Forecasting the black Sigatoka development rate: A comparison of machine learning techniques

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Abstract

Pending.

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1. Introduction

The black Sigatoka disease caused by the fungus *Mycosphaerella fijiensis Morelet* is the major pathological problem of banana and plantain crops in Central America, Panama, Colombia and Ecuador, as in many parts of Africa and Asia [6].

This disease attacks the plant leaves producing a rapid deterioration of the leaf area, affects the growth and productivity of the plants due to the impairment of their photosinthetic ability causes a reduction in the quality of the fruit, and promotes premature maturation of bunches, which is the major cause of product losses associated with the black Sigatoka. Figure.1 shows three stages of this disease.

Phytopathological studies point out that precipitation, temperature, relative humidity and wind are the main climatic variables that affect its development

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Figure 1: Examples of three disease stages of the black Sigatoka. (a) Initial stage. (b) Intermediate stage, and (c) Advanced stage.

According to studies by the National Banana Corporation of Costa Rica (Corbana) made in 2013, considering on average between 53 thru 57 cycles of fungicide applications per farm, the cost per hectare per year ranged between $1800 USD and $1900 USD. This represents about 0.76 cents of the price of a box of 18.14 kilograms. Overall, this represents 10% to 12% of the total production cost Brescani [1].

The past and present rates of disease development can in principle be used to predict its future behavior and to determine whether particular fungicide spray schedules will be able to effectively and economically control the disease Chuang and Jeger [3].

There are efforts to apply machine learning methods for decision-making in agriculture, including the control of crop diseases. For example, [Camargo et al.,2012] present an intelligent system for the assessment of crop disorders, [17] introduce a plant virus identification method based on neural networks with an evolutionary preprocessing stage, [5] summarize in their survey crop pests prediction methods using regression and machine learning approaches, while [7] present an intelligent agricultural forecasting system based on wireless sensor networks.

In this work, we compare four machine learning techniques (support vector regression (SVR), echo state networks (ESN), ridge regression and ordinary least squares linear regression) to predict the development rate of the black Sigatoka disease.

The main contribution of this work is a comparison between machine learning

methods to forecast black Sigatoka development rate. (FALTA COMPLETAR)

2. Materials and methods

2.1. Concepts

2.1.1. Biological warning system

This system measures the disease development state to determine when to apply fungicides [6]. This system is based on two components: a climate component, which is given by the Piche evaporation and a biological component, given by the stage of progress or the rate of disease development. Originally, this system was designed to work with young plants. One selected plant must exhibit a normal growth and be in a place that enforces a healthy development. The plant must start with 5 to 6 true leaves. The assessments are made at fixed intervals of seven days as long as possible, on the same plant. The first observations should consider the leaf emission, also the level of infection on the leaves should be evaluated considering the stages of development [6].

2.1.2. Support Vector Regression (SVR)

From the perspective of Support Vector Regression (SVR) the regression function $y = f(s)$ for a given dataset $D = \{(s_i, y_i)\}_{i=1}^{n}$, is represented as a linear function of the form [8]:

$$f(s) = w^T s + b$$

where w and b are respectively the weight vector and the intercept of the model, and they are selected to find an optimal fit to the data available in D.

For nonlinear cases, one proceeds by mapping the input p-dimensional vectors via a nonlinear function $\phi : R^p \rightarrow F$, onto the feature space F. After nonlinear mapping, the regression function evolves to a pervasive form:

$$f(s) = w^T \phi(s) + b$$

SVR uses the $\epsilon - insensitive\ loss\ function$:

$$l = \Big|y - f(s)\Big|_{\epsilon} = \begin{cases} 0 & \Big|y - f(s)\Big| \leq \epsilon \\ \\ \Big|y - f(s)\Big| - \epsilon & else \end{cases}$$

which ignores the error if the difference between the prediction value and the actual value is smaller than ϵ. The $\epsilon - insensitive\ loss\ function$ allows to find the coefficients w and b by solving a convex optimization problem, which balances the empirical error and the generalization ability. In SVR, the empirical error is measured by the loss function -insensitive and the generalization ability is measured by the Euclidean norm of w [9]. Then, the optimization problem to identify the regression model can be formulated by [8]:

$$\begin{aligned} \text{miimize} \quad & J(w, \xi_i, \xi_i^*) = \frac{1}{2}\Big|\Big|w\Big|\Big|^2 + C\sum_{i=1}^{n}(\xi_i, \xi_i^*) \\ & y_i - w^T\phi(s) - b \leq \epsilon + \xi_i \\ \text{subject to} \quad & w^T\phi(s) + b - y_i \leq \epsilon + \xi_i^* \quad i = 1, 2, ..., n \\ & \xi_i, \xi_i^* \geq 0 \end{aligned} \tag{1}$$

where C denotes the penalty parameter between empirical and generalization errors, and ξ_i, ξ_i^* are slack variables. Figure.2 shows this situation.

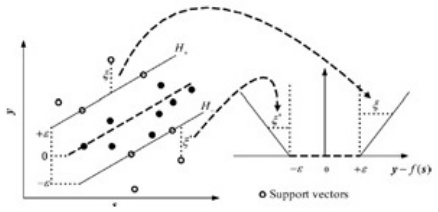

Figure 2: $\epsilon - insensitive\ loss\ function$[8].

The solution of this optimization problem by the Lagrange method is given by:

$$f(s) = w^T\phi(s) + b = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(s, s_i) + b$$

where $\alpha_i - \alpha_i^*$ are the Lagrange multipliers of the optimization problems dual form and $K(s_i, s_j)$ is the kernel function satisfying the Mercer condition, and holds:

$$K(s_i, s_j) = \left\langle \phi(s_i), \phi(s_j) \right\rangle$$

Operations in the kernel function $K(s, s_i)$ are performed in the input space rather than in the potentially high dimensional feature space of ϕ [10].

2.1.3. Ordinary least squares regression

This method fits a linear model with coefficients $w = (w1, .., wp)$ to minimize the residual sum of squares between the observed responses in the dataset, and the responses predicted by the linear approximation. Mathematically it solves a problem of the form [**?**]:

$$\min_w \left|\left| Xw - y \right|\right|_2^2$$

where X denotes the features matriz.

According Pedregosa et al. [11] the coefficient estimates for Ordinary Least Squares rely on the independence of the model terms. When terms are correlated and the columns of the design matrix X have an approximate linear dependence, the design matrix becomes close to singular and as a result, the least-squares estimate becomes highly sensitive to random errors in the observed response, producing a large variance. This situation of multicollinearity can arise, for example, when data are collected without an experimental design

2.1.4. Ridge regression

The ridge regression addresses some of the problems of ordinary least squares regression by imposing a penalty on the size of the coefficients. The ridge coefficients minimize a penalized residual sum of squares [11]:

$$\min_w \left|\left| Xw - y \right|\right|_2^2 + \alpha \left|\left| w \right|\right|_2^2$$

Here, $\alpha > 0$ is a complexity parameter that controls the amount of shrinkage: the larger the value of α, the greater the amount of shrinkage and thus the coefficients become more robust to collinearity.

2.1.5. Echo State Networks (ESN)

Recurrent Neural Networks (RNN) are useful for temporal patterns, but when they are trained with backpropagation methods, they are very slow. Echo State Network (ESN) is an alternative training method to solve that problem. ESN is based on the observation that if a random RNN possesses certain algebraic properties, training only a linear readout from it is often sufficient to achieve excellent performance in practical applications [12]. For a given training input signal $u(n) \in R^{N_u}$ a desired target output signal $y^{target}(n) \in R^{N_y}$ is known. Here $n = 1, ..., T$ is the discrete time and T is the number of data points in the training dataset. The task is to learn a model with output $y(n) \in R^{N_y}$, where $y(n)$ matches $y^target(n)$ as well as possible, minimizing an error measure $E(y, y^target)$, and, more importantly, generalizes well to unseen data. The untrained RNN part of an ESN is called a dynamical reservoir, and the resulting states x(n) are termed echoes of its input history [13]. Finally, these signals are sent to an output layer as shown in the Figure.3.

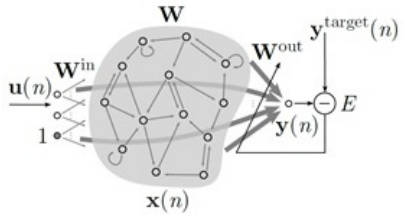

Figure 3: An echo state network [13].

