MACHINES AND FIRE: DEVELOPING A RAPID DETECTION SYSTEM FOR GRAPEVINE SMOKE CONTAMINATION USING NIR SPECTROSCOPY AND MACHINE LEARNING MODELLING

Authors:Vasiliki SUMMERSON, Claudia GONZALEZ VIEJO, Damir TORRICO, Sigfredo FUENTES*

The University of Melbourne, School of Agriculture and Food, Faculty of Veterinary and Agricultural Sciences, Parkville 3010, Victoria, Australia

*Corresponding author: sigfredo.fuentes@unimelb.edu.au

Abstract:

Context and purpose of the study - Bushfires are a common occurrence throughout Australia and their incidence is predicted to both rise and increase in severity due to climate change. Many of these bushfires occur in areas close to wine regions, which receive different levels of exposure to smoke. Wine produced from smoke-affected grapes are characterised by unpalatable smoky aromas such as "burning rubber", "smoked meats" and "burnt wood". These smoke tainted wines are unprofitable and result in significant financial losses for winegrowers. This study investigated the use of near-infrared (NIR) spectroscopy and machine learning (ML) modelling for the rapid and non-destructive detection of grapevine smoke exposure by analysing grapevine leaves and/or grape berries.

Materials and methods - The trial was conducted during the 2018/2019 season at the University of Adelaide's Waite campus in Adelaide, South Australia (34° 58' S, 138° 38' E) and involved the application of five different smoke and water misting treatments to Cabernet Sauvignon grapevines at approximately seven days post-veraison. Treatment vines were exposed to straw-based smoke for one hour under experimental conditions described previously by Kennison et al. (2008) and Ristic et al. (2011). Near-infrared (NIR) measurements were then taken from berries and leaves a day after smoking using the microPHAZIR TM RX NIR Analyser (Thermo Fisher Scientific, Waltham, USA) which has a spectral range of 1600-2396 nm. The NIR spectra were then used as inputs to train different ML algorithms, which resulted in two artificial neural networks (ANNs) with the best classification performance for either berry or leaf readings according to the different smoke treatments.

Results - Both ANN models found were able to correctly classify the leaf and berry spectral readings with high accuracy. The leaf model had an overall accuracy of 95.2%, 97.7% accuracy during training with a mean square error (MSE) 0.0082, 90.9% during validation with a MSE of 0.0353 and 88.1% during the testing stage with a MSE of 0.0386, while the berry model had an overall accuracy of 91.7%, 95.2% accuracy during training with a MSE of 0.0173, 86.4% during validation with a MSE of 0.0560 and 80.2% during the testing stage with a MSE of 0.0560. These results showed the potential of developing a rapid, non-destructive, in-field detection system for assessing grapevine smoke contamination following a bushfire using NIR spectroscopy and artificial neural network modelling.

Keywords: Bushfires, Machine learning, Smoke taint, Climate change, Non-destructive

1. Introduction.

Machines and fire: Developing a rapid detection system for grapevine smoke contamination using NIR spectroscopy and machine learning

THE UNIVERSITY OF MELBOURNE

Vasiliki Summerson, Claudia Gonzalez Viejo, Damir Torrico, Sigfredo Fuentes*

The University of Melbourne, School of Agriculture and Food, Faculty of Veterinary and Agricultural Sciences, Parkville 3010, Victoria, Australia

*Corresponding author: sigfredo.fuentes@unimelb.edu.au

Introduction and Objective

Bushfires are a common occurrence throughout the world including Australia, the Mediterranean as well as North and South America. Unfortunately, their incidence is predicted to rise due to increases in temperature, wind and drought brought on by climate change (CSIRO 2018). Many of these bushfires occur in areas close to wine regions, resulting in grapevine smoke exposure. Wine produced from these smoke-affected grapes are characterised by unpalatable smoky aromas such as "burning rubber", "smoked meats" and "burnt wood" Bell, Stephens & Moritz 2013). These wines are unprofitable and result in significant financial losses for winegrowers. Currently there is no in-field detection system that growers can use to assess whether their grapevines have been contaminated by smoke, instead they must harvest grapes and conduct mini-ferments which are then sent off to a commercial laboratory for analysis. This process is incredibly time consuming and destructive. **This study aimed to assess the use of near-infrared (NIR) spectroscopy and machine learning (ML) modelling for the rapid and non-destructive detection of grapevine smoke exposure by analysing grapevine leaves and/or grape berries.**

