out in the Scopus, Ebsco Host and Scielo databases, considering as an inclusion criterion the works that used experimental design in data collection. The studies included in this review were 22, 64% of which came from the top two coffee-roducing countries in Latin America (Brazil and Colombia); the analysis of these studies revealed that the input variables were climatic, soil fertility properties, management and physical properties of the crops. In addition, they used supervised (decision tree, artificial neural networks, multiple linear regression, among others) and unsupervised (clustering) algorithms, with the support of experts in the study of the fungus and used statistics such as coefficient of determination, root mean square error, among others, to validate the proposals. Overall, this systematic review provides evidence of the effectiveness of data mining algorithms implemented to detect the occurrence of rust in coffee plantations.

Keywords: Plant Product, Simulation Model, Statistical Inference, Statistical Inference, *Hemileia Vastatrix*

Introduction

Coffee is the second most traded commodity in the world after oil (Yosa and Regalado, 2021). Coffee production and quality are strongly affected by diseases and pests, the intensity of which depends on climatic conditions (Verhage *et al*., 2017); (Harvey *et al*., 2018). Destructive disease and causes a 40-50% decrease in crop yields (Hernández *et al*., 2021); (Cressey, 2013). It infects coffee leaves through the stomata and subsequently world after oil (Yosa and Regalado, 2021). Coffee develops inside the tissue; its effect generates the production and quality are strongly affected by diseases appearance of orange circles and causes defoliation of coffee trees, leading to low coffee yields and even plant conditions (Verhage *et al*., 2017); (Harvey *et al*., 2018); death (Hernández *et al*., 2021). Likewise, climate change *Hemileia vastatrix* is the most economically important influences the proliferation of coffee rust; due to fungus in Arabica coffee production, severely affecting alterations in weather patterns which tend to increase the several countries in Latin America and the Caribbean incidence, severity and vulnerability of the crop to other during the last decade. It is considered the most diseases (Chakraborty and Newton, 2011); (Alvarado-Huamán *et al*., 2020).

Agriculture faces challenges in maximising yields, including inadequate soil treatments, disease infestation,

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pests, among others. Therefore, the need for data mining management is a fundamental requirement in this sector to increase knowledge between farmers and technology (Segovia *et al*., 2021). Therefore, it is required to create systems that allow the integration of modern technologies, to consider new variables that allow the construction of predictive models for decision making. For example, data mining approaches have generated models for monitoring the incidence of pests and diseases considering several variables such as climatic conditions and physical properties of the crop. These variables generate data that technology and computer programs use to search for answers based on trends and statistics.

The analysis must start with the search for association between the variables that represent cause and effect, which allows explaining the phenomenon under study. For this reason, variable selection plays an important role in Data Mining, because in real-world problems, a set of variables is usually processed. However, in many situations, not all variables contribute to explaining the behaviour of the evaluated response variable to a significant degree; this can have negative effects on the interpretation of the dependent variable (Solorio Fernández, 2010).

Machine learning algorithms are promising for large-scale, fast, efficient and accurate analysis. Examples of machine learning algorithms are k-Nearest Neighbor (KNN), Multiple Linear Regression (MLR), Artificial Neural Networks (ANN) and Random Forest (RFT) (Badnakhe *et al*., 2018).

In research that measures potentially explanatory variables, the methods discussed above often define several model alternatives, hence the need to apply algorithms that best describe and explain the phenomenon under study. In this regard, it should be noted that there are certain statistical criteria that are useful to achieve an adequate selection, such as: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), coefficient of determination (R^2), corrected coefficient of determination (R^2_{aj}), residual variance and Mallows' *Cp*.

Methods

Information Sources and Search Equation

A systematic review was conducted following the recommendations proposed by the Cochrane Handbook (Higgins and Green, 2009) and the PRISMA statement (Moher *et al*., 2014). The search was conducted in the Scopus, Ebsco Host and Scielo databases.

