

# Research Trends in Optical Spectrum for Honey Analysis

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**Abstract**—The high demand for genuine honey leads to fraud practices in the market which have disadvantaged top graded genuine honey production. The conventional chemical analysis procedures are usually used to ensure the quality and authenticity of honey. Yet, some drawbacks, such as time-consuming, laborious, invasive and required complex sample preparation, in the chemical approaches make the optical spectrum based honey analysis an advantageous alternative method. This paper reports a comprehensive survey of peer-reviewed articles in honey analysis using spectroscopy techniques. The technologies, features, and preprocessing and prediction methods from the observed articles have been discussed to give an overview about optical spectrum approaches for honey analysis. This paper quickly introduces researchers to modern honey analysis research.

## I. INTRODUCTION

Optical spectrum based food analysis is a modern approach which provides contact-less, non-invasive, fast, and fully automatic methods with minimum sample preparation. Those characteristics give answers to the drawbacks of conventional chemical methods which are time-consuming, laborious and required complex sample preparations. Optical spectrum, which can be captured by spectrometers, is basically optical information showing the energy distribution in a particular range of wavelengths [1]. Different spectral responses from different materials introduce material fingerprints for prediction purposes. Chemistry analysis methods called *chemometrics* usually is used to do the prediction based on multivariate statistics, mathematical modeling and machine learning [2]. The utilization of chemometrics methods in spectral data makes superiority of optical spectrum based approaches compared with conventional methods.

Honey, which is an important commodity in market, has become a research focus in optical spectrum based analysis. The high demand of honey makes it a big business in food industry. Fig. 1 show upward trend of production and price of honey over years in New Zealand [3]. Indeed, this situation leads challenges for the honey industry to deliver good quality honey products.

This paper presents a comprehensive survey in honey analysis using the spectroscopy techniques and chemometric through an observation of peer-reviewed scientific journals. There was 61 papers in total recorded from 1998 to 2015 (Appendix A). The discussion about technology, features and methods in the honey analysis gives insight to researchers

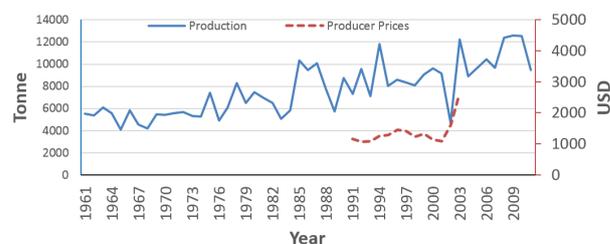


Fig. 1: Honey production from 1961 to 2011 and producer prices from 1991 to 2003 in New Zealand.

about state of the art methodologies in optical spectrum based honey analysis.

## II. RESEARCH AIMS IN OPTICAL SPECTRUM BASED HONEY ANALYSIS

In general, optical spectrum based honey analysis can be classified into two major groups, which are constituents prediction and types classification. Research aims were recorded from each research articles to investigate the trend. In case of more than one objective in an article, all objectives mentioned in the article would be recorded.

More than half studies were focused to differentiate many types of honey. Types of honey could be based on its botanical origin [4–20], geographical origins [15, 16, 21–27], authenticity (adulterated honey or not) [4, 7, 28–40] and brand identification [11]. The botanical origin and authenticity determination were the two most popular research focuses. A part from types classification, there were also studies which focused on visualization of the data, such as [5, 41–44].

Almost 40% of the studies investigated constituents prediction, such as Methylglyoxal and antibacterial activity [45]; Melissopalynological characteristics and mineral composition [46], Glucose [43, 47–56], Fructose [47–56], Melezitose [47], Turanose [47, 52], Maltose [47–49, 51, 52, 55], Sucrose [48, 49, 51–53, 55–57] electrical conductivity [5, 52, 58], Pollen vectors [5], rice syrup adulterant [59], sugar syrups adulterant [60], jaggery syrup adulterant [61], Corn syrup adulterant [25, 53], High Fructose Corn Syrup (HFCS) adulterant [25, 32], invert sugar adulterant [25, 38], inverted beet syrup (IB) adulterant [32, 40], antioxidant compounds [62], Tetracycline (drug residues) [63], water content [58], pH [52, 58], HMF [55, 58], Ash [58], Colour [58], Trehalose

[52], Isomaltose [52], Erlöse [52], Moisture [52, 54–56], free acidity [52, 55], Proline [52], Invertase [52], Polarimetric Parameters [57], cane invert adulterant [40], and Lactone [55]. It can be seen clearly that Fructose and Glucose, which are two major components of honey [64], were the two most popular research focuses in the constituent prediction.

