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Research article

Low-cost Multispectral Acquisition Device Coupled with Machine Learning for Detecting Adulteration of Honey

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Abstract

Honey is a natural sweetener created by honeybees from the nectar of flowers. Honey's extensive health benefits have led to its widespread use across multiple industries. Honey adulteration with inferior substances undermines its quality, reducing natural nutrients and antioxidants, and diminishing its health benefits. This study aimed to study the possibility of detection of honey adulteration with a low-cost multispectral device coupled with machine learning. The adulterated honey came from deliberate adulteration with cane syrup in the 1 to 90% range. Spectral data was collected for pure honey and the adulterated honey samples at the wavelengths of 610, 680, 730, 760, 810, and 860 nm. The detection models for distinguishing pure and adulterated honey were developed by Linear Discriminant Analysis (LDA), Partial Least Squares Discriminant Analysis (PLS-DA), C-Support Vector Machine (C-SVM), and K-Nearest Neighbors (KNN). All models achieved high accuracy between 0.91 and 0.98 and maintained balanced precision and recall metrics. This study serves as a guideline for developing a low-cost portable honey authentication device that is practical for real-world applications.

Keywords: low-cost multispectral device; machine learning; honey; adulteration

1. Introduction

Honey is a naturally sweet substance made by honeybees as they process nectar collected from flowers. Primarily, chemical components of honey consist of fructose, glucose, maltose, sucrose, higher sugars, minerals, vitamins, antioxidants, etc. (Valinger et al., 2021). Due to its numerous health benefits, honey has been widely used in various fields, including foods, pharmaceuticals, cosmetics, and skincare products. Bee honey is significantly more expensive than other sweeteners like refined cane sugar and corn syrup.

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The adulteration of honey with inferior substances to increase volume and reduce costs is a crucial issue in the honey industry. Adulteration negatively impacts the quality of honey by reducing its natural nutrients and antioxidants, thereby significantly diminishing its health benefits. Therefore, many countries have implemented regulations to control the quality of commercial honey based on specific physical characteristics and chemical composition. Various methods have demonstrated the capability to accurately and reliably detect honey authentication and adulteration, including nuclear magnetic resonance (NMR) (Song et al., 2020), isotope ratio mass spectrometry (IRMS) (Xu et al., 2020), enzyme-linked immunosorbent assay (ELISA) (Naila et al., 2018), and near infrared spectroscopy (NIRS) (Bodor et al., 2023; Calle et al., 2023; Caredda et al., 2024). However, these techniques have some disadvantages such as the requirement for expert analysis and high costs per sample.

One particularly interesting piece of equipment is the low-cost multispectral sensor, the AS7263 sensor. The AS7263 spectral sensor is a remarkable low-cost multispectral device designed to capture and analyze wavelengths in the range of 610 nm to 860 nm, effectively covering both the visible spectrum and shortwave near-infrared radiation. This compact device facilitates seamless integration into portable applications, making it especially advantageous in field scenarios that do not accommodate traditional, larger spectrometers. The AS7263 sensor has found extensive application across various research domains, particularly in agriculture and food quality control. Kapse et al. (2023) reported the effectiveness of this sensor in evaluating banana maturity using the Multiple Linear Regression (MLR) method and an Artificial Neural Network (ANN) model with R^2 of 0.768 and 0.840, respectively. Wang et al. (2023) developed a portable multi-spectral instrument to detect protein and fat in milk. The prediction models were developed using the XGBoost algorithm, which demonstrated R^2 values of 0.9816 for the protein model and 0.9978 for the fat model, respectively. Furthermore, the ripeness of berries and grapes was accurately monitored using the AS7263 sensor, as reported by Wang et al. (2022) and Pampuri et al. (2021), respectively. ANN and MLR algorithms were employed to create prediction models, achieving R^2 values ranging from 0.69 to 0.86. To detect adulteration in food, Sulistyo et al. (2023) investigated the sensor's effectiveness when paired with an ANN algorithm to identify cane sugar adulteration in granulated coconut sugar, achieving an accuracy exceeding 90%. Emerging research by Lapcharoensuk et al. (2024) also investigated the AS7263's applications in detecting adulteration of onion powder. Four algorithms including MLR, partial least square regression (PLS-R), nu-support vector regression (nu-SVR), and black propagation neural network (BPNN) were utilized to train the models, achieving R^2values between 0.888 and 0.959. All the information presented above indicates that the low-cost multispectral sensor (AS7263) has potential applications for detecting adulteration in honey.