The connections between the different elements of an Echo State Network have weights randomly generated. The weights of the internal connections of the reservoir (W) as well as the weights of the input layer (W_in), after being generated are set statically during all stages of implementation of the algorithm. The weights between the reservoir and the output layer (W_out) are subject to changes of a supervised learning algorithm to correct the degree of error generated by the entire system [13].

2.2. Related works

Huang et al. [17] surveyed the development of soft computing techniques in agricultural and biological engineering, including fuzzy logic, artificial neural networks, genetic algorithms, bayesian inference and decision trees.

A related work, proposed by Romero [14] relies on regression models using a stepwise procedure to predict incubation and latency times of black Sigatoka. The author performed experiments on two farms located in Costa Rica (Rita and Waldeck, the same as those used in this study but with different names). The study used data from: December 1993 to August 1995. Romero concluded that the model to predict the incubation period accounted a R^2 of 69% in his observed data but it was not a good predictor when it was validated against an independent dataset (cross validation). For latency, he developed two models that accounted a R^2 of 78% PONER EL VALOR OBTENIDO in the observed data, however, when validated against an independent dataset (cross validation), the model was incorrect PONER EL VALOR OBTENIDO for Weldeck, and for Rita obtained an adjusted R^2 of 82%.

Glezakos et al. [15] proposed to use Genetic Algorithms (GA) and Neural Networks (NN) to identify plant virus (Tobacco Rattle Virus (TRV) and the Cucumber Green Mottle Mosaic Virus (CGMMV)). This is achieved by the development of ana- lytical tools of evolutionary adaptive width, propelled by Genetic Algorithms (GAs) and Neural Networks (NNs). The method was tested against some of the most commonly used classifiers in machine learning (Bayes, Trees and k-NN) via cross-validation and proved its potential towards the identification.

In the agricultural context, Alves et al. [16] used geoinformation techniques to develop predictive models to study the areas of risk to soybean rust in soybean, coffee leaf rust in coffee, and black Sigatoka in banana, considering Brazils climatic characterization and the distribution of soybean, coffee and banana crops. Temperature and rainfall data were obtained for the period from 1950 to 2000, and of simulations for 2020, 2050 and 2080 using the SRES A2 climate change scenarios. Using principal components analysis, a single variable

was generated based on 57 variables, in order to determine an index explaining 87%, 88% and 90% of the variability of soybean, coffee and banana crops, respectively, in municipal districts across Brazil. The climatic model was used to generate the zoning of the three plant diseases, using temperature and leaf wetness as input. Areas of favorability for the diseases were plotted against the main coffee, soybean and banana growing areas in Brazil. This methodology enabled the visualization of the changes in areas favorable for epidemics under possible future scenarios of climate change.

Other applications of machine learning methods in precision agriculture include the use of support vector regression to predict carcass weight in beef cattle in advance to the slaughter [10], machine learning assessments of soil drying for agricultural planning [18], and early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance [19].

Furthermore, there have been attempts to generate software tools. Camargo et al. [Camargo et al.,2012] presented an information system for the assessment of plant disorders (Isacrodi). They proposed that experts will attain a much better accuracy than the Isacrodi classifier, particularly when provided with samples from the affected crop. However, those cases where such expertise is not available, they suggest that Isacrodi can provide valuable support to farmers. Isacordi includes 15 crop disorders, but the black Sigatoka no is one of them. The prediction process is based on multi-class support vector machines.

Regarding the prediction of the develpment of the black Sigatoka with machine learning methods, Bendini et al. [20] presented a study about the risk analysis of black Sigatoka occurrence based on polynomial models. A case study was developed in a commercial banana plantation located in Jacupiranga, Brazil. It was monitored weekly during the period from February to December 2005. Data included the weekly monitoring of the diseases evolution stage, time series of meteorological data and remote sensing data. They obtained a model to estimate the evolution of the disease from satellite imagery. This model relates gray levels (NC) of the band 2 images of the Landsat-5 satellite, with the progress status or disease severity (EE). The authors claim to reach an R^2 of 90%.