### III. SPECTROSCOPY FOR HONEY ANALYSIS

Spectroscopy which literally means *Ghost Watcher* from Latin and Greek words, gives foundation to the spectroscopic method and refers to a study related with interaction between matter and energy [65]. The responses from this interaction are used to determine a fingerprint of a particular object. The spectroscopy techniques used in honey analysis are listed below:

- **Ultraviolet (UV), Visible-Near Infrared (VIS-NIR) and Infrared (IR) spectroscopy**  
UV, VIS and IR spectroscopies work with a same principle measuring the energy differentiation when molecules transit from one vibrational or rotational energy state to another state as interaction between matter and energy [65]. A difference among them is in wavelength regions. The UV spectroscopy works in the UV region which can be divided into far UV (10-200nm), and near UV region (200-350nm). The VIS-NIR spectroscopy works on the visible region (350-800nm) and near infrared region (800-2500nm). The IR spectroscopy works on the infrared region which can be divided into three sub-regions; Near-Infrared (NIR) covered  $12,800 - 4000\text{cm}^{-1}$ , mid-infrared (MIR) covered  $4000 - 200\text{cm}^{-1}$  and far-infrared covered  $200 - 10\text{cm}^{-1}$  [65, 66]. Now days, Fourier transform (FT) spectrometer is more often used in Infrared (IR) spectroscopy (FT-IR, FT-NIR or FT-MIR) than the previous dispersive type spectrometer. The FT spectrometer has better signal-to-noise ratio, larger energy throughput, multiplex advantage, and wavelength precision than the dispersive spectrometer [65, 67]. Attenuated total reflectance (ATR) based on internal reflectance measurement is a sampling technique which is considered to have faster and simpler sample preparation than others and also can handle many form of objects including liquids, semi-solids, polymers, powders, and solids [67]. It is reasonable if a lot of researchers used the ATR-FT Spectrometer for honey analysis.
- **Raman spectroscopy**  
Raman spectroscopy is a vibrational spectroscopy and working in a similar wavelength range as the IR spectroscopy. Raman and infrared spectroscopy complement each other. Raman spectroscopy uses symmetric vibration and infrared spectroscopy uses asymmetric vibrations [68]. Raman spectroscopy can uses Fourier transform spectrometer also, which is called FT-Raman, which has the similar advantages with FT-IR [65].
- **Fluorescence spectroscopy**  
Fluorescence spectroscopy is quiet different with the two previous spectroscopy methods in terms of principles

and also wavelength ranges. Fluorescence spectroscopy is related with phenomena of photon emission during transition of electrons from excited states to ground states which happens in the ultraviolet-blue-green region [69]. The fluorescence spectral data is recorded in two-dimensional data according to the excitation and emission spectra [70]. The front-face technique is intended to examine original objects without prior sample preparation through measuring exiting and emitted light from the same cuvette face [71].

The survey of the spectroscopy methods is shown in Fig. 2. Fourier Transform Infrared Spectroscopy dominated with more than 34% articles and the Near Infrared spectroscopy was in the second place with more than 26% articles.

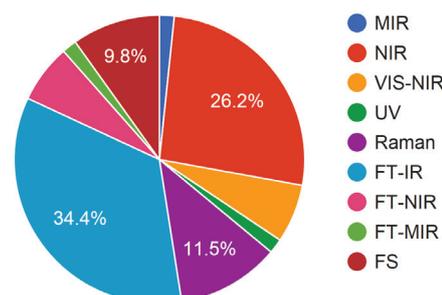


Fig. 2: The spectroscopic methods of the 61 studies listed in Appendix A.

The comparison among all spectroscopic techniques has not been done for honey analysis. However, Ruoff, Kaspar, et al. in 2006 wrote three different articles investigated NIR [17], MIR [16] and Fluorescence spectroscopy [15] to classify botanical origins of honey using relatively same samples and methodologies. It can be concluded from direct comparison of those three paper that the fluorescence spectroscopy was the best among the others.

