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PRECISION VITICULTURE'S STATE-OF-THE-ART TECHNOLOGICAL ADVANCEMENTS

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ABSTRACT
The research demonstrates how having access to this knowledge enables winemakers to strategically harvest fruit packages based on yield and/or fruit quality requirements and product requirements. Economic advantages of each of these outcomes include lower input costs, increased productivity, and a better final product. The cost of integrating decision-support systems on a field scale, as well as the accessibility of operating systems and devices, will be key factors in the implementation and regular use of smart sensing techniques because they present enormous opportunities for producers at all stages. To enable the wide adoption of such technology, the issue of data rights and security, especially when data is obtained through third parties, needs to be resolved in the upcoming years.

KEYWORDS: ***viticulture, digital wine industry, artificial intelligence, and wine production***

INTRODUCTION

As technology develops and advances, many agricultural sectors assess what improvements can be incorporated into their operations to provide management support (Fountas, Espejo-Garca, Kasimati, Mylonas, & Darra, 2020). This is crucial for the wine industry in particular because farmers around the world are facing challenges from climate change, varying atmospheric conditions, compressed seasons, drought, heat, labor shortages, and rising production costs (Koufos, Mavromatis, Koundouras, & Jones, 2020; Soar, Sadras, & Petrie, 2008). In order to examine vineyard management strategies, regular monitoring of biophysical variables and grapevine performance is therefore necessary. Today, winemakers can access and use precise data and information about their vineyards as a basis for making the best decisions they can in order to maintain productivity while also remaining financially and environmentally sound. This toolbox consists of GPS, GIS, geostatistics, AI, and DSS in addition to remote and local sensing technologies. In the viticulture sector, the terms "precision" or "digital viticulture" are frequently used to describe the prudent creation and application of such procedures (Ammoniaci, Kartsiotis, Perria, & Storchi, 2021).

Non-invasive sensing methods, including as spectroscopy, MSI, HSI, Chl fluorescence, thermography, ER, LiDAR, and CV, can be utilized in wine grape production systems to gather crucial information about the vineyard and the plants growing there (Fountas, Mylonas, et al., 2020). They can be used as portable sensors, installed on or incorporated into machinery, automated robotic systems, and ground-based platforms like piloted vehicles, as well as aerial platforms like satellites, small planes, and UAVs or drones (Matese & Di Gennaro, 2018; Matese et al., 2015). Additionally, the widespread use of cellphones and "apps" has completely changed how vineyard producers may access and gauge vine performance and fruit attributes. Thanks to the use of specifically constructed robotic devices with non-invasive sensing technologies, many vineyard operations will likely be mechanized in the future (Matese et al., 2015; Suarez et al., 2021).

With the aid of these spatially enabled digital technologies, grape growers can monitor changes in vine parameters such as canopy size (Sanz et al., 2018), water (Gutiérrez, Diago, Fernández-Novales, & Tardaguila, 2018), and nutritional status (Diago et al., 2016). They can also monitor changes in yield (Aquino, Millan, Diago, & Tardaguila, 2018), grape composition (Gut Wine makers can more effectively apply inputs like fertilizers, sprays, and irrigation water through targeted applications thanks to the ability to trace the geographical distribution in the vine, soil, and geographical aspects across vineyards. They can also harvest fruit parcels carefully in accordance with various yield and/or fruit quality standards and product specifications (Bramley, Ouzman, & Trought, 2020).

This article's goal is to showcase several digitally-based viticulture applications that are either already in use locally or are being developed. The study will assess the prospects that these methods provide for growing grapes and making wine in response to growing environmental issues, such as changes in climatic and soil conditions. The objective is to increase the efficiency of the winemaking processes and lower production costs. The study will also discuss how various sensing methods work and how artificial intelligence might be used in viticulture.

A positive implication for viticulture is artificial intelligence.

Since AI can transform data into different types of information that grape farmers may use to make informed decisions, it may be highly useful. All of the sensing methods and platforms mentioned earlier work together to give today's grape growers a high level of data collection proficiency, even at tiny scales. But further research development will be necessary. To learn more about how to model the crop into precise statistics and extract more information, a variety of other uses and developments must be investigated. Furthermore, as crop data enables precise management of ecologically vital resources like water and soil, in addition to being significant to grape producers for farming methods, it has both direct and indirect environmental uses.

The most widely used field for automating knowledge in agriculture, particularly viticulture, is machine learning (ML) (Cai et al., 2019; Fuentes et al., 2018). The study of getting computers to learn on their own, generally speaking, so they can transform input into useful knowledge is known as machine learning (ML), and it is at the core of artificial intelligence (AI) (Jordan & Mitchell, 2015). Therefore, grape farmers and winemakers can use machine learning in conjunction with the numerous data collection options presently available to deploy data-driven solutions to enhance and optimize their production processes. Training is used to do this, which comprises building mathematical models that are fed input from data. There are various processes involved in machine learning.