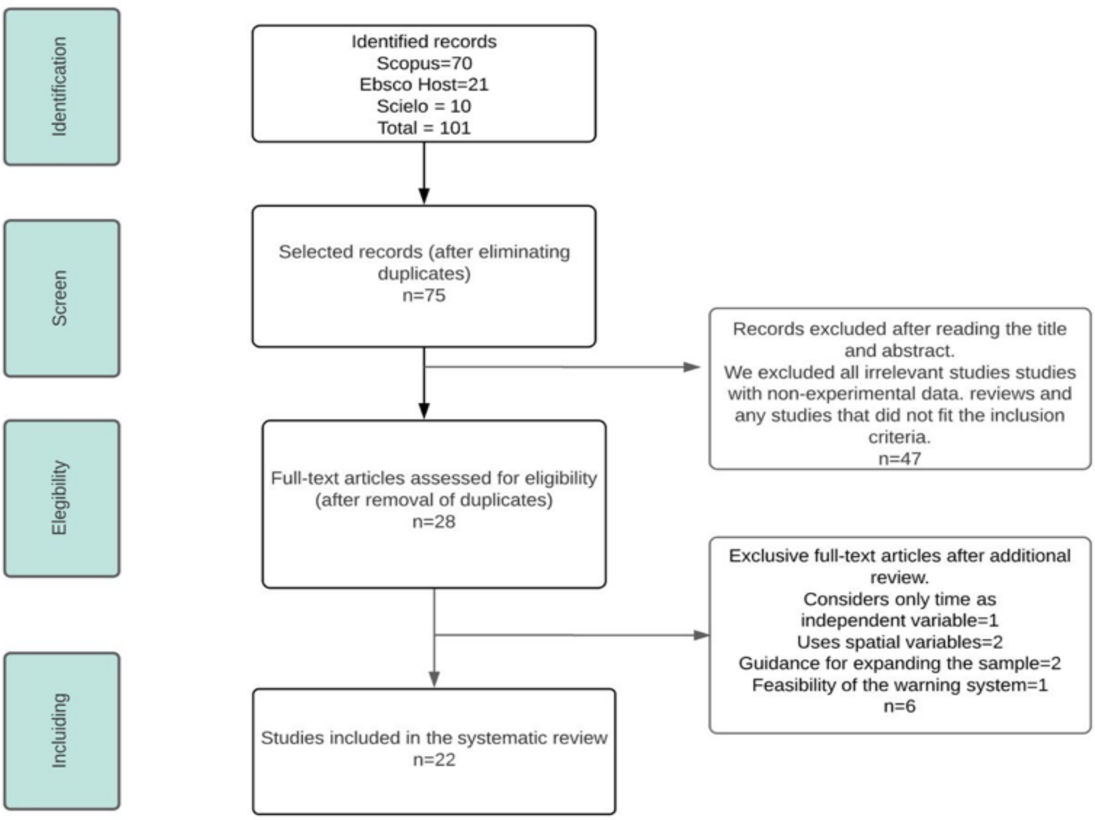

Fig. 1: Multiple case study design

The search equation was performed using the keywords: "Data mining and coffee rust" or "*Hemileia vastatrix* and detection early" or "coffee rust disease and machine learning" or "*Hemileia vastatrix* and statistical modelling" or "coffee rust and graph pattern" or "classifier and coffee rust" or "prediction of coffee rust" or "*Hemileia vastatrix* and equation modelling".

Restriction on the type of experimental study was applied. The search for articles was limited by year of publication from 2001 to 2021 and only papers published in the English language were searched. The bibliographic references of the selected articles were also analysed in order to retrieve other papers whose contribution could be significant.