### IV. PREPROCESSING METHODS

Almost all researchers used preprocessing or pretreatment techniques prior learning processes. A preprocessing step is needed because multi or hyperspectral data generally contains noise. The common data pretreatment methods for optical spectrum data are baseline correction, scattering correction, smoothing and normalization.

Standard Normal Variate (SNV) and De-trending (DT) are the most common baseline correction methods. SNV tries to eliminate different slopes among samples with same constituents which may occur because of different particle size [72]. DT standardizes the spectra responses from offset and curvilinearity through an elimination using a general trend which can be calculated with a particular curve-fitting model [73]. DT can correct the baseline spectra and keeps the original pattern of particle size characteristic [72]. Other baseline correction methods are offset method using linear baseline subtraction and adaptive iteratively reweighted Penalized Least Square (airPLS) which a complex baseline will

be approximated using an iterative procedure and smoothness of the baseline will be determined using a penalty item [74]. airPLS is different from the other methods because it preserves small peaks.

Multiplicative Scatter Correction (MSC) is the only scattering correction method mentioned in the observed articles. MSC deals with phenomenon of light scattering which can lead to wrong spectral responses because of absorbance shift [75]. MSC uses intercept and slope properties of a linear regression between a spectrum and an average of an ideal spectrum from calibration set to correct an original spectrum [76].

Smoothing can efficiently remove random noise in the form of small fluctuations because of unknown low frequencies. Savitzky-Golay (S-G) smoothing fits original data points in a particular curve [77]. Another way to get a smoother spectral data is by lowering resolution which the total number of bands will be reduced by averaging several adjacent bands [43].

Several normalization techniques were mentioned in the observed articles to enhance original hyperspectral signals. Area normalization basically calculates a relative area under a spectra curve to correct spectral data where a path-length is unknown [78]. The different distances for light to travel through the object (*path-length*) will lead to different spectral responses according to Beer's law [79]. Autoscaling or unit variance scaling normalizes major and minor peaks in spectral data. Spectral data will be divided by a standard deviation from a training set after a mean-centering process [78]. Vector normalization is a normalization procedure based on an unit vector where the mean-centered original spectra is divided by a square of sum of each band in mean-centered original spectra squared [80]. Maximum normalization converts each spectral data in a range of 0 to 1 by dividing the spectral data by the maximum absolute value of the wavelength responses [81].

Almost half of the observed papers did performance comparison among preprocessing methods. However a firm conclusion could not be drawn because different papers used different set of preprocessing methods and concluded different best performance methods. It leads that the performance of preprocessing methods are vary for different samples, instruments and settings. It is highly recommended that each research work explores the best pretreatment methods based on their own configurations.

## V. FEATURE SELECTION

Usually, spectral data needs to be transformed into different features to get better predictive power because the original spectral normally contains noise or overlapping information. The common feature extraction strategies in the observed articles are derivative spectral data, reduced spectral data and selective spectral data.

The derivative of the original spectral data produces more sensitive spectral to minor features [82]. The original spectra could be transformed to the first and second derivative spectral. Savitzky-Golay (S-G) algorithm is not only very common for

smoothing but also the most common method to approximate derivative spectral data.

A transformation of spectral data into more compact features is also very common because spectral data is a high dimensional data which most of the recorded values are not informative or high correlated to each other. The feature reduction techniques are very important to visualize the data and also make more robust predictors. Feature reduction techniques used in the observed studies were Principal Component Analysis (PCA), Partial Least Square (PLS), PARALLEL FACTOR analysis (PARAFAC) modeling, and Wavelet coefficient. PCA has been used by around 80% of the observed articles utilizing feature reduction techniques. PCA uses the variance as a measurement for data separation. Actually, higher variance does not guarantee better discrimination power as depicted in Figure 3.