However, raw spectral data cannot be directly used to detect honey adulteration due to several factors related to the sensor’s capabilities, measurement characteristics, and data collection, such as the complex patterns of reflectance signals, environmental variability, and high dimensionality. Therefore, chemometric and machine learning (ML) techniques are essential for accurately analyzing and interpreting the insights provided by spectral data. ML is a branch of artificial intelligence (AI) focused on developing algorithms that allow computers to learn from and make predictions based on data. Rather than being explicitly programmed with specific rules for each task, a machine learning model identifies patterns within data. This capability enables it to make decisions or predictions independently. Currently, ML algorithms have been applied to spectral data from various instruments including NIR spectrometers, FTIR (Fourier-transform infrared) spectrometers, and Raman spectrometers, as well as the AS7263 sensor in the detection of food adulteration.

Although the AS7263 sensor has been successfully applied in agricultural and food analysis. However, there is currently no published research specifically investigating its use for detecting honey adulteration. Previous research was largely focused on food items (e.g., milk, fruits, sugars and spices) and highlights a clear gap in the application of low-cost spectral sensing to chemically complex substances like honey. Furthermore, existing research has predominantly focused on the utilization of basic regression or classification algorithms such as MLR and ANN. However, a comparative analysis of multiple machine learning algorithms optimized for classification tasks—such as LDA, PLS-DA, C-SVM, and KNN—has not yet been explored in this context. Thus, this study builds upon prior work by shifting the focus to honey and expanding the methodological scope with a systematic comparison of ML models tailored to classify adulterated versus pure samples using the low-cost multispectral acquisition device.

To date, there have been no published reports concerning the use of the AS7263 sensor coupled with ML algorithms in the analysis of honey adulteration. Therefore, the objective of this work was to study the possibility of detection of honey adulteration with a low-cost multispectral device (AS7263). Key contributions of this study include: 1) the design of an appropriate sample holder for honey spectral scanning, 2) the integration of spectral data with advanced machine learning algorithms such as LDA, PLS-DA, C-SVM, and KNN, which allows for a comparative evaluation of classification performance in distinguishing pure from adulterated honey, and 3) the development of models through careful optimization of input features and hyperparameter tuning to enhance classification accuracy. Moreover, the combination of a compact and affordable sensor with open-source ML tools demonstrates the feasibility of creating an accessible system which is portable and suitable for real-time and on-site quality screening. This approach is especially beneficial for small producers, sellers, and regulatory agencies. The successful application of AI-driven analysis with low-cost hardware highlights the potential for scalable solutions in food quality assurance and the advancement of smart agriculture.

2. Materials and Methods

2.1 Pure and adulterated honey sample

Ten honey samples from the same brand were gathered from ten different local supermarkets across Bangkok, Thailand, with each supermarket providing a single sample. Each pure honey brand was divided into 10 samples for spectral data collection, which were indicated as 0% adulteration. In this study, cane syrup was used as an adulterant material. Twelve adulteration levels, specifically, 1%, 2%, 3%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% (w/w) were prepared by mixing various doses of cane syrup with every pure honey brand in a beaker. Each sample was carefully weighed to a total of 100 g using a high-precision electronic balance with a 0.001 g resolution. The blended samples were thoroughly mixed using a magnetic stirrer for 30 min. Total samples for spectral data collection were 220 samples (i.e., 100 and 120 samples for pure honey and adulterated honey, respectively). After thorough mixing, all samples were kept at room temperature and then used for spectral data collection.