Table 1: Provenance and identification of study variables

Study	Source of data	Input variables	Output variable
Lozada *et al*. (2017)	Colombia	Climate: Relative humidity, temperature (minimum, average and maximum), rainfall. Crop property: Shade	Three infection rates: Declining, moderate growth and accelerated growth
Lasso *et al*. (2020)	Costa Rica	Meteorological: Maximum, average and minimum air temperature, thermal amplitude, average and minimum relative humidity, number of days with precipitation, daily precipitation. Crop properties: Shade, type of management	Incidence
Merle *et al*. (2020a)	Costa Rica	Leaf stratum, shade, type of fungicide applied, fruit load, leaf growth, leaf drop, leaf area	Rust area: Latent, sporulation, inoculum, necrosis
Meira *et al*. (2009)	Brasil	Number of rainy days in the infection period (PINF), average daily precipitation in the PINF, average daily hours with a relative humidity of 95% in the PINF, accumulated precipitation in the PINF, average daily temperature during the hours of 95% relative humidity in the PINF, temperatures (minimum, average and maximum) in the PINF, temperatures (minimum, average and maximum) daily in the incubation period for the days in the PINF, average daily relative humidity in the PINF	Binary infection rate: 1 for rates greater than or equal to 5 (10) percentage points; 0 otherwise
Corrales *et al*. (2014b) Corrales *et al*. (2015) Corrale *et al*. (2016) Corrales *et al*. (2018)	Colombia	Meteorological conditions: Average relative humidity, hours of relative humidity >90%, average temperature variation, rainy days, cumulative precipitation, accumulated nocturnal rainfall. Soil fertility properties: pH, organic material, K, Ca, clay. Physical crop properties: Variety, plant density per hectare, plant spacing, row spacing, age, shade. Crop management: Coffee rust control, fertilisation, fruit load	Incidence
Study Girolamo Neto *et al*., 2014)	Source of data Colombia	Input variables Meteorological conditions: Average relative humidity, hours of relative humidity > 90%, average temperature variation, rainy days, cumulative precipitation, accumulated nocturnal rainfall. Soil fertility properties: pH, organic material, K, Ca, clay. Physical crop properties: Variety, plant density per hectare, plant spacing, row spacing, age, shade. Crop management: Coffee rust control, fertilisation, fruit load.	Output variable Incidence
Meira *et al*. (2008)	Brasil	Fruit load, spacing, mean daily river rainfall in the PINF, mean daily night hours with relative unit greater than 95%, accumulated river rainfall in the PINF, temperatures (minimum, mean and maximum) in the PINF	Infection rates in three classes: Reduced or stagnant; moderate; and accelerated

Table 1: Continue

Lasso *et al*. (2015; Lasso *et al*., 2017)	Colombia	Variables given in (Corrales *et al*., 2014a)	Three infection rates: Reduced or latent, moderate and accelerated
(de Oliveira Aparecido *et al*., 2020)	Brasil	Average temperature (average minimum and maximum), precipitation, number of days with precipitation, average relative humidity, number of days with relative humidity ≥ 90% and number of days with relative humidity ≥80	Percentage of coffee with rust
Buitrón *et al*. (2019)	Colombia	Zone, temperature amplitude, month, relative humidity, quarter	Percentage of coffee with rust
Study	Source of data	Input variables	Output variable
Cintra *et al*. (2011)	Brasil	Number of rainy days, spacing, average precipitation, Average maximum precipitation, average night hours with relative 0 otherwise air humidity ≥95%, average daily hours when relative air humidity ≥95%, wind speed, average daily temperature when relative air humidity ≥95%, average daily temperatures (minimum, average and maximum), average daily temperatures (minimum, average and maximum) for IP, daily relative air humidity, average daily wind speed, number of unfavorable days for infection, number of favorable and very favorable days for infection	Binary infection rates greater equal to 5 (10) points;
Luaces *et al*. (2011)	Brasil	Temperature, solar radiation, number of hours of sunshine, wind speed, rainfall, relative humidity, number of hours with relative humidity above 95%, average temperature during these hours and the same values, but during the night, fruit load, plant spacing, percentage of fungus incidence on leaves on date d0, days from d0 to the day we make the prediction, days	Percentage of leaves infected
Corrales *et al*. (2014b)	Colombia	Plant density, shade level, soil acidity, rainfall intensity in the last night and days, relative humidity	System yielding classes: None, very low, low, low, medium, high and very high
Plazas *et al*. (2016)	Colombia	Relative humidity, temperature, wind speed and rainfall	Validate early warning system warnings
Pérez-Ariza *et al*. (2012)	Brasil	Year, month of occurrence, fruit load, distance between plants, days between previous 1st of month and forecast date	Percentage of infected leaves
Pinto *et al*. (2002)	Brasil	Precipitation, average relative	Incidence