The next step is to train the models that make up machine learning after all the data has been correctly structured and handled (i.e., training models using algorithms fed by data). Model training is the most challenging stage and one that requires user experience. This is due to the need of comprehending the various algorithms that can be used, their advantages and disadvantages, and the best selection for the data at hand. In viticulture, numerous machine learning techniques have been applied to achieve a variety of objectives. For instance, SVMs for disease detection, classification of grape types, and yield forecasting, an ideal method for disease identification using imaging, deep learning for image classification in vineyards, and disease detection using hyperspectral data evaluation (Bendel et al., 2020). Advanced models for precision agriculture have been built using a variety of deep learning techniques, including convolutional neural networks (Barré et al., 2019; Hsieh & Kiang, 2020); autoencoders (Karim et al., 2020; Yu, Lu, & Liu, 2018); and recurrent neural networks (Chen, Xiao, Zhang, Xie, & Wang, 2020; L.-W. Liu, Hsieh,

A model can be used for more things when it has been adjusted, trained, and verified. For instance, combining a sensor and a system with the learned model would be necessary in digital viticulture. The model would continuously gather data from the sensor and produce forecasts based on the discovered directions and relationships. Although it is possible to take advantage of this and restart the process utilizing the newly gathered data because this is also a data-gathering procedure. It's crucial to keep in mind that a model's output should be considered more of a tool than a final product.

CONCLUSION

This article provides a thorough overview of several digital non-invasive procedures that are either currently being developed or used in the wine and grape business. Enhancing resource use efficiency across all agricultural systems is necessary to address current and future issues like climate change, the environment, waste, labor shortages, and growing production prices. The use of various proximal and remote sensing technologies has improved our understanding of vineyard variation with respect to spatial disparities, sequential dynamics, and underlying causes. According to the study, having this knowledge enables winemakers and grape producers to use inputs more efficiently through targeted applications and harvest fruit packages strategically in accordance with yield and/or fruit quality criteria and product requirements. Economic advantages of each of these outcomes include lower input costs, more productivity, and a better final product. It is difficult to demonstrate how precise, digital viticulture and related technology benefit the environment. There are currently no known examples from the wine and grape industries. However, environmental benefits are inevitable given the tightening regulations on the use of chemicals in agriculture and the ongoing commercialization of equipment outfitted with sensors and VRA technology to measure canopy size.

REFERENCES

1. *S. Fountas, N. Mylonas, I. Malounas, E. Rodias, C. Hellmann Santos, & E. Pekkeriet (2020). robotics for farming tasks in the field. 20(9), 2672. Sensors*
2. *Escalona, J. M., Bota, J., Viejo, C. G., C. Poblete-Echeverra, S., Hernández-Montes, E.,... H. Medrano (2018). automated classification of grapevine cultivars based on machine learning employing factors from near-infrared spectroscopy, fractal dimension, and leaf morpho-colorimetry. Agriculture and Computer Technology, 151, 311-318.*
3. *Priovolou, A., Lougkos, N., Tassopoulos, D., Kalivas, R., & Giovos (2021). A review of remote sensing vegetation indices used in viticulture. 11(5), 457; Agriculture.*
4. *Geladi and Grahn, H. (2007). methods and uses for analyzing hyperspectral images. Wiley & Sons, Inc.*
5. *J. Grimm, K. Herzog, F. Rist, A. Kicherer, R. Toepfer, & V. Steinhage are among the authors (2019). a flexible method for automatically spotting plant parts using the visual sense with applications in grapevine breeding. 170-183 in Biosystems Engineering, 183.*
6. *Diago, M. P., J. Fernández-Novales, S. Gutiérrez, and J. Tardaguila (2018). Assessment of the condition of the vineyard water using mobile thermal imaging and machine learning. 13(2) of PLoS One, e0192037.*
7. *S. Gutiérrez, J. Tardáguila, J. Fernández Novales, and M. P. Diago (2019). Hyperspectral imaging on-the-go for determining the anthocyanin and soluble solids content of grape berries in the field. 25(1), 127–133, Australian Journal of Grape and Wine Research*
8. *Hall, D. W. Lamb, B. P. Holzapfel, and J. P. Louis (2011). relationships between vineyard canopy, winegrape composition, and yield that vary seasonally within seasons. 103–117 in Precision Agriculture, 12(1).*
9. *& Kiang, J.-F. Hsieh, T.-H. (2020). CNN algorithm comparison for classifying hyperspectral images in agricultural areas. 20(6), 1734; Sensors.*
10. *Mitchell, T. M., and Jordan, M. I. (2015). Trends, perspectives, and possibilities in machine learning. 349(6245), pp. 255–260 in Science. https://doi.org/10.1126/science.aaa8415*
11. *Kaya, H., Güzel, M. S., Tolun, M. R., Elebi, F. V., and Mishra, A. Karim, A. M. (2020). a cutting-edge framework for data classification utilizing a linear model based on deep auto-encoders. 6378. Sensors, 20(21).*
12. *Jones, G. V., Koundouras, S., Mavromatis, & Koufos, G. C. (2020). Current patterns and outlook for the ability of Greek wine grape varietals to adapt to climate change. 54(4), 1201-1219 Oeno One.*
13. *Wang, Y.-M., Liu, L.-W., Hsieh, S.-H., Lin, S.-J., and Lin, W.-S. (2021). Machine learning analysis of the main factor*

sensitivity and the likelihood of the rice blast (Magnaporthe oryzae) occurring. 11(4):771 in Agronomy.

14. *Sun, D.-W., Pu, H., and Liu, Y. (2017). A discussion of recent applications of the hyperspectral imaging technology for determining the quality and safety of food during various operations. Food Science & Technology Trends, 69, 25–35.*
15. *W. H. Maes and K. Steppe (2012). A review of the use of ground-based thermal remote sensing in agriculture for estimating evapotranspiration and drought stress. 4671–4712 in Journal of Experimental Botany, 63(13).*