2.2 Multispectral acquisition device

The pure honey, cane syrup and adulterated samples were separately placed in a vial after which spectral data was collected using the low-cost multispectral device. The spectral sensor (SparkFun AS7263, Sparkfun Electronics, Colorado, USA) was connected to a microcontroller broad (Arduino Uno R3). The Arduino board acted as an interface between the sensor and the computer. The absorbance value of each sample from the AS7263 sensor was relayed to the computer. The Arduino board also powered and managed the sensor's functions by controlling the scanning process. The computer laptop was used to process and visualize the data from the sensor via the Arduino IDE software (Version 1.8.19). Figure 1 shows a schematic diagram of components used for the low-cost spectral acquisition device. The sensor can collect reflectance values in the visible and near-infrared spectrum, specifically at wavelengths of 610, 680, 730, 760, 810, and 860 nm. Each of these bands features a full-width half-maximum (FWHM) detection width of 20 nm. Each sample was poured into a glass vial, and an aluminum reflector was put in the vial. The vial was then inserted into the sample holder for spectral data scanning. Figure 2 shows the design of sample socket for the low-cost spectral acquisition device. An average spectrum for each sample was generated by averaging the data from 10 scans. All spectral data was collected at a controlled room temperature of 25°C. Each spectral scanning may have been affected by several factors, including slight inconsistencies in sample placement, fluctuations in ambient conditions, and sensor noise. In addition, adulterated samples may not have been fully homogenized after mixing, which could have led to variations in spectral characteristics due to uneven component distribution. These issues highlighted the need for 10 scans per sample to reduce spectral data variability.

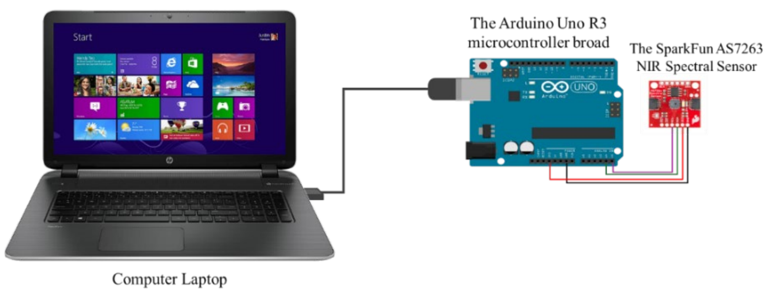


Figure 1. Schematic diagram of components used for the low-cost spectral acquisition device

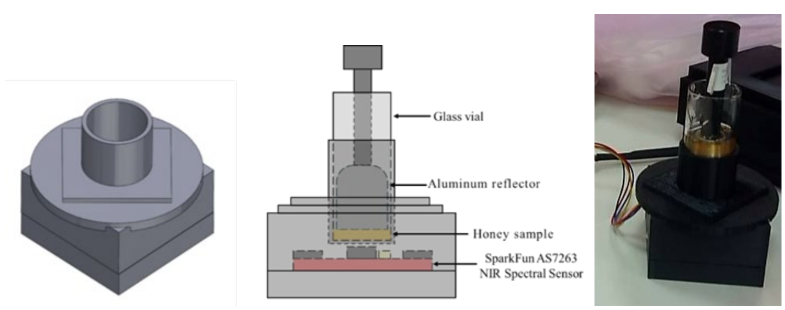


Figure 2. Design of the sample holder for the low-cost spectral acquisition device

2.3 Precision test of the sensor

The precision of the low-cost multispectral device scanning capability was assessed by examining its repeatability and reproducibility parameters. Repeatability and reproducibility were evaluated according to the method outlined by Pornchaloempong et al. (2022) with necessary modifications made to fit the specific conditions of this study. To analyze repeatability, the Vis-NIR spectral data of the pure honey sample was scanned 10 times in the same position, providing a measure of the reliability of the low-cost multispectral sensor (Williams et al., 2019). Reproducibility was assessed by repeatedly scanning the Vis-NIR spectral data of a 50% adulterated honey, collecting ten readings while reloading the sample each time. Reproducibility assesses the stability and consistency of the blended adulterated honey, ensuring that the spectral readings are uniform across repeated tests. The reliability of the measurement process was assessed by analyzing repeatability and reproducibility through the mean and standard deviation of absorbance values across all wavelengths.