Table 2: Study, algorithm or technique employed and statistics

Study	Test technique or algorithm	Test statistic
Lozada *et al*. (2017)	Algorithms for the calculation of similarity: A*, Beam, Hungarian, Volgenant-Jonker	True positive rate, false positive rate, positive predictive value, Rand index, F-measure and Matthews correlation coefficient
Lasso *et al*. (2020)	XGBoost, Suppor vector regressiony decision tree regressor	Random forest regressor, Mean absolute error
Merle *et al*. (2020a)	Structural equation modelling	P value
Meira *et al*. (2009)	Decision tree	Accuracy, error rate, sensitivity, specificity, positive reliability, negative reliability
Corrales *et al*. (2014b)	Support Vector Regression, ANN and Regression Trees	Pearson's correlation coefficient, mean absolute error, root mean square error, relative absolute error
Corrales *et al*. (2016)	The ensemble approach focuses on the use of multiple classifiers (BPNN, M5 and SVR), used interquartile range and k-mean algorithms to improve performance	Pearson's correlation coefficient, mean absolute error, mean square error, precision, recall, F-measure
Liebig *et al*. (2019)	Structural equations	P value
Merle *et al*. (2020b)	Generalised linear models	Akaike Information Criteria
Girolamo Neto *et al*. (2014)	RNA, support vector machine, Random Forest	Hit rate, sensitivity, specificity, ROC curve
(Meira *et al*., 2008; Corrales *et a*l., 2015)	Decision tree. Bagging, Ran. Subspaces, Rot. Forest and Stacking	Error rate, acuity Pearson's correlation coefficient, mean absolute error, mean square error
Lasso *et al*. (2015)	Graphical patterns as a representation of rules extracted from decision trees (C45, J48) Regressor, random forest regressor and ANN	Confusion matrix (de Oliveira Aparecido *et al*., 2020) Multiple linear regression, K Neighbors Accuracy, Willmott's 'd', root mean square error, adjusted R^2

Table 2: Continue

Buitrón *et al*. (2019)	Rule-based, where rules are created taking into account the expert knowledge of specialists	Precision, accuracy, recall
Cintra *et al*. (2011)	Fuzzy DT, J48	Error, standard deviation
Luaces *et al*. (2011)	SVM, multiclass deterministic classifiers	
	SVM and logistic regression	Absolute error, correlation, recall
Corrales *et al*. (2014b)	Error-correcting output codes with SVM	Percentage
Lasso *et al*. (2017)	Graphical pattern with decision trees and expert	Correct and incorrect instances
Plazas *et al*. (2016)	Complex event processing	Latency, success rate
Pérez-Ariza *et al*. (2012)	Bayesian Networks	Error
Pinto *et al*. (2002)	ANN, linear regression	Correlation coefficient, mean prediction error and mean square of deviations
Corrales *et al*. (2018)	Joint (SVR, K-NN R, MP, RBF, M5) and expert approach	Pearson's correlation coefficient, mean absolute error, mean square error

After the search results, the guidelines for choosing the papers to be analysed were: First, to select them by title and by reading their abstract in order to find out if they were related to the aspects of interest; second, the content of the chosen articles was analysed to find out if the contribution to this study could be useful for the fulfilment of the objective.

Inclusion and Exclusion Criteria

The systematic review included papers from the agronomic, biological and computational fields in order to obtain a multidisciplinary approach to issues related to coffee rust detection based on data mining algorithms. Regarding the type of study, articles using experimental, longitudinal, quasi-experimental, correlational or observational design were analysed in order to work with different levels of generalisation.

Articles with only an agronomic, biological or computational approach to coffee rust disease were excluded from the search.

The search was conducted from 01 July to 15 September 2021 and 101 articles were found after applying the search method. Twenty-two articles were selected after applying the inclusion and exclusion criteria (Fig. 1).

