How artificial intelligence (AI) is helping winegrowers to deal with adversity from climate change

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Article extracted from the presentation held during Enoforum Web Conference (23-25 February 2021)

Introduction

Precision viticulture (PV) has been around for more than two decades, which deals with sensor technology and instrumentation to aid different viticultural operations. However, considering the scale of applications, the main broad implementation of PV has been in the automation of machinery aided by geo-positioning data. Digital Agriculture and Viticulture (DA and DV) have gained more recognition and have been adopted by different research institutions and universities worldwide as an effective and easier system to be implemented to viticultural and winemaking operations. The main difference between PV and DV is that the former deals with the technology and hardware used, such as sensors and sensor networks, sensors attached to machinery for automation of viticultural management remote sensing using different platforms, such as satellite airborne and unmanned aerial vehicles (UAVs) offering different temporal and spatial resolutions. In the DV case, it deals more with what is done with the data obtained from different sensors and platforms and how these data are analyzed. Data analysis in DV can be from signal analysis to computer vision algorithms and different modelling strategies [1]. For automation purposes, the latest modelling strategies have been performed in the context of Artificial Intelligence (AI), from which machine learning is one of its sub-disciplines. AI can interact with other digital disciplines, such as computer vision, robotics, biometrics, integrated sensor, and sensor networks, to obtain data, learn from them through different machine learning algorithms and target different parameters of interest for management purposes for viticultural and winemaking operations.

This paper explores the latest DV applications and AI combined in viticulture and winemaking to help winegrowers deal with the complexities posed by climate change conditions. It is important to note that many of the latest research and applications using PV technologies have not used machine learning or AI for data analysis. In that case, those studies were considered outside the scope of this paper.

Biological sensors and digital viticulture

One of the novel technologies that have been implemented in DV is the introduction of biological sensors in combination with digital sensors. In the case of DV, dogs have been trained to detect different pests and diseases. This application of dogs is not new since they have been trained to detect illicit drugs, money, and food at border control points such as airports. However, novel applications using trained dogs have been recently implemented to detect diseases in plants and humans, such as COVID-19, with high precision that can reach over 95% [2, 3]. Dogs have 100 times more sensitive noses than humans and can be trained to detect compounds that can be present in parts per trillion. In DV, dogs have been trained to detect one of the most important insects in the industry, Phylloxera. It has been shown that dogs can detect the insect even underground (unpublished data).
The digital approach adopted with these biological sensors is in the form of computer applications (apps) in smartphones located on dog's backpacks, which can record the accelerometer and geo-position data from the mobile devices. This system has been used to train an AI algorithm to detect when the dog is running or detecting the targeted stimuli. The AI algorithm needs to be calibrated by different dogs trained to sit, crouch, or scratch the place where the specific stimuli are detected. The first app developed for these purposes is Inspector Paw © [4], which has been tested to create different AI models for dogs by the Digital Agriculture, Food and Wine Research group (University of Melbourne).

Remote sensing and AI

In the context of the soil-plant-atmosphere continuum, applications of DV and AI are less in number for soil applications compared to plant-based and mainly based on soil moisture predictions [5], soil organic carbon [6], prediction of soil properties [7]. For applications based on the grapevines, the number of applications is significantly higher, mainly to assess vine water status for irrigation purposes using multispectral [8], hyperspectral [9] and proximal [10] remote sensing. Prediction of pests and diseases using DV and AI [11] present more complex machine learning modelling [12], including deep learning [11, 13, 14] and remote sensing [15]. Other novel applications using integrated sensor technologies, such as electronic noses (e-noses), have been used in viticulture to detect diseases [16]. Further research, including DV and AI, have focused on fertilizer deficiency detection and smart application [17-19]