2.4 Data analysis

The mean and standard deviation of the absorbance values at each wavelength were calculated to assess the overall distribution and variability of the spectral data. This step provided a quantitative understanding of how the absorbance values were distributed across the spectral range. A T-test was conducted to compare the mean absorbance values between the two groups: pure honey and adulterated honey. The T-test was applied with a 95% confidence interval to determine the statistical significance of any observed differences between the two groups. Evaluation of the p-value obtained from the T-test facilitated the determination of whether the observed differences in absorbance values resulted from random variation or constituted statistically significant distinctions between the sample groups. This approach enabled more informed conclusions to be drawn regarding the impact of adulteration on the spectral properties of honey. The use of the T-test ensured that any differences observed in absorbance values were both reliable and meaningful in terms of their potential to differentiate between pure and adulterated honey.

2.5 Principal component analysis

Principal Component Analysis (PCA) is a mathematical technique used for dimensional reduction and cluster analysis. A dataset with numerous variables can be simplified by converting them into a smaller number of independent variables called principal components (PCs). These PCs retain the most significant variance from the original data, making analysis more efficient. For clustering, PCA is particularly helpful because it can provide clear visualizations by plotting the scores of the first few PCs (PC score plots). This allows similar samples to be grouped together, making it easier to identify patterns, clusters, and outliers within complex datasets. Additionally, the X-loading plot was analyzed to illustrate the contribution of each wavelength to the principal components, specifically pinpointing those wavelengths that most significantly impacted the clustering between pure and adulterated honey. The PCA function from the Scikit-learn library was used to compute principal component (PC) values up to the third principal component (from PC-1 to PC-3).

2.6 Machine learning modeling

Spectral data was pre-processed to minimize unwanted influences, such as baseline shifts, light scattering, and variable noise levels before model development. Two sequential preprocessing techniques were applied to the raw spectra: Multiplicative Scatter Correction (MSC) to minimize light scattering effects, followed by Mean Normalization (MN) to standardize the data for consistent model training (Lapcharoensuk & Moul, 2024). The detection models for distinguishing pure and adulterated honey were developed by LDA, PLS-DA, C-SVM, and KNN. These algorithms represent both linear and non-linear classification approaches, allowing for a comprehensive evaluation of model performance under different data characteristics. LDA and PLS-DA are commonly used in chemometric analysis due to their efficiency in handling high-dimensional and collinear data, while C-SVM provides the ability to model non-linear decision boundaries, which is beneficial in complex classification tasks. KNN was included as a widely recognized, non-parametric method that offers a straightforward yet effective approach for spectral classification. The dataset was randomly split into training and testing sets, with 176 samples used for training and 44 samples for testing, corresponding to 80% and 20% of the total samples, respectively. This split was performed using the train_test_split function in the Scikit-learn platform. The training set was used to develop detection models, where optimal hyperparameters for each algorithm were identified and fine-tuned using the GridSearchCV function from the Scikit-learn library (Pedregosa et al., 2011). This approach enabled systematic testing of various parameter combinations to improve model accuracy and performance. The procedure was carried out as follows: (1) Tailored value ranges for each classifier (LDA, PLS-DA, C-SVM, and KNN) were defined based on a literature review, domain expertise, and preliminary experiments as presented in Table 1. (2) GridSearchCV was then employed to systematically explore all combinations of these values using a 10-fold cross-validation strategy to ensure robustness and generalizability. (3) The highest accuracy and shortest fitting time were used as key metrics with the configuration yielding the highest average accuracy across folds selected as optimal. (4) The models were subsequently retrained on the complete training dataset using these optimal parameters and evaluated on the test set to confirm performance and assess potential overfitting. This process involved exhaustive fine-tuning to achieve a balance between accuracy, precision, recall, and generalization, ensuring robust detection and classification. Model performance was evaluated using confusion matrix, accuracy, precision, recall and F1- score. These parameters are calculated as follows:

$$\text{accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{precision}=\frac{TP}{TP+FP} \tag{2}$$

$$\text{recall}=\frac{TP}{TP+FN} \tag{3}$$

$$\text{F1-score}=\frac{2\times\text{precision}\times\text{recall}}{\text{precision}+\text{recall}} \tag{4}$$

where the value of TP (True Positive) indicates a sample of pure honey that was accurately identified as pure, whereas TN (True Negative) represents an adulterated honey sample that was correctly classified as adulterated honey. Conversely, a false positive (FP) indicates a sample that was incorrectly classified as adulterated honey when it was pure honey, while a false negative (FN) denotes a pure honey sample that was mistakenly identified as adulterated honey.

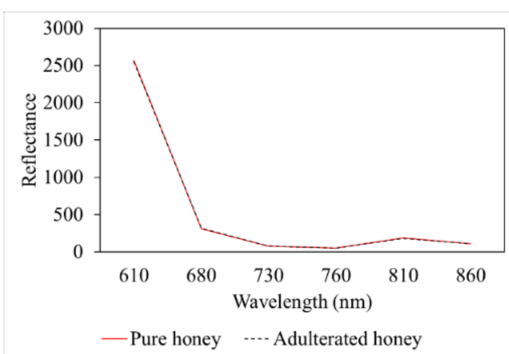
Table 1. Predefined parameters for fine and turning

Algorithm	Hyperparameter	Tailored value ranges
LDA	solver	svd, lsqr and eigen
PLS-DA	n_components	range from 1 to 20 with a step of 1
C-SVM	Kernel	linear, poly, rbf and sigmoid
	degree	range from 2 to 7 with a step of 1
	coef0	range from 0 to 0.3 with a step of 0.1
	gamma	range from 0.01 to 1.00 with a step of 0.01
KNN	n_neighbors	1, 3, 5, 7 and 9

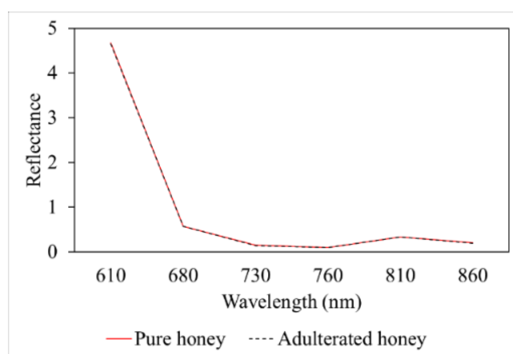
3. Results and Discussion

3.1 Spectral data

The raw and preprocessed spectra of pure and adulterated honey are shown in Figure 3. The spectral of pure honey and adulterated honey exhibited similar characteristics in both the raw spectra and the pre-processed spectra. This similarity emphasized the difficulty of distinguishing pure from adulterated honey using spectral data alone. Advanced computational methods, particularly machine learning, are essential for effectively identifying subtle variations. However, a comparison of the mean absorbance values at different wavelengths revealed statistically significant differences at all wavelengths except at 860 nm (Table 2). This finding point indicated the feasibility of pure and adulterated honey detection using spectral data obtained from the low-cost multispectral sensor.



(a)



(b)

Figure 3. Raw (a) and preprocessed (b) spectra of pure and adulterated honey

3.2 Precision test of the sensor

Table 3 presents the precision results of the low-cost multispectral sensor. The repeatability values across all wavelengths ranged from 0.001 to 0.008, while reproducibility values varied between 0.006 and 0.026. The repeatability values were lower than the reproducibility values at all wavelengths. In spectral scanning processes, repeatability is often lower than reproducibility due to increased variability under different conditions. This observation indicates that the sensor may be influenced by inherent noise or fluctuations, underscoring the critical need for rigorous preprocessing of spectral data to enhance its reliability and quality for subsequent modeling.

