USE OF ARTIFICIAL INTELLIGENCE FOR THE PREDICTION OF MICROBIAL DISEASES OF GRAPEVINE AND OPTIMISATION OF FUNGICIDE APPLICATION

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Abstract:

Context and purpose of the study

Plasmopara viticola, the causal agent of downy mildew (DM), and *Uncinula necator*, the causal agent of powdery mildew (PM), are two of the main phytopathogenic microorganisms causing major economic losses in the primary sector, especially in the wine sector, by wilting bunches and leaves with a consequent decrease in the photosynthetic rate of the plant and in the annual yield. Currently, the most widespread methods for planning spraying are based on the 3-10 rule, which states that the first application should take place when: (i) the air temperature is greater than 10°C; (ii) shoots are equal or greater than 10 cm; and (iii) a minimum of 10 mm rainfall within 24–48 hours has occurred, or at the beginning of the bud break with periodic applications according to the manufacturer's instructions. These rules are applied to prevent possible infectious events that may occur while new tissues are forming on the vine, which are more susceptible to infection. In addition, establishing a starting point for spraying is crucial, as the pathogen can complete the infection cycle in one to two weeks depending on environmental conditions. However, this approach is not completely effective, as the chemical compound can be washed off the leaves, photo-oxidized, applied at higher doses than necessary, negatively affecting the biodiversity of the agroecosystem, or in discordance with the life cycle of the pathogen. Therefore, the aim of the VitiGEOSS disease early warning service focuses on the application of Artificial Intelligence models to predict the appearance of diseases in the vineyard and consequently apply fungicide products at the right time and dose, minimizing crop losses and the use of pesticides and water.

Material and methods

A total of six study plots located in three countries of the European Union were used: Quinta do Bomfim (Portugal), L'Aranyó (Spain) and Mirabella Eclano (Italy). Disease monitoring was carried out from March to October 2021 and 2022, with field visits every 7 days to measure the percentage of incidence and severity of infection on leaves. To analyze these data, eight different Machine and Deep Learning models were evaluated to classify the degree of infection and provide treatment recommendations using climatic features and phenological change events in the plant.

Results

The three study regions showed significant climatic differences. On one hand, the best prediction algorithm was the one based on conditional probability obtaining a precision metric of 90% for DM and 79% for PM, respectively. On the other hand, a comparative analysis showed that the incorporation of plant phenological stages in the model increased the accuracy rate up to 9%, so it would be interesting to consider the effect of other physiological aspects of the plant for future analyses. Finally, it should be noted that model recommendations reduce water consumption by 21% on average. In any case, it is advisable to continue collecting data, as two production seasons can lead to overfitting issues, and to incorporate climatological and phenological predictions to be able to develop short- and medium-term warnings.

Keywords: Mildew diseases, risk anticipation, effective vineyard management, Artificial Intelligence.

1. Introduction

Grape production is an important activity in the primary sector worldwide. Considering grape production data between 1981 and 2021 (no data available for 2022 and 2023), Europe has been the main producer (48.6%), followed by Asia (24.9%), America (19%), Africa (5.3%) and Oceania (2.3%) (FAOSTAT, https://www.fao.org/faostat/en/#data/QCL/visualize, last accessed 29th March 2023). Among all the potential threats facing grape and wine production, those related to two phytopathogens stand out: *Plasmopara viticola*, the causal agent of downy mildew (DM) and *Uncinula necator*, the causal agent of powdery mildew (PM). DM is the main disease of grapevine impacting negatively grape yield and quality by reducing photosynthetic activity of affected leaves, inducing premature vine defoliation (Rossi *et al.,* 2008; Gessler *et* al., 2011; Chen *et al*., 2020); while PM also infects green plant tissues, causing large losses in yield and wine quality, and being able to remain for long periods as a resistant propagule in the soil or in the basal part of the bark of grapevines in the form of cleistothecia (Halleen *et al*., 2001). The damage caused by these phytopathogens in viticulture is directly related to the environment, causing yield-related losses of around 12% (Pimentel, 2005).