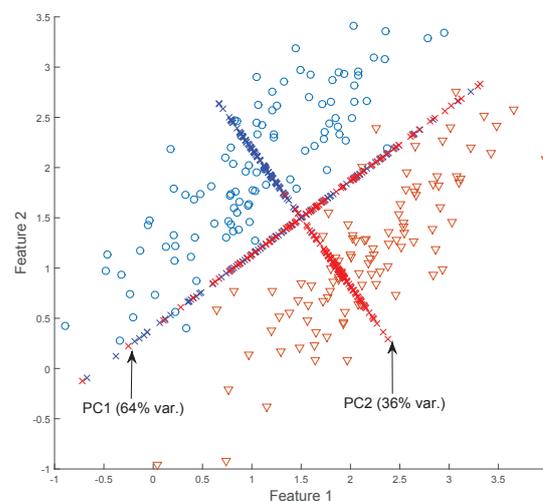


Fig. 3: The projection into PC 2 (36% of variance) has much better separation than projection into PC 1 (64% of variance).

Another strategy to prepare features is to select the most related bands to the targeted classes. Spectral selection techniques apparently were not quite popular to be explored. It may be because there was a firm research about relation between chemical constituents and related bands. For example, Glucose is observed at 1145, 1105, 1077, 1047, 1017 and 992  $cm^{-1}$  [66]. Only four articles utilized feature selection techniques which are Fisher Ratios [22], PCA [7, 13] and Marten's Uncertainty Test [24].

More than 85% of the observed papers did not explore and compare the performances of features. A few papers which compared features also concluded the different best features and some of them had an opposite result. Features exploration is very important in classification problems which a good feature will perform very well even with a very basic classifier.

## VI. PREDICTORS BASED ON HIDDEN FEATURES

As can be seen from CC (Classification) and R (Regression) section in Appendix A, predictors based on hidden features

were commonly used to build prediction models in honey analysis. These predictors use transformed independent variables instead of original independent variables, to determine discrete or continuous targeted outputs. Projection of original spectral data from one to another space might be necessary to reduce noisy and to omit unnecessary information.

The predictors used in the observed studies were Soft-Independent Modeling by Class Analogy (SIMCA) which is based on Principal Components, Linear Discriminant Analysis (LDA), Partial Least Square (PLS), Canonical Variate Analysis (CVA), Artificial Neural Network (ANN) and Support Vector Machine (SVM). The comparison of the methods according to the number of usages is shown in Figure 4. Indeed, PLS based predictor has been the most widely successful method for both regression and classification problems.

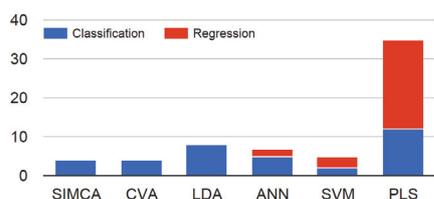


Fig. 4: The predictors from the 61 recorded publications.

A same story with exploration of preprocessing method; there were almost 40% of papers which compared some predictors. Although most of them concluded that the PLS method was better than others, the performance of classifier is highly determined by the characteristics of data which is affected by samples, instruments and settings. The exploration of classifier methods for a specific configuration is highly recommended.

## VII. PERFORMANCE EVALUATION

A proper choice of performance evaluation indicators will firmly convince readers and also be easier to be compared with other performances. In case of classification problems, one possible way to report a result is using overall correct classification accompanied by Cohen's kappa. Cohen's kappa ( $\kappa$ ) is a coefficient of agreement between two predictors where 1 is the perfect agreement and below 0 is zero agreement [83]. Others possible measurements are sensitivity and specificity which measure the portion of positive and negative identified results in two classes (binary) classification problem. Sensitivity and specificity can be extended for a multi-class classification problem as discussed in [84].

In the case of regression problems, common performance evaluation indicators are correlation coefficient ( $r$ ) or correlation of determination ( $r^2$ ).  $r$  can be explained as an association between a ground-truth and a predictor's output which is from -1 (strong negative correlation) to +1 (strong positive correlation); 0 means no correlation.  $r^2$  can be interpreted as strength of a linear association or proportion of variable's variance that can be correctly predicted.

## VIII. CONCLUSIONS

In this paper a survey of technologies, features and methods for honey analysis based on optical spectrum have been depicted. The aim of honey analysis can be classified into two groups. These are: types determination (majority in botanical origin and authenticity determination) and constituents prediction (majority in Fructose and Glucose prediction). Spectroscopy with chemometric has shown promising results for honey analysis with many advantages over the conventional methods. FT-IR Spectroscopy has been dominantly used as a spectral capturing technology. Baseline and scattering correction have become common pretreatment strategies to ensure correctness of spectral responses. PCA, as a dimensionality reduction technique, has been dominating to reduce an original spectral for data visualization and increasing predictors' performances. Performance of prediction methods could not be directly compared among different studies because it depends on experimental set ups which are normally different. However, PLS based predictors have been recorded as successful predictors in the majority of studies. Finally, the choice of performance evaluation indicators is very important for the development of honey analysis research.

