How AI and MATLAB Are Helping Winegrowers Analyse Bushfire Smoke Contamination

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The vineyard of the future initiative
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Inspector Paw App
Automated Recognition of Cattle Features for Data Extraction
Monitoring Cattle Biometrics

Respiration Rate: IR-Non radiometric

Body Temperature: InfraRed Thermography Radiometric

Heart Rate: Video Magnification Analysis
Big Data and Machine Learning to achieve Artificial Intelligence to maximize productivity and quality of milk in a robotic dairy farm.
Artificial Intelligence Application to Minimise Dark Cutting Beef (DCB)

Inputs: Non-contact Animal Biometrics
Target: Minimise Dark Cutting Beef (DCB)
Automatic Robotic Pourer to assess foamability (RoboBEER)

• 14 Peer Reviewed Papers since 2014
• Featured in Science and Forbes Magazines
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Global Warming
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Bushfire Events

Source: Hormick, 2019
Smoke Contamination / Taint: Machine Learning modelling
Smoke Contamination / Taint: Machine Learning modelling

11:30 a.m. – 2:30 p.m. Within 1 hr after smoke exposure

Averaged stomatal conductance, $g$, using a Porometer
2 sunlit fully expanded leaves from top, middle, and bottom canopy sections

Berry NIR measurements
Diffuse reflectance spectra on full and halved berries using ASD FieldSpec®

Infrared thermal images using FLIR B360
Infrared index $I_5$ (Fuentes et al. 2012)

New and Emerging Technologies Integration System (NETIS)

Plant water status
Vigour
Fertiliser demand
Leaf Area Index
Fruit recognition

UNMANNED AERIAL SYSTEMS
Spatial mapping of Visible, multispectral and Infrared thermal imagery

Dogs trained to detect invasive weeds, pests and diseases with computer App + AI

DECISION-MAKING

PROXIMAL REMOTE SENSING
Using phone attachments such as e-nose and devices / apps to capture visible infrared images and NIR data
Smoke Contamination / Taint: Machine Learning modelling
Smoke detection in Canopies

**Canopy Conductance**

**Infrared Index**

\[ y = 0.0026x \]
\[ R^2 = 0.85 \]

\[ y = 0.0019x \]
\[ R^2 = -0.39 \]

Stomata

**Stomata**
Smoke detection in Canopies

Sequential order weight and bias

Training = 97%
Test = 93%
Overall = 96%
Smoke detection in Berries

11:30 a.m. – 2:30 p.m.
Within 1 hr after smoke exposure

Averaged stomatal conductance, $g_s$, using a Porometer
2 sunlit fully expanded leaves from top, middle, and bottom canopy sections

Berry NIR measurements
Diffuse reflectance spectra on full and halved berries using ASD FieldSpec

Infrared thermal images
Using FLIR B360

Berry NIR measurements
Diffuse reflectance spectra on full and halved berries using ASD FieldSpec

Smoke detection in Berries

Sequential order weight and bias

Training = 91%
Test = 91%
Overall = 93%

Guaiacol (glycoconjugates) in berries, Guaiacol in wine, and 4-methyl guaiacol in wine (Observed)

\[ R = 0.97 \]

Guaiacol (glycoconjugates) in berries, Guaiacol in wine, and 4-methyl guaiacol in wine (Predicted) = 0.93 * Target + 0.055
Smoke detection in Canopies and Berries

Non-invasive tools to detect smoke contamination in grapevine canopies, berries and wine: A remote sensing and machine learning modeling approach

Sigfredo Fuentes*, Eden Jane Tongson, Roberta De Beč, Claudia Gonzalez Viejo, Renata Ristic, Stephen Tyerman, Kerry Wilkinson

1 School of Agriculture and Food. Faculty of Veterinary and Agricultural Sciences. The University of Melbourne. Parkville 3010, Victoria
2 School of Agriculture, Food and Wine. The University of Adelaide, PMB 1, Glen Osmond, SA 5064, Australia
Development of an e-Nose coupled with Machine Learning

Gas Sensors (x9)

- Methane
- Hydrogen
- Carbon monoxide
- Ammonia
- Alcohol
- Carbon dioxide
- Hydrogen sulfide
- Benzene
- Ketones
- Toluene
- N-hexane

Gas Chromatography outputs

Example of outputs

Electronic board + Sensors

Steam Ale

Porter
Development of an e–Nose coupled with Machine Learning

Gas Sensors (x9)
- Methane
- Hydrogen
- Carbon monoxide
- Ammonia
- Carbon dioxide
- Hydrogen sulfide
- Benzene

Electronic board + Sensors

Gas Chromatography outputs

Sensors and Actuators B: Chemical
Volume 308, 1 April 2020, 127688

Example of outputs

Development of a low-cost e-nose to assess aroma profiles: An artificial intelligence application to assess beer quality

Claudia Gonzalez Viejo, Sigfredo Fuentes, Amruta Godbole, Bryce Widdicombe, Ranjith R Unnithan

Porter

Ethanol
Butanol
Hydrogen gas
Methanol
Helium
Hydrogen sulfide
Monoxide
Ethane
Propane
Development of an e-Nose coupled with Machine Learning

Gas Sensors (x9)

Electronic board + Sens

Gas Chromatography outputs

sensors

Assessment of smoke contamination in grapevine berries and taint in wines due to bushfires using a low-cost e-nose and artificial intelligence

1. Article
2. Sigfredo Fuentes1, Vasiliki Summerson2, Claudia Gonzalez Viejo3, Eden Tongson4, Nir Lipovetzky2, Kerry Wilkinson3, Colleen Szeto3, and Ranjith R. Unnithan4
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4. 2 School of Computing and Information Systems, Melbourne School of Engineering, The University of Melbourne, Parkville, VIC 3010, Australia
5. 3 School of Agriculture, Food and Wine, The University of Adelaide, Waste Campus, PMB 1, Glen Osmond, SA 5064, Australia
6. 4 School of Engineering, Department of Electrical and Electronic Engineering, The University of Melbourne, Parkville, VIC 3010, Australia
Development of a Biosensory Computer Application to Assess Physiological and Emotional Responses from Sensory Panelists

Sigfredo Fuentes *, Claudia Gonzalez Viejo, Damir D. Torrico and Frank R. Dunshea

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Software Development

- BioSensory Computer App

  Biometrics:
  a) Eye Tracking:
     - Pupil dilation, Fixations
  b) Heart Rate:
     - Rate, Amplitude, Frequency
  c) Body Temperature
  d) Face expressions:
     - Sad, Disgusted, Contempt, Neutral, Angry, Happy, Surprised
     - Posture Tracking
     - Brain Waves:
       - Alpha, Beta, Gamma, Attention, Meditation, Blinking, Zone.

  Machine Learning Modelling to obtain:
  - Liking
  - Emotional Response
Integration of technologies: From Tree to the Palate

**Remote sensing**
- Plant water status
- Vigour
- Fertilizer demand
- Leaf Area Index
- Fruit recognition

**UNMANNED AERIAL SYSTEMS**
- Spatial mapping of NDVI and infrared imagery

**PROXIMAL REMOTE SENSING**
- Using phone attachments and apps to capture visible and infrared images

**Sensory Laboratory**
- Harvest for sensory analysis
- Ground-truth for remotely sensed information

**Non-destructive/ GCMS assessment**
- Liking and sensory profile to be related with field data
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Thank You