Table 2. Absorbance of pure and adulterated honey

Wavelength (nm)	610	680	730	760	810	860
Pure honey	4.669±0.007[a]	0.570±0.003[a]	0.147±0.007[a]	0.092±0.009[a]	0.340±0.007[a]	0.200±0.007[ns]
Adulterated honey	4.655±0.002[b]	0.576±0.002[b]	0.144±0.002[b]	0.092±0.007[b]	0.334±0.005[b]	0.199±0.007[ns]

Note: Mean values that share the ns in a column are not significantly different ($p > 0.05$); mean values that show the difference letter in a column are significantly different ($p \leq 0.05$).

Table 3. Precision test of the low-cost multispectral sensor

Wavelength (nm)	610	680	730	760	810	860
Repeatability	0.001	0.008	0.003	0.003	0.004	0.002
Reproducibility	0.007	0.026	0.006	0.009	0.006	0.007

3.3 Principal component analysis

PCA was applied to the preprocessed spectral data to effectively cluster pure and adulterated honey. The first three PCs collectively explained 99.99% of the total variance in the dataset, with PC1, PC2 and PC3 for 99.73%, 0.24%, and 0.02%, respectively. The first three principal components (PC1, PC2, and PC3) demonstrated the strongest separation, as illustrated in the 3D score plot (Figure 4). The pure honey samples were distinctly positioned on the left side of PC1, whereas all adulterated honey samples were located on the right side of PC1. This observation indicated the capability of PCA in clustering and distinguishing between pure and adulterated honey by visualization and interpretation of complex spectral variations with clarity.

3.4 Performance of machine learning

The performance of four machine learning algorithms including LDA, PLS, C-SVM, and KNN on both the training and test datasets for detecting pure and adulterated honey are presented in Table 4. All models demonstrated high effectiveness in detecting pure and adulterated honey which achieved test set accuracies ranging from 0.91 to 0.98. The KNN model showed the highest performance with superior generalization (test set accuracy of 98%) and balanced precision-recall metrics. These findings emphasized the performance of machine learning models (LDA, PLS-DA, C-SVM and KNN) in accurately identifying between pure and adulterated honey with minimized classification errors. Figure 5 presents the confusion matrix for test sets from LDA, PLS-DA, C-SVM and KNN.