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APPENDIX A SUMMARY OF 61 OBSERVED STUDIES ABOUT OPTICAL SPECTRUM BASED HONEY ANALYSIS.

Note: PP: Preprocessing, FR/S: Feature Reduction/Selection, CC: Classification/Clustering, R: Regression D: to determine types, P: to predict constituents, V: to visualize, Spec.: Spectroscopy, FS: Fluorescence, FF-FS: Front-face Fluorescence, ex: Excitation, em: Emission,  $a\text{ cm}^{-1} = 10^7/a\text{ nm}$ , ID: 1<sup>st</sup> derivative, 2D: 2<sup>nd</sup> derivative, AN: Area Normalization, BC: Baseline Correction, As: Autoscaling, Vn: Vector normalization, Mn: Maximum normalization, Avg: Averaging bands, Om: Offset method, S-G: Savitzky-Golay smoothing, MC: Mean Centering, SIMCA: Soft-Independent Modeling by Class Analogy, LDA: Linear Discriminant Analysis, PLS-DA: Partial Least Square Prediction - Discriminant Analysis, BP-ANN: Back-Propagation Artificial Neural Network, SVM: Support Vector Machine, LS-SVM: Least Square SVM, CVA: Canonical Variate Analysis, DUS: Discriminant based Univariate Split for Trees based classifier, PLSR: Partial Least Square Regression, MPLSR: Modified PLSR algorithm, MLR: Multiple Linear Regression, HCA: Hierarchical Cluster Analysis, LV: Latent Variable, PC: Principal Component, RSQ: multiple correlation coefficient, RPD: Ratio of Performance to Deviation, AUC: Area Under Curve, ?: unknown.

No	Citation	Year	Aim	# of Samples	Spec.	Range	Methods				Features	Results
							PP	FR/S	CC	R		
1	Sultambawa, Yasmina, et al. [45]	2015	P	144	ATR-MIR	4000-375 $\text{cm}^{-1}$		PCA		PLSR	$r^2 = 0.63-0.75$	
2	Escuredo, Olga, et al. [46]	2015	P	60	NIR	1100-2498nm	ID or 2D MSC DT SNV	PCA		MPLS	RSQ= 0.778 - 0.971	
3	Lenhardt, Lea, et al. [4]	2015	D	95	FF-FS	Em:270-640nm Ex:240-500nm		PARAFAC	PLS-DA	6 factors	Fake vs authentic: sens. =1 spec. =1 Botanical origins: sens. & spec. > 0.8	
4	Anjos, Ofilia, et al. [47]	2015	P	63	ATR-FTIR	4000-450 $\text{cm}^{-1}$	ID MSC SNV			PLSR	mostly $r^2 > 80\%$	
5	Corvucci, Francesca, et al. [41]	2015	V	308	Raman	3500-200 $\text{cm}^{-1}$	AN BC As	PCA			Reasonable separation	
6	Gok, Seher, et al. [42]	2015	V	144	ATR-FTIR	4000-650 $\text{cm}^{-1}$	Vn ID	PCA	HCA		Heterogeneity value: up to 10	
7	Svenjak, Lidija, et al. [5]	2015	V	506	ATR-FTIR	3700-600 $\text{cm}^{-1}$	S-G MSC	PCA			3700-600 $\text{cm}^{-1}$ For some types, a clear cut with some outliers was found.	
			D					PLS-DA		1800-700 $\text{cm}^{-1}$ 100% correct classification		
			P					PLSR		1800-700 $\text{cm}^{-1}$ & 3700-600 $\text{cm}^{-1}$ Electrical conductivity: $r^2 = 0.987$		
			P+D	84				LDA		PLSR	pH: $r^2 = 0.939$ - 2 of 6 components; $r^2$ from 0.66-0.7. - 100% correct classification	
8	Lenhardt, Lea, et al.[6]	2014	D	130	ATR-FTIR	4000-500 $\text{cm}^{-1}$	S-G	PCA	SVM	22 PCs	98.6% success classification	
9	Lenhardt, Lea, et al. [7]	2014	D	109	FF-FS	Em:30-300nm Ex:240-500nm		PCA for feature selection	PLS-DA		8 LVs; Em:160nm Ex:240-500nm; Sens. and Spec. >0.9	
										7 LVs; Em: 215nm Ex: 240-500 nm Sens. and Spec. >0.99		
10	Chen, Quansheng, et al. [59]	2014	P	164	FS	Em:250-750nm Ex:200-580nm		PCA		BP-ANN	$r = 0.9787$	
11	Mouazen, Abdul M., and Noura Al-Walaan. [43]	2014	V	60	VIS-NIR	305-2200nm	Mn Avg Om ID S-G	PCA			PCI, PC2 Good separation	
			P	345						PLSR	340-2148nm ? LVs RPD=2.06 (good model prediction)	
12	Latorre, C. Herrero, et al. [21]	2013	D	30	NIR	4000-9000 $\text{cm}^{-1}$	SNV	PCA	ANN	10 PCs	Sens. = 1.0; Spec. = 0.933	
13	Liang, Xiu Ying, Xiao Yu Li, and Wen Jun Wu. [8]	2013	D	147	NIR	4000-10000 $\text{cm}^{-1}$	S-G	PLS	ANN	5 LVs (5303-6591 $\text{cm}^{-1}$ )	100% correct classification	
14	Ozbalci, Beril, et al. [48]	2013	P	90	Raman	200-2000 $\text{cm}^{-1}$	BC			ANN	$r > 0.95$	
15	Roshan, Abdul-Rahman A., et al. [9]	2013	D	38	UV	200-400nm				SIMCA	interclass dist. = 380 discriminant power > 3 modeling power > 0.8	