Regardless of the specific disease control strategy adopted, conventional or organic, many growers begin to apply fungicides in early spring as a preventive measure, when the first buds have not yet appeared, at intervals of 7 to 14 days. This practice, in addition to representing an environmental hazard (Chen *et al*., 2020) involves a significant investment in fungicides and water. The study of the epidemiology of these pathogens makes it possible to monitor their development cycle and even to anticipate their appearance and design effective protocols for their control. However, climate change is already altering the phases of phenological cycles and plant-pathogen interactions (Caffarra *et al.*, 2012). The shift to a non-stationary climate now implies that observed datasets and developed models are no longer sufficient, even in the specific locations where the data were collected (Donatelli *et al.,* 2017). Even pathogens that for decades have had no impact on crops in specific environments are now becoming key determinants of crop yields (Berger *et al*., 2007; Gramaje *et al*., 2016). Therefore, the main objective of this work is to develop new models for the anticipation of infective events in grapevine, taking advantage of the benefits of Artificial Intelligence to detect the different interrelationships between variables in an increasingly changing scenario and generate accurate alerts.

2. Material and methods

Selection of sampling plots and data collection - For this experiment, three case studies (CS) of wine production in the European Union were monitored: Quinta do Bomfim (Portugal), L'Aranyó (Spain) and Mirabella Eclano (Italy). These subplots were not subjected to any type of fumigation until a threshold level at which the integrity of the vines could be compromised was reached. Each subplot consisted of a total of 20 plants divided into 4 blocks. Disease monitoring was carried out during 2021 and 2022 from March to October making field measurements every 7 days. On each measurement date, a total of 100 leaves per treatment were visually inspected to measure the percentage of affected leaves and the percentage of affected leaf blade surface. These data were subsequently translated into low, medium, and high-risk disease levels. Regarding the treatments applied, historical data were collected on products and doses supplied during 2021 and 2022. Climatological data from nearby weather stations (mean, minimum and maximum air temperature, relative air humidity, rainfall, wind speed and solar irradiation) and vine phenological data were also collected.

Initial model selection and effectiveness evaluation - Once all the necessary data was collected and standardized if needed, eight different classification Machine and Deep Learning models (Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, K-Nearest Neighbors, Naïve Bayes, Support Vector Machines and Deep Neural Networks) were developed using the scikit-learn library (Pedregosa *et al.,* 2011) in Python3. For this purpose, a battery of different hyperparameters was prepared for each of the models, which were trained with a 10-fold cross validation. The degree of success in predicting the models was expressed in terms of F1-Score, an accuracy metric which considers not only the quality of the prediction, but also the completeness.

Statistical analysis - Climatological differences between plots were determined by Repeated Measures Analysis of Variance using the Least Significance Difference as a post hoc test. Student's t-tests were used to compare the actual and recommended spraying regimes.

3. Results and discussion

3.1. *Climatic characterization of the study regions.*

Considering the environmental variables (Figure 1), it is possible to observe significant differences between the different regions for the studied period. Specifically, the Mirabella Eclano CS presented higher relative air humidity, precipitation, and irradiation than the other two locations, while the L'Aranyó CS presented the highest average wind speed, as well as the lowest amount of precipitation, and Quinta do Bomfim CS presented the highest average air temperature in this two-year period. It seems reasonable to find these differences between case studies given that the CS corresponding to Italy and Spain (Mirabella Eclano and L'Aranyó, respectively) belong entirely to Mediterranean climate, while the CS corresponding to Portugal belongs to an Atlantic climate with Mediterranean-like distribution of precipitations, also named Lusitenean environmental zone (Metzger *et al*., 2005). In addition, according to the European Centre for Medium-Range Weather Forecasts – ECMWF, the weather in 2022 was particularly harsh in the three regions, which suffered from high temperatures and low rainfall, as well as strong gusts of wind caused by differences in atmospheric pressure. This fact had consequences on the appearance of diseases, which due to the specific conditions were not detected in some plots, as well as on plant health, since, in the case of Portugal, many vines withered completely after consecutive days with maximum air temperatures above 42 °C.

