

# Quality assessment of New Zealand mānuka honey using hyperspectral imaging combined with deep learning

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## Introduction

- New Zealand mānuka honey contains antibacterial and anti-inflammatory activities corresponding to MGO and Leptosperin, giving it value over traditional honeys.
- Quality is measured by UMF™ while purity depends on *Leptospermum scoparium* nectar content.
- Mono-floral is more valuable than multi-floral honey and value decreases when manuka honey is diluted with honeys from other nectar sources.
- Honey varies between and across all of regions, sites, apiaries, beehives and honey frames.
- Dilution may be by bee or by man. During extraction, rich and lean frames are lumped together.
- Quality assessment of honey in-frame could help prevent mixing of rich honey with lean.
- Current chromatography-based methods are too slow and expensive to evaluate frame by frame.



*Leptospermum scoparium* var. *scoparium*



*Leptospermum scoparium* var. *incanum*



Apiary



Extraction process

## Methods

- We aimed to develop rapid methods to evaluate manuka honey before bulk extraction.
- 1656 honeys from 8 districts were scanned by hyperspectral imaging camera (547-1701 nm).
- The images were segmented to extract spectral information by sample for modelling.
- Chemometrics, machine learning and deep learning were employed to analyze the spectral data.

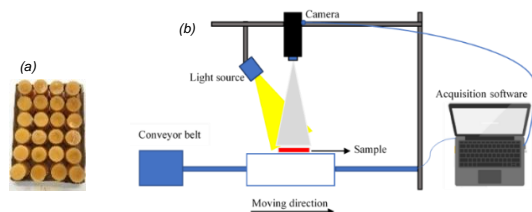


Figure 1. A 24-honey tray (a) and a line-scanning hyperspectral imaging (547-1701 nm) (b)

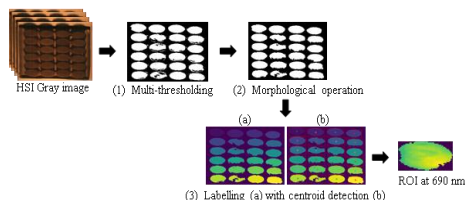


Figure 2. The used segmentation approach to extract regions of interest (ROIs) from hyperspectral images.

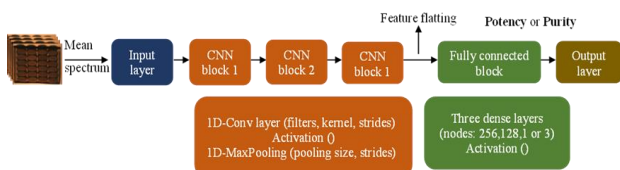


Figure 3. The proposed architecture of one-dimensional convolutional neural network framework to predict potency or purity of honey from hyperspectral images.

## Results and conclusion

- Prediction of UMF™ scores (potency) gave 72 % accuracy (test set) (Fig. 4b).
- Classification of mono-mānuka honey gave > 90 % accuracy (Table 1).
- Multi-mānuka could be separated from non-mānuka up to 74 % (Table 2).
- Potentially, HSI & deep learning can be used for on-line automating assessment of comb honey prior to lumped extraction.

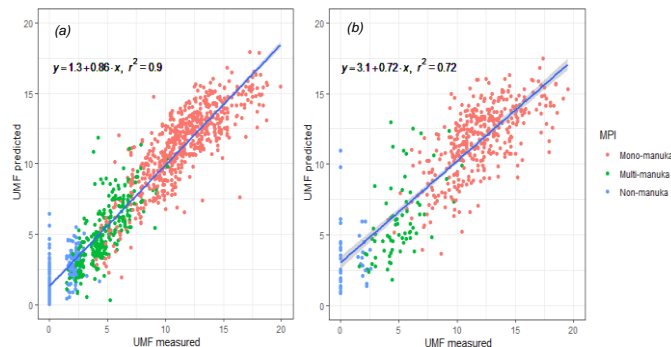


Figure 4. Prediction of UMF™ score using 1D-CNN: calibration (a) and validation (b)

Table 1. Classification of mono-manuka, multi-manuka and non-manuka honeys using 1D-CNN versus PLSDA & SVMDA

Model	Recall			Precision			F1			O.A
	Mono	Multi	Non	Mono	Multi	Non	Mono	Multi	Non	
PLS-DA	0.90	0.69	0.48	0.83	0.89	0.97	0.93	0.59	0.52	84.48 %
SVM-DA	0.97	0.43	0.55	0.63	0.95	0.98	0.94	0.51	0.60	86.29 %
1D-CNN	0.91	0.55	0.68	0.93	0.53	0.60	0.92	0.54	0.64	84.27 %

Table 2. Classification of multi-manuka and non-manuka honeys using 1D-CNN versus PLSDA & SVMDA

Model	Recall		Precision		F1		O.A
	Multi	Non	Multi	Non	Multi	Non	
PLS-DA	0.75	0.61	0.61	0.75	0.75	0.61	69.57 %
SVM-DA	0.81	0.62	0.62	0.81	0.79	0.65	73.91 %
1D-CNN	0.80	0.59	0.76	0.65	0.78	0.62	71.74 %

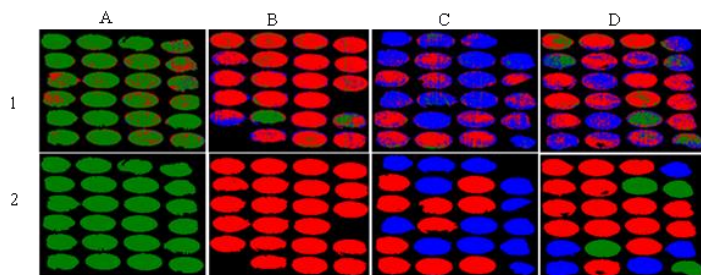


Figure 5. Prediction maps for honey trays from a pixel-wise 1D-CNN classification model of mono-mānuka honeys (green), multi-mānuka honeys (red) and non-mānuka honeys (blue) using majority voting mechanism: predicted images (1) and ground truth (2) where A, B, C, D are honey trays.

## Acknowledgements