16	Escuredo, Olga, et al. [62]	2013	P	60	NIR	1100-2798nm	MSC			MPLS	? LVs	mostly RPD > 2.5
17	Chen, Hongqian, et al. [63]	2013	P	153	FT-NIR	12500-3600cm <sup>-1</sup>				LS-SVM	12500-3600cm <sup>-1</sup>	r = 0.6618
18	Chen, Lanzhen, et al. [10]	2012	D	250	FT-NIR	12000-4000cm <sup>-1</sup>	ID		BP-ANN		10000-4200cm <sup>-1</sup>	89.3% overall correct classification
19	Li, Shuifang, et al. [28]	2012	D	149	Raman	2600-175cm <sup>-1</sup>	airPLS As		PLS-DA		1300-300cm <sup>-1</sup>	Sens. = 0.7188; Spec. = 0.8462
20	Chen, Lanzhen, et al. [29]	2011	D	144	FT-NIR	10000-4000cm <sup>-1</sup>	ID MC		PLS-DA		10000-6000cm <sup>-1</sup>	100% correct classification
21	Svenjak, Lidija, et al. [44]	2011	V	144	FT-IR	1200-700cm <sup>-1</sup>	S-G	PCA			1200-700cm <sup>-1</sup>	good separation
22	Pierna, Juan Antonio Ferrnandez, et al. [22]	2011	D	374	Raman	3500-200cm <sup>-1</sup>	MSC	Fisher Ratio	SVM		15 bands	Sens. = 0.9373; Spec. = 0.8419
23	Rios-Corripio, M. A., et al. [60]	2011	P	?	FT-IR	4000-650cm <sup>-1</sup>			PLSR		?	r <sup>2</sup> > 0.9
24	Zhao, Xiangdong, Yong He, and Yidan Bao. [11]	2011	D	230	VIS-NIR	325-1075nm	S-G	PCA	BP-ANN		10 PCs	78.57% overall correct classification
25	Wang, Jun, et al. [49]	2010	P	37	ATR-FTIR	4000-400cm <sup>-1</sup>	2D MC		PLSR		4-11 LVs	r <sup>2</sup> = 0.948 - 0.988
26	Zhu, Xiangrong, et al. [30]	2010	D	135	NIR	10000-4000cm <sup>-1</sup>	2D SNV	WT	LS-SVM		102 Wavelet Coefficients	AUC = 0.952
27	Yang, Yan, et al. [12]	2010	D	232	VIS-NIR	346-1038nm	BC Smoothing Standardization	PCA	SVM		10 PCs	90.62% correct classification
28	Hennessy, Siobhan, Gerard Downey, and Colm P. O'Donnell. [23]	2010	D	373	ATR-FTIR	2500-12500nm	2D		PLS-DA		7 LVs	87% overall correct classification
29	Mishra, Sumita, et al. [61]	2010	P	56	NIR	1380-1960nm			PLSR		?	r <sup>2</sup> = 0.81