Also there are works related to banana fruit. Soares et al. [21] apply two techniques: artificial neural networks (ANNs) and multiple linear regression (MLR) in banana plant to predict the yield, their results show that the neural network proved to be more accurate in forecasting the weight of the bunch in comparison to the multiple linear regressions in terms of the mean prediction-error ($MPE = 1.40$), mean square deviation ($MSD = 2.29$) and coefficient of determination ($R^2 = 91\%$).

In general, the machine learning methods applied to predict the evolution of plant diseases, can be classified in two main approaches: 1) Those whose main inputs are images, and 2) Those whose main inputs are environmental and biological variables. Our study focuses in the second case.

2.3. Data

In this work we used data acquired in two research farms of Corbana in Costa Rica: 1) 28 Millas (located at Matina) and La Rita (located at Pococ), both in the province of Limn, Costa Rica. The banana type is Musa AAA, subgroup Cavendish, cv. Grande Naine. Table 1 shows the variables considered initially. Table 1 Variables used in the study Variable Meaning

The value to be predicted in all cases was ES, that is the total measure of the biological warning system. The data on the biological warning system are collected once a week. Although Corbana has meteorological stations that take data every five minutes, for these experiments, weekly averages generated by nearby stations to each of the farms were used. The time intervals used for this study were: La Rita, week 48 of 2002 to week 17 of the 2015 (647 weeks) and for 28 Miles, week 37 of 2003 to week 18 of 2015 (605 weeks). Data preprocessing In 28 Miles farm we detect that 1% of the data were missing, while in La Rita 2.25% of the data were missing. To complete the missing value we use spline interpolation. The data collected did not exhibit outliers. Due the fact that the variables measure meteorological or biological process, they are discretized in order to reflect trends in the data rather than the specific continuous values. The coefficient of variation $C_v(x)$ of each variable x was used to determine the

numbers of discretizations with:

$$n = 100C_v(x)$$

Each discretization range was uniformly partitioned. Besides enabling the capture of tendencies, the discretization removes the effect of small variations in the data collection, either by inaccuracies of the instruments (meteorological variables) or by subjective bias introduced by the human who collects the data (biological warning system). Each feature was scaled in a range 0 between 1. The variable to be predicted was not scaled.

2.4. Evaluation criteria

Although there are many types of indicators to assess the quality of the prediction, we selected the root mean square error (RMSE) and the determination coefficient (R2). This decision is supported by the widespread use in machine learning and agriculture areas (Soares, Pasqual and Lacerda (2013); Soares, Pasqual and Lacerda (2014); Ibrahim and Wibowo (2014) and Demir and Bruzzone (2014)).

2.5. Methods

This research had two phases.

Phase one

In the phase one, we did ten-fold-cross-validation and did a lot of proofs with different machine learning methods and different configuration. We proved with several combinations: Patterns: From one week of observed data to predict the next week until nine weeks before to predict two weeks later. Algorithms: Support vector regression with different kernel functions: linear, RBF (Gaussian) and sigmoid; echo state networks; ordinary least squares linear regression and ridge regression. Variables included in the model. We proved the following combinations: All variables. Only variables that according to expert judgment have more impact on the black Sigatoka development: humidity, precipitation,

temperature and wind speed (Marin Vargas and Romero Caldern, 1995). From the four variables listed in the previous paragraph, runs were conducted using each of the variables separately, and combining other runs all the possible pairs of those four variables.

Phase two

In the second phase, we used the best configurations obtained en la phase one and did validation with the last 52 and 102 weeks. This second phase pretended to show how these methods behaved on a time of important climate change how are 2014 and 2015 years.

Programming environment We use python programming language with the Integrated Development Environment (IDE) Spyder, particularly with libraries: pandas (Comunity, 2014); numpy (numpy.org, 2013); for SVR, ridge and ordinary least squares, we used sklearn (Pedregosa, et al., 2011); and for ESN the python-based code used belongs to Dr. Mantas Lukoeviius (2012) from which we made the necessary adjustments for the experiments of this research. The computer was a Lenovo ThinkPad, processor Intel(R) Core i7-4800MQ CPU @ 2.70GHz, 16.0 GB RAM, running Windows 8 Pro.

3. Results

4. Discussion and conclusions

5. References

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