Results and Discussion

Input Variables

Diseases affecting agricultural sectors are often closely related to weather conditions and crop management (Lozada *et al*., 2017). Assuming that the weather dynamics that most impact disease development occur in the same time periods is simplistic (Lasso *et al*., 2020). It is shown how micro-climatic indicators vary as a function of season, altitude and coffee shading and how this in turn is related to rust (Liebig *et al*., 2019).

Determination of Rust

In this sense, the variable to be predicted has been defined as the Rust Incidence Rate; it is calculated following the methodology developed by Cenicafé (Corrales *et al*., 2014b). In addition, the percentage of infected leaves on the target day has been determined (Pérez-Ariza *et al*., 2012), (Luaces *et al*., 2011). The determination of the disease is given as dependent variable, in the chosen works different approaches are given, Table 1.

Data Mining Algorithms

The algorithms calibrated and tested for disease prediction were multiple linear regression, K Neighbors Regression (KNN), Random Forest Regression (RFT) and artificial neural networks (de Oliveira Aparecido *et al*., 2020). Also, they presented and compared two decision tree methods for coffee rust disease warning: A fuzzy model and a classical one such as J48 (Cintra *et al*., 2011). The use of non-deterministic predictors could be successfully generalised to other prediction tasks where target values are not easily predictable by conventional classifiers or regressors (Luaces *et al*., 2011). However, different authors show that the results are not sufficiently accurate using a single classifier. Computer science authors propose alternatives to this problem, making use of techniques that combine the results of classifiers. Therefore, an empirical multi-classifier is proposed for the detection of coffee rust in Colombian crops (Corrales *et al*., 2015). They proposed two-level classifier ensembles for coffee rust estimation using neural networks, M 5 regression tree and support vector regression. Their ensemble approach outperformed classical approaches such as simple classifiers (Corrales *et al*., 2016).

Test Statistics

The accuracy of the model for the 5%-point threshold was 81% by cross-validation, reaching up to 89% according to the optimistic estimate. This model showed good results for other important assessment measures, such as sensitivity (80%), specificity (83%) and positive (79%) and negative (84%) confidence. The model for the 10%-point threshold had an accuracy of 79% and did not show the same balance among the other measures (Meira *et al*., 2009). For the regression-adjusted models, the highest value of the coefficient of determination was also considered (Pinto *et al*., 2002). Table 2 shows the various test statistics, according to the type of dependent variable, which could be ordinal or nominal.

Guidance from Plant Pathology Experts

From a computer science perspective, several investigations have been proposed to reduce the effects caused by the occurrence of coffee rust. One of the important proposals is the use of expert systems. A rule-based one has been proposed in which the knowledge base contains the variables and the set of rules that define the problem (Buitrón *et al*., 2019). Similarly, coffee rust expert knowledge has been considered during the definition of the training set resulting in a set of variables closely related to the disease, which are the main input for the development of the algorithm (Corrales *et al*., 2018).

Conclusion

This systematic review included 22 studies that determined the conditions for rust occurrence in coffee plantations through data mining. The results indicate that the variables used were climatic variables, soil fertility properties, management and physical properties of the crops. In addition, supervised and unsupervised algorithms were used, with the support of experts in the study of the fungus and the proposals were validated through the use of test statistics.

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Author's Contributions

Lenin Quiñones Huatangari: Conceptualisation, drafting, linking of contributions and editing of the manuscript.

Candy Lisbeth Ocaña Zúñiga: Conceptualisation, drafting and revision of the manuscript.

Annick Estefany Huaccha Castillo: Conceptualisation, drafting and revision of the manuscript.

Rubén Eusebio Acosta Jacinto, Manuel Emilio Milla Pino, Milton Ríos Julcapoma, Ricardo Yauri Rodríguez and Eduardo Mendoza Villaizán: Conceptualisation and drafting of the manuscript.

Aladino Pérez Cabrera: Contributed to the drafting of some technical terms on *Hemileia vastatrix*.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all authors have read and approved the manuscript and that there are no ethical issues.

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