30	Woodcock, Tony, Gerard Downey, and Colm P. O'Donnell. [24]	2009	D	373	NIR	1100-2498nm	2D	Martens' Uncertainty Test	PLS-DA		Selected bands	Correct classification Coarctian = 90.4% Non-Coarctian = 86.3%
31	Gallardo-Velzquez, Tzayhri, et al. [25]	2009	P	235	ATR-FTIR	4000-650cm <sup>-1</sup>	ID		PLSR		4-8 LVs	r <sup>2</sup> = 0.97-0.99
32	Hennessy, Siobhan, Gerard Downey, and Colm O'Donnell. [26]	2008	D	150	ATR-FTIR	2500-12500nm	SNV		SIMCA		3 PCs	100% correct classification
33	Einar Eizold and Birgit Lichtenberg-Kraag [85]	2008	D	1,075	FTIR	5012-926cm <sup>-1</sup>		PCA	LDA		Distant between a sample and the mean of calibrated honey types	vary
34	Bertelli, D., et al. [13]	2007	D	82	FT	4000-600cm <sup>-1</sup>		PCA for feature selection	DUS		3649-2401cm <sup>-1</sup> + 1501-751cm <sup>-1</sup>	100% correct classification
35	Karoui, Romdhane, et al. [14]	2007	D	62	FS	Em:280-480nm Ex:250,290,373nm	AN	PCA	FDA		10 PCs Em: 290nm; Em: 305-500nm	90% correct classification
36	Woodcock, Tony, et al. [27]	2007	D	292	NIR	1100-2498nm	SNV		PLS-DA		5 LVs	75%-100% correct classification
37	Toher, Deirdre, Gerard Downey, and Thomas Brendan Murphy. [31]	2007	D	478	NIR	400-2498nm			PLS-DA		10-40 LVs	>90% correct classification
38	Ruoff, Kaspar, et al. [15]	2006	D	371	FS	Em:420 & 490nm & Em:220-440nm Em:220-600nm & Ex:210,270,310,350, 390,440nm		PCA	LDA		Ex: 220-440nm; Em: 420nm	91% overall correct classification Unifloral: > 90% correct classification Polyfloral: 55% correct classification
39	Kelly, J. Daniel, Cristina Petisco, and Gerard Downey[33]	2006	D	179	NIR	1100-2498nm			SIMCA		5 PCs	90.9% correct classification
			P	96					PLSR		BF: 7 LVs HFCS: 8 LVs	BF: r=0.79 HFCS: r=0.72
40	Ruoff, Kaspar, et al. [17]	2006	D	364	FT-NIR	10000-4000cm <sup>-1</sup>		PCA	LDA		20 PCs 9947-4112cm <sup>-1</sup>	45% overall correct classification Unifloral: 29-100% correct classification Polyfloral: 19% correct classification