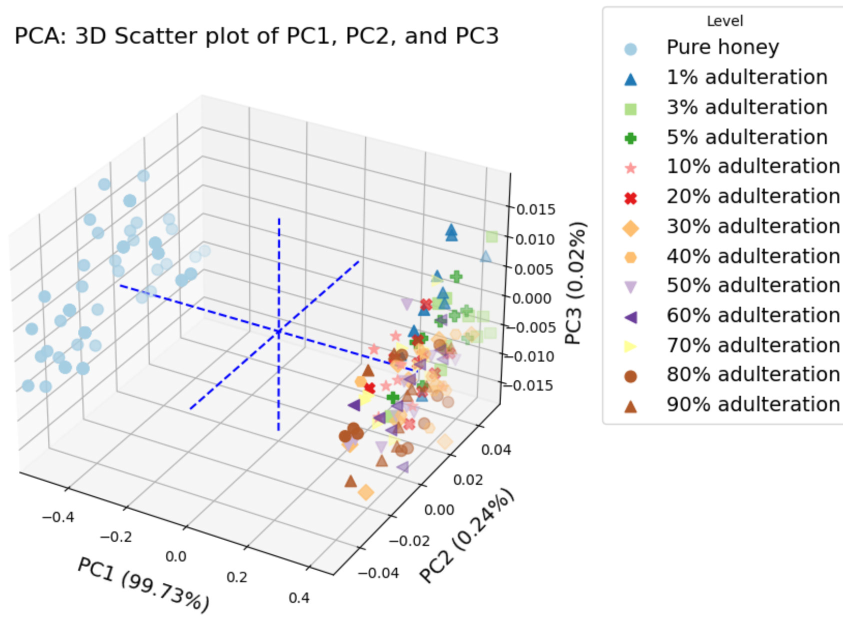


Figure 4. PC1, PC2 and PC3 score plots

Table 4. Results of pure and adulterated honey detection with ML models

Estimator	Optimal Hyperparameter	Training Set				Test Set			
		Acc	Pre	Rec	F1	Acc	Pre	Rec	F1
LDA	solver = svd	0.93	1.00	0.84	0.92	0.93	1.00	0.82	0.90
PLS-DA	n_components = 5	0.93	1.00	0.84	0.92	0.93	1.00	0.82	0.90
C-SVM	kernel = poly, degree = 7, coef0 = 0, gamma = 0.09	0.91	1.00	0.81	0.89	0.91	1.00	0.76	0.87
KNN	n_neighbors = 1	0.96	0.95	0.96	0.96	0.98	0.94	1.00	0.97

Note: Acc - accuracy; Pre - precision; Rec - Recall; F1 – F1-score

3.5 Discussion

This study demonstrated the successful integration of a low-cost multispectral sensor (AS7263) with ML algorithms (LDA, PLS-DA, C-SVM, and KNN) for the effective detection of adulterated honey. Conversely, previous studies were focused on employing more expensive and complex spectroscopic techniques such as NIR (Guelpa et al., 2017), FTIR (Cherigui et al., 2024) and Raman (Aykas & Menevseoglu, 2021) spectroscopy for authentication and adulterant detection of honey. These methods required advanced setups and specialized expertise for operation. The SparkFun AS7263 sensor is considered low-cost in comparison to traditional high-end instruments (e.g., NIR, FTIR and Raman spectrometers), which tend to be significantly more expensive. Additionally, the