3.2. *Accuracy of Artificial Intelligence models and estimation of their potential effect on field application.*

The best classification algorithm was found to be the one based on conditional probability (Naïve Bayes), that yielded short-term disease prediction F1-Score values of 90% for DM and 79% for PM. Likewise, F1-Score values of up to 95% were obtained in the model responsible for predicting the type and doses of treatments. Furthermore, the addition of variables related to the phenological stage of the crop increased the precision of the models by up to 9%, which seems to indicate that infection is mainly mediated by atmospheric variables, but it depends to some extent on host physiology for successful colonization (Thind *et al.,* 2004, Fung *et al*., 2008).

The possibility of foreseeing the critical phases of pathogen infection has the advantage of allowing better spraying procedures by applying fungicides only when they are really necessary and effective, thus avoiding waste of resources. For this reason, a comparison was made between the overall average of actual treatments and the spraying receipes proposed by the model. The results showed that following the recommendations of the model would result in an average decrease of 20% in the number of applications (Figure 2A), an average saving of 21% of water during an entire campaign (Figure 2B) and 3% in each application (Figure 2C).

4. Conclusions

The results obtained in 2021 and 2022 look promising, however, it is necessary to continue improving the models by collecting data from future vegetative seasons to provide more variance to the dataset. Likewise, data from other climatic regions should be incorporated to generalize the model and provide more robust conclusions on resource savings.

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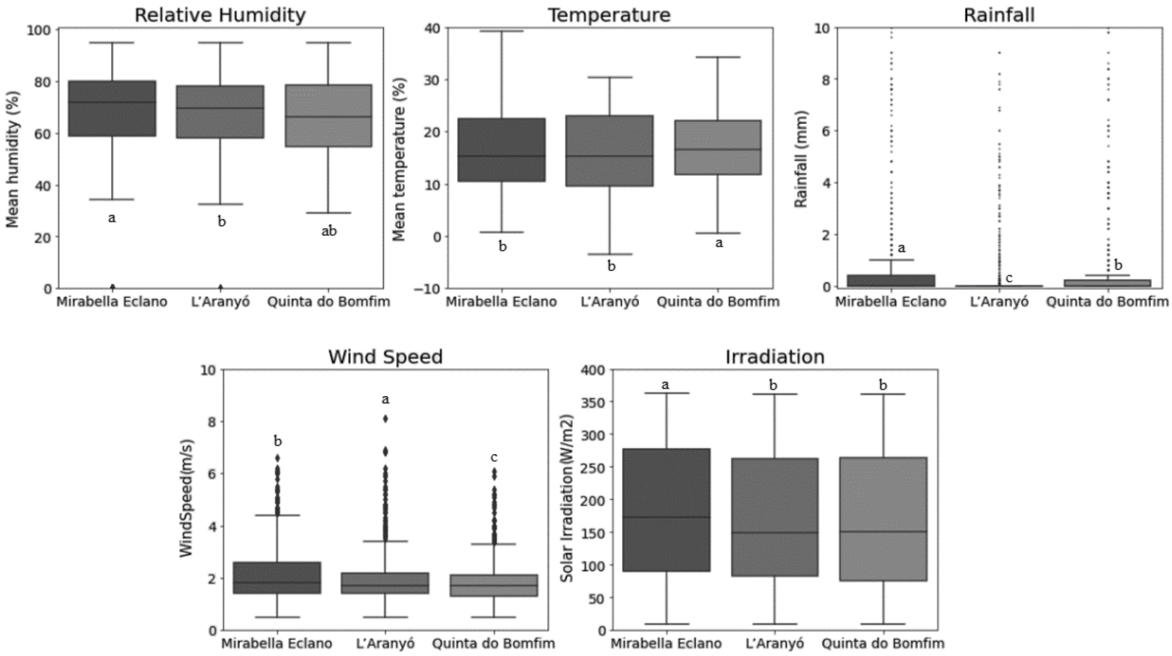