41	Kelly, J. Daniel, Cristina Petisco, and Gerard Downey. [32]	2006	D	1380	ATR-FTIR	2500-12500nm							6 PCs 2500-12500nm	54.5% total correct classification
42	Ruoff, Kaspar, et al. [16]	2006	D	411	FT-MIR	4000-550 $cm^{-1}$	Spectral cutting 3718-631 $cm^{-1}$	PCA	LDA			20 PCs	82.65% overall correct classification Uniflora: >90% correct classification Plyfloral: 26% correct classification	
43	Batsoulis, Apostolos N., et al. [50]	2005	P	21	FT-Raman	1700-700 $cm^{-1}$						?	PLSR	Statistically equivalent with HPLC
44	Ruoff, Kaspar, et al. [18]	2005	D	57	FF-FS	Ex:250nm and Em:280-480nm Ex:290nm and Em:305-500nm Ex:373nm and Em:380-600nm Ex:290-440nm and Em:450nm	Vn	PCA	LDA				19 PCs Ex:250nm; Em:280-480nm Ex: 290; Em:305-500nm Ex:373nm; Em:380-600nm Ex:290-440nm; Em:450nm	94% overall correct classification
45	Kelly, JF Daniel, Gerard Downey, and Vanessa Fouratier [34]	2004	D	320	ATR-FTIR	4000-800 $cm^{-1}$	AN ID		PLS-DA			6 LVs	93.7% overall correct classification	
46	Tewari, Jagdish, and Joseph Irudayaraj. [51]	2004	P	112	ATR-FTIR	1500-750 $cm^{-1}$						6 LVs	PLSR	$r^2 > 0.95$
47	Downey, Gerard, Vanessa Fouratier, and J. Daniel Kelly. [35]	2003	D	300	NIR	400-2498nm	ID		PLS-DA			9 LVs	Correct classification: - Unadulterated: 96% - Adulterated: 99%	
48	Irudayaraj, J., R. Xu, and J. Tewari. [36]	2003	D	48	ATR-FTIR	1500-800 $cm^{-1}$	AN	-PCA - none	-LDA -BPNN			- 5 PCs - 1500-800 $cm^{-1}$	93.75% correct classification	
49	Cozzolino, D., and E. Corbella. [58]	2003	P	110	NIR	400-2500nm	SNV DT ID					5-12 LVs	MPLS	$r^2 = 0.61 - 0.97$
50	Lichtenberg-Kraag, Birgit, Christoph Hettke, and Kaspar Bienefeld. [52]	2002	P	1707	FTIR	5012-926 $cm^{-1}$						2971-926 $cm^{-1}$ 5-17 LVs	PLSR	$r^2 = 0.84 - 0.98$
51	Sivakesava, Sakhamuri, and Joseph Irudayaraj. [37]	2002	D	?	FTIR	?		PCA or PLS	LDA			2PCs 1500-800 $cm^{-1}$		100% correct classification for simple & complex adulteration
52	Garcia-Alvarez, M., et al. [57]	2002	P	156	NIR	400-2500nm	SNV DT ID					8-10 LVs	MPLS	mostly $r^2 > 98\%$
53	Davies, Anthony MC, et al. [19]	2002	D	51	NIR	1100-2498nm	2D	PCA	CVA			10 PCs		68% correct classification
54	Goodacre, Royston, Branka S. Radovic, and Elke Anklam. [20]	2002	D	43	Raman	3000-100 $cm^{-1}$		PCA	BP-ANN			10 PCs		93% correct classification
55	Sivakesava, S., and J. Irudayaraj. [39]	2001	P	50	ATR-FTIR	4000-800 $cm^{-1}$	ID					1500-950 $cm^{-1}$ 14 LVs	PLSR	$r^2 = 0.818$
56	Paradkar, M. M., and J. Irudayaraj. [40]	2001	P	47	FT-Raman	4000-200 $cm^{-1}$	?	PCA	CVA			10 factors 1600-200 $cm^{-1}$ 3-4 LVs	PLSR	78.4% overall correct classification $r^2 > 0.9$
57	Sivakesava, S., and J. Irudayaraj. [53]	2001	P	153	ATR-FTIR	4000-400 $cm^{-1}$	MC					10 factors	PLSR	91% overall correct classification
58	Sivakesava, S., and J. Irudayaraj. [38]	2001	P	53	ATR-FTIR	1500-800 $cm^{-1}$	AN ID		CVA			15 LVs		$r^2 = 0.824$
59	Garcia-Alvarez, M., et al. [54]	2000	P	161	NIR	400-2500nm	SNV DT ID					10 Factors 12 LVs	PLSR	78.4% overall correct classification $r^2 = 0.766$
60	Qiu, P. X., et al. [55]	1999	P	74	VIS-NIR	400-2500nm	SNV DT					7-9 LVs	MPLS	$r^2 > 0.95$
61	Ha, Jaeho, Minseon Koo, and Hyunee Ok. [56]	1998	P	126	NIR	1100-2500nm						400-2500nm 2-8 LVs	MPLS	Reliable for major components
												1100-2500nm	MLR	$r = 0.68-0.98$