Materials and Methods

The trial was conducted during the 2018/2019 season at the University of Adelaide's Waite campus in Adelaide, South Australia (34° 58' S, 138° 38' E) and involved the application of five different smoke treatments (high smoke coupled with water misting (HS M) (Fig. 2), high smoke with no water misting (HS NM), low smoke (LS) using half the amount of fuel used in the high smoke treatments to achieve half the smoke density, control with mist (Con M and control with no mist (Con NM)) to Cabernet Sauvignon grapevines at approximately seven days post-veraison. Treatment vines were exposed to straw-derived smoke for one hour under experimental conditions described previously by Kennison et al (2008) and Ristic et al. (2011) (Fig. 1). Near-infrared measurements were then taken a day after smoking using the microPHAZIR TM RX NIR Analyser (Thermo Fisher Scientific, Waltham, USA), which has a spectral range of 1600-2396 nm. Spectral readings were then used as inputs to train different ML algorithms using a customised code written in Matlab® R2019a (Mathworks Inc., Matick, MA. USA) which resulted in two artificial neural network (ANN) models with the best classification performance for either berry (Model 1) or leaf (Model 2) readings according to the different smoke treatments. The ANN models were trained to classify the leaf or berry NIR readings according to the smoke treatments (HS M, HS NM, LS, Con NM or Con M). The two models were developed using a random data division with 70% (n = 378 for berries and 1132 for leaves) scaled conjugate gradient training algorithm, 15% (n = 81 for grapes and 323 for leaves) for validation with a cross entropy algorithm for performance and 15% (n = 81 for grapes and 323 for leaves) for testing for the leaf

Figure 1: Tents used to smoke grapevines

Figure 2: Water misters

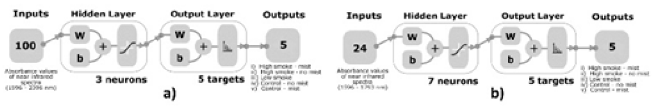

Figure 3: Two-layer feedforward network model diagram with tan-sigmoid function in the hidden layer and a Softmax transfer function in the output layer showing the inputs and targets / outputs of (a) Model 1 to classify

Results

The models were able to correctly classify the leaf and berries using the spectral readings as inputs with high accuracy. The leaf models had an overall accuracy of 92% (Model 1), 95% (Model 2). Principal component analysis (PCA) performed on the spectral readings resulted in the biplots shown in Figure 4a for berries and b for leaves. For berries Control mist and HS NM grapes tended to cluster in the left quadrant, while HS M and LS clustered towards the right. For leaves, there was a clear separation for the HS M leaves which clustered towards the top right quadrant, while HS NM was on the bottom right and Con M towards the left.

a)

	Con NM	Con M	LS	HS NM	HS M	
Con NM	94 17.4%	1 0.2%	1 0.2%	4 0.7%	1 0.2%	93.1% 6.9%
Con M	1 0.2%	105 19.4%	2 0.4%	3 0.6%	0 0.0%	94.6% 5.4%
LS	10 1.9%	2 0.4%	102 18.9%	0 0.0%	3 0.6%	87.2% 12.8%
HS NM	0 0.0%	0 0.0%	0 0.0%	90 16.7%	0 0.0%	100.0% 0.0%
HS M	3 0.6%	0 0.0%	3 0.6%	11 2.0%	104 19.3%	86.0% 14.0%
Accuracy Error	87.0% 13.0%	97.2% 2.8%	94.4% 5.6%	83.3% 83.3%	96.3% 3.7%	91.7% 8.3%

b)

	Con NM	Con M	LS	HS NM	HS M	
Con NM	314 19.4%	4 0.2%	3 0.2%	1 0.1%	1 0.1%	97.2% 2.8%
Con M	1 0.1%	298 18.4%	1 0.1%	0 0.0%	8 0.5%	96.8% 3.2%
LS	3 0.2%	8 0.5%	318 19.7%	8 0.5%	5 0.3%	93.0% 7.0%
HS NM	4 0.2%	8 0.5%	2 0.1%	307 19.0%	7 0.4%	93.6% 6.4%
HS M	2 0.1%	6 0.4%	0 0.0%	5 0.3%	303 18.7%	95.9% 4.1%
Accuracy Error	96.9% 3.1%	92.0% 8.0%	98.1% 1.9%	95.6% 4.4%	93.5% 6.5%	95.2% 4.8%

Figure 4: Overall confusion matrices for model 1 (a) and model 2 (b)

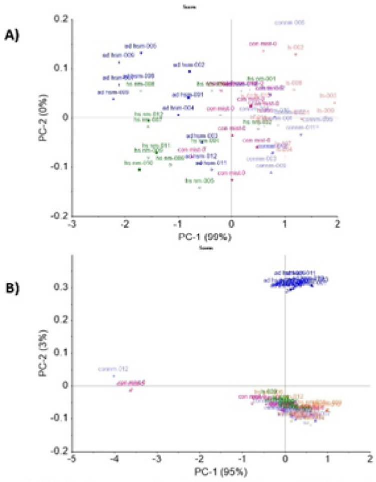

Figure 5: Principal component analysis biplots for model 1 (a) and model 2 (b)

Conclusion

Near-infrared spectroscopy and ANN modelling demonstrate great promise for the detection of grapevine smoke contamination. Further research is required to relate the spectral readings to the level of volatile phenols in grapes and smoke taint development in wine .

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