Figure 1: Relative air humidity, air temperature, precipitation, wind speed, and irradiance corresponding to the period in which the experiment was conducted (2021-2022) for the three case studies. The whiskers of the boxplots indicate the value of Q1 and Q3 ± 1.5 IQR and the diamonds indicate the outliers. Different letters indicate significant differences between experimental sites according to the post hoc test.

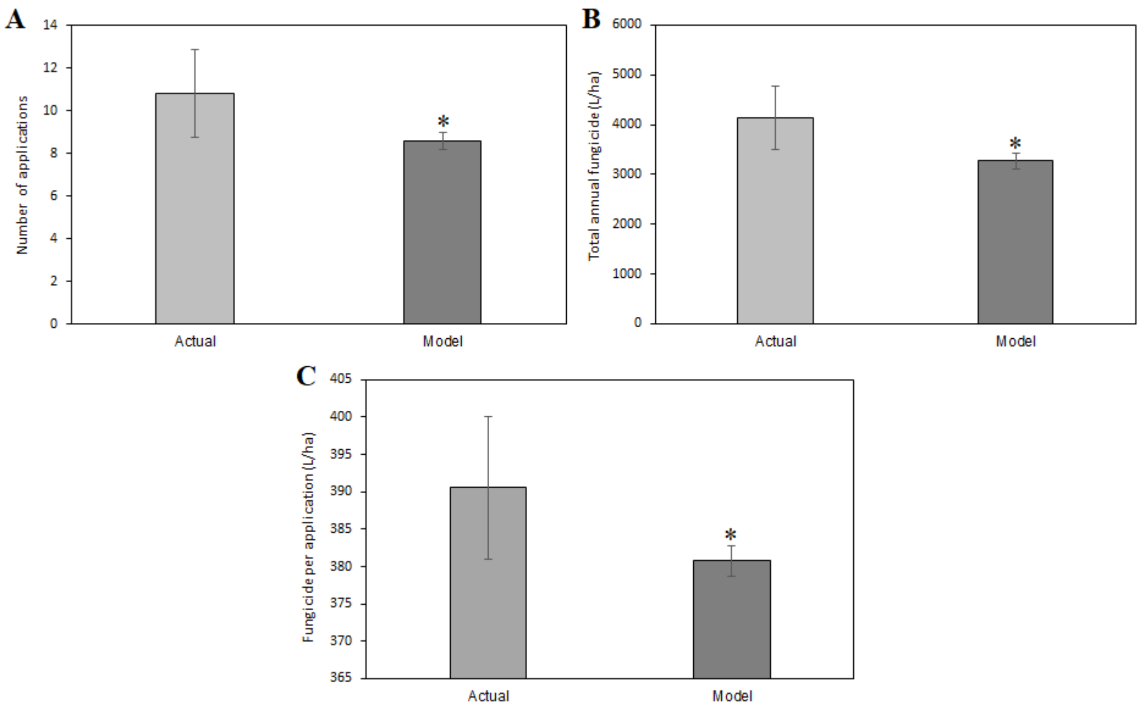

Figure 2: Actual (left) and predicted (right) spraying data for the 2021-2022 period for the three case studies illustrated as: **(A)** average number of fungicide applications per season, **(B)** average liters per hectare of fungicide applied over the entire season, and **(C)** average liters per hectare of fungicide per application. (*) Within each panel, asterisks above bars indicate significant differences ($p \leq 0.05$) in the measured parameters between the actual spraying campain and the model simulations.