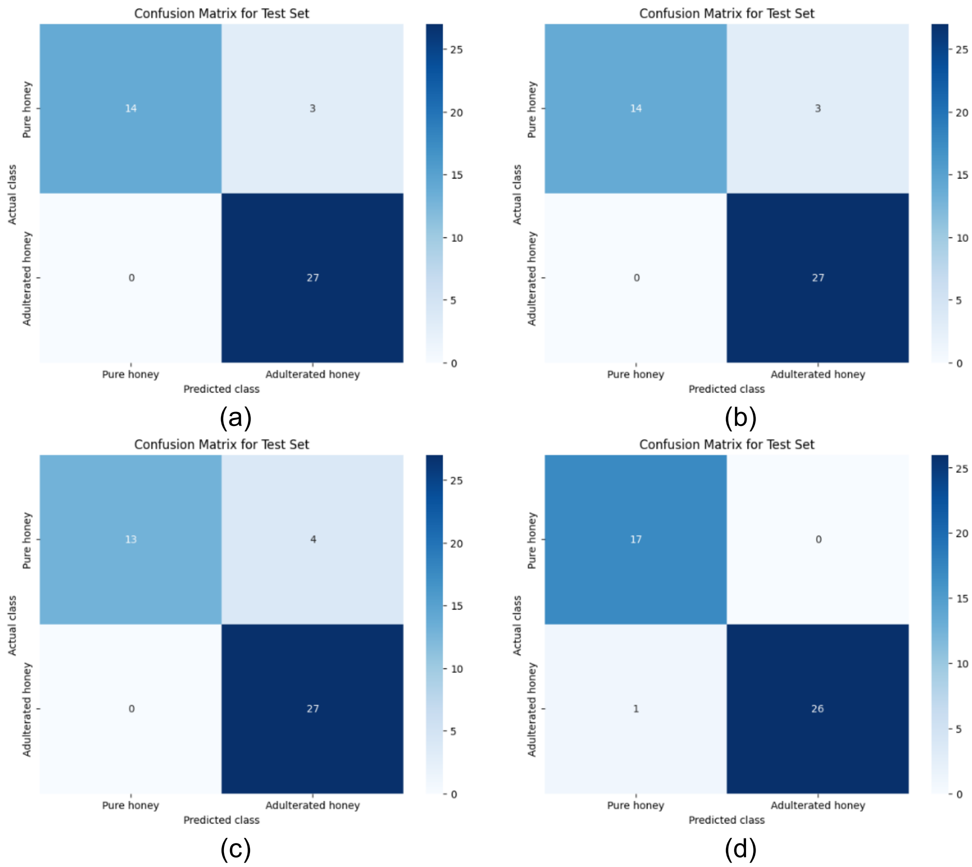


Figure 5. Confusion matrices for test sets from LDA (a), PLS-DA (b), C-SVM (c) and KNN (d)

integration of a low-cost sensor, a microcontroller board, and the use of open-source ML software for data analysis further contributed to reducing the overall costs. Our study demonstrated the feasibility of utilizing a low-cost multispectral sensor that could be developed into an optimal portable device, offering real world applications. However, a low-cost multispectral sensor has lower spectral resolution, a limited wavelength range, and greater sensitivity to noise compared to advance spectroscopic techniques (such as NIR, FTIR and Raman spectroscopy), which can impact its precision and reliability. For future work, developing higher-performance sensors with an extended spectral range (i.e., multispectral sensor AS7265X covering wavelength range on 410-940 nm) is a key area of focus. These advancements could enhance the detection capabilities for a broader range of adulterant materials and enable the development of quantitative models for accurately estimating adulteration levels.

Furthermore, previous studies predominantly employed chemometric methods such as PCA, PLS-DA, Soft Independent Model of Class Analogies (SIMCA), Hierarchical Cluster Analysis (HCA) and Discriminant Factor Analysis (DFA) which demonstrated high performance in authenticating and detecting adulteration in honey, achieving accuracy levels exceeding 90%. However, these techniques are less adaptable when compared to advanced ML algorithms, which can better handle complex datasets and provide improved precision and scalability for diverse applications. In our research, the various ML algorithms (e.g., LDA, PLS-DA, C-SVM, and KNN) and fine-tuning hyperparameter techniques were engaged to establish the detection models which achieved an impressive accuracy of up to 98%. The integration of diverse ML algorithms and the application of fine-tuning hyperparameters significantly enhanced the performance and versatility of the developed models. Nevertheless, these models are not suitable for evaluating honey varieties or adulterants different from those analyzed in this study. More robust models need to be developed in the future to enhance the detection of diverse kinds of honey and adulterants. A diverse and extensive dataset capturing wide variability (honey varieties and adulterant substances) is essential for developing and validating more robust ML models in the future.

4. Conclusions

The findings of this study suggest that the integration of low-cost multispectral sensors with advanced ML algorithms (including, LDA, PLS-DA, C-SVM, and KNN) offers a promising approach for the effective detection of honey adulteration. Spectral scanning with the developed sample holder demonstrated repeatability and reproducibility within acceptable ranges. Although the raw spectral data still required preprocessing, all ML models yielded high classification accuracy, ranging from 91% to 98%. This point presented that the combination of the low-cost multispectral device with ML algorithms could establish a robust, fast, and reliable method for detecting adulterated honey effectively. Moreover, all ML models showed good fitting during the testing set validation, indicating that the models achieved robust generalization through systematic hyperparameter optimization using the GridSearchCV method. This study serves as a guideline for developing a low-cost portable honey authentication device that is practical for real-world applications. The successful application of AI-driven analysis using low-cost hardware demonstrates strong potential for scalable solutions in food quality assurance and supports the development of smart agricultural systems.

5. Acknowledgements

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6. Authors' Contributions

Wutthiphong Boodnon designed research; performed research; Thayanont Lunvongsa designed research; performed research; Phanchay Suntisakoonwong designed research; performed research; Agustami Sitorus performed research; and Ravipat Lapcharoensuk designed research; coordinated research; analytic tools; analyzed data; wrote the paper.

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7. Conflicts of Interest

The authors declare no conflicts of interest.

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