Classification of varieties through a digital ampelography approach could offer the differentiation and recognition of different cultivars and strategies to detect small differences from established vineyards that can be related to changes due to biotic and abiotic stresses [20, 21]. Similar approaches have been used to detect invasive weeds implemented using low-cost smart technology [22], computer vision and deep learning, and smart spray [23]. In the case of canopy management, a dedicated free App: VitiCanopy(The University of Adelaide, Australia) to acquire information from canopies using computer vision was developed in 2014 and has been used by many researchers and viticultural managers worldwide [24]. Parameters from VitiCanopy have been used to link them to grape quality trait parameters [25] and the same using machine learning for grapevines (unpublished) in a similar manner of published data for cocoa trees [26]. Finally, big data, based either on historical records of phenology and meteorological information, have also been implemented AI for cultivar identification [27] and to predict harvest time [28]. Finally, yield prediction has gained a special interest in DV implementing AI-based on computer vision and deep learning [29], based on berries and clusters [30, 31] and for phenotyping purposes [32-34].

Winemaking and consumer acceptability using AI

One of the major threats for grape production and winemaking is the increased number, severity, and window of opportunity of bushfires around the world for grape-growing regions due to climate change. Smoke affecting vineyards can contaminate berries passing these smoke-related compounds to the wine known as smoke taint [35]. Different digital and non-destructive sensors coupled with AI, such as infrared thermography for canopies, have been used to detect smoke contaminated vines and near-infrared spectroscopy to detect smoke-related compounds in grapes and final wine [36-38]. Low-cost e-noses have also been developed to detect smoke taint in berries and wine [39].

New sensory analysis technologies have been developed to assess more objective responses from panellists towards different food and beverage products, including wine. These new technologies are based on biometrics and physiological responses from panellists assessed from video analysis and remote sensing techniques while tasting different products [40, 41]. AI application based on biometrics, has been applied for different beverages [42, 43], combined with robotic beverage pourers and integrated e-noses [44-48].

Wine quality assessment using AI has also gathered the attention of researchers [49, 50]. Supervised machine learning has been applied to assessing different wine features [51-54]. Big data has also been applied along with AI for early prediction of aroma profiles of final wines [55] and the use of non-destructive NIR readings to predict the effect of the berry mesocarp cell death on grape quality traits and aroma profile of final wines [56].

Data access, ownership and security access using AI

One of the main problems in DV and any AI implementation is the insecurity from the winegrower's perspective regarding data access, data ownership and security. For them, it is not always clear who owns the data acquired from their vineyards and wineries. There is also a great uncertainty towards whether third parties can use the data and corresponding analysis to benefit competitors. The latter, especially if providers of DV and AI solutions, are private companies working with cloud computing. One relatively straightforward solution to this problem would be treating the data generated from specific vineyards or wineries as currency and secured using an electronic ledger format for traceability, such as blockchain [57-62]. This will ensure winegrowers and winemakers that access to the data is restricted, and there will be indelible records of who access the data, how many times and when.

Conclusion

Even though the latest DV and AI advances in the last five years have been promising, there is still no integratory vision in the newest research. This could be mainly related to specific skills from different research groups specialized either in viticultural or winemaking and sensory analysis processes. The Digital Agriculture, Food and Wine research group has proposed an integrative approach from the vineyard to the palate, which essentially implements novel AI tools developed though DV from the vineyard, harvest, grape processing, winemaking, and consumer sensory perception. Information of this production chain can then be fed back to the vineyard through AI models to target specific quality traits or wine styles preferred by consumers and winemakers. This novel approach will consider climate change constraints and the complexity of the variability related to weather, seasonality, and consumer preference changes. This integrative approach could revolutionize the winemaking industry and secure competitiveness in international markets by small, medium, and big companies.

Abstract

Climate change has posed major risks for viticulture and winemaking around the world, related to increased ambient temperatures, the variability of rain events, higher occurrence and intensity of

climatic anomalies, such as frosts and bushfires. These changes have directly impacted grapevine phenology by compressing stages and pushing forward in time harvest to hottest months, producing a dual warming effect. Bushfires also directly impact berry smoke contamination, which can be passed to the wine in the winemaking process producing smoke taint. Due to these events' complexities and their effects on viticulture and winemaking, a smarter approach is required to obtain relevant information and process it efficiently for more appropriate decision-making by different practitioners. In the last 10 years, artificial intelligence has offered various applications to be included in viticultural and winemaking operations, which has rendered important advances and information to deal with climate change adversities.

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