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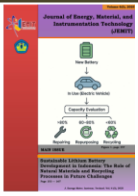

Development of a Portable Low-Cost Multispectral Sensor Integrated with IoT and Machine Learning for Classifying Honey Types

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Abstract

Accurate honey type authentication is a significant challenge for small-scale producers, as conventional methods are often costly and impractical. This study aims to design and develop a low-cost honey classification prototype by integrating the AS7265X multispectral sensor with Internet of Things (IoT) technology and machine learning. Spectral data from 18 channels of various Indonesian honey types were acquired using the AS7265X sensor and analyzed exploratively using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). The data were then normalized and used to train Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM) classification models. An ESP32-based IoT system was developed for real-time monitoring and cloud data storage. The results demonstrate that AS7265X spectral data effectively differentiate honey types, with the ANN model achieving 94.05% accuracy, supported by a responsive IoT system (1–2 seconds) for monitoring and centralized storage. This prototype shows potential as a practical, rapid, accurate, and efficient honey authentication solution for various stakeholders.

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Abstrak

Autentikasi jenis madu yang akurat merupakan tantangan signifikan bagi produsen skala kecil karena metode konvensional umumnya mahal dan kurang praktis. Penelitian ini bertujuan merancang dan membangun prototipe klasifikasi jenis madu berbiaya rendah dengan mengintegrasikan sensor multispektral AS7265X, teknologi Internet of Things (IoT), dan machine learning. Data spektral 18 kanal dari berbagai jenis madu Indonesia diakuisisi menggunakan sensor AS7265X, kemudian dianalisis secara eksploratif menggunakan Principal Component Analysis (PCA) dan Linear Discriminant Analysis (LDA). Data selanjutnya diproses melalui normalisasi dan digunakan untuk melatih model Artificial Neural Network (ANN), Random Forest (RF), dan Support Vector Machine (SVM). Sistem IoT berbasis ESP32 dikembangkan untuk pemantauan real-time dan penyimpanan data di cloud. Hasil penelitian menunjukkan bahwa data spektral AS7265X efektif membedakan jenis madu, dengan model ANN mencapai akurasi 94,05%, didukung sistem IoT yang responsif (1–2 detik) untuk pemantauan dan penyimpanan terpusat. Prototipe ini berpotensi menjadi solusi autentikasi madu yang praktis, cepat, akurat, dan efisien bagi berbagai pemangku kepentingan.

1. Introduction

Honey is a natural product widely valued for its health benefits, nutritional content, and economic importance (Suhesti et al., 2023). Its commercial value depends not only on sensory attributes such as flavor and aroma but also

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on its botanical type, geographical origin, and authenticity (Da Silva et al., 2016; Riswahyuli et al., 2020). However, small-scale honey producers often face difficulties in proving that their honey is genuine and in demonstrating its type and origin to consumers. This condition creates a gap between market demand for trustworthy honey and the limited ability of local producers to verify and communicate product authenticity.

Conventional laboratory-based techniques such as chromatography and spectroscopy are the most reliable methods for identifying honey authenticity and classification (Tsagkaris et al., 2021; Zhang & Abdulla, 2022). Nevertheless, these methods require sophisticated instruments, trained personnel, high operational costs, and long processing times, making them inaccessible for most honey farmers and impractical for rapid field verification. Consequently, the lack of affordable, easy-to-use tools hinders both producers and consumers in ensuring the quality of honey.

Several alternative methods have been explored to achieve faster and more accessible honey type classification. Simple approaches, such as colorimetric tests and handheld refractometers, are inexpensive and user-friendly, but they provide limited capability in distinguishing honey types (Mohamat et al., 2023). More advanced approaches, including electronic nose and electronic tongue systems, have shown good capability in capturing aroma and taste fingerprints of honey, yet they often require complex calibration and remain relatively costly (Gonçalves et al., 2023; Ihsan et al., 2025; Leon-Medina et al., 2023). Similarly, portable near-infrared (NIR) and fluorescence-based devices offer rapid and accurate analysis but are still not widely affordable for small producers (Tsagkaris et al., 2021). These approaches highlight the trade-off between accuracy, cost, and practicality, thus necessitating a method that can balance these aspects.

Recent advances in smart sensor technology, particularly multispectral sensors, offer new opportunities to overcome the limitations of conventional and existing portable methods. Multispectral sensors can capture material responses across multiple wavelengths, producing spectral fingerprints that correlate with chemical composition (Nguyen et al., 2020). The AS7265X sensor, with 18 channels spanning the visible (VIS) to near-infrared (NIR) range, has been successfully applied for food classification such as olive oil (Noguera et al., 2022), milk (Durgun, 2023), tempeh (Syahputra et al., 2025), and coffee (Sagita et al., 2024, 2025). Combined with Internet of Things (IoT) technology for real-time monitoring and machine learning for automated data analysis, such systems can provide portable, accurate, and user-friendly solutions ((Aira et al., 2022; Habibullah et al., 2020)). However, to date, no study has applied this approach specifically for honey type classification, particularly in the context of local Indonesian honey.

Therefore, this study aims to develop a prototype of a portable, low-cost honey classification system that integrates the AS7265X multispectral sensor with IoT connectivity and machine learning algorithms. The proposed system is expected to provide a rapid, accurate, and affordable tool for identifying and verifying honey types, thus empowering small-scale producers, enhancing consumer confidence, and supporting the competitiveness of local honey in the market.

2. Research Methods

This research was carried out through four main stages, namely: (1) hardware design and fabrication, (2) Internet of Things (IoT) architecture development, (3) sample preparation and spectral data acquisition, and (4) data pre-processing and machine learning modeling.

2.1. Instrument Design and Fabrication

The hardware was designed as an integrated, portable spectral acquisition system, as illustrated in the block diagram in **Figure 1**. At the core of the system is an ESP32 microcontroller, which manages spectral data acquisition, signal processing, and wireless connectivity. Spectral measurements are performed using the AMS AS7265x triad multispectral sensor, which communicates with the ESP32 via an I²C interface. This sensor can capture light intensity across 18 spectral channels spanning wavelengths from 410 to 940 nm (covering the visible to near-infrared range), with a full width at half maximum (FWHM) bandwidth of approximately 20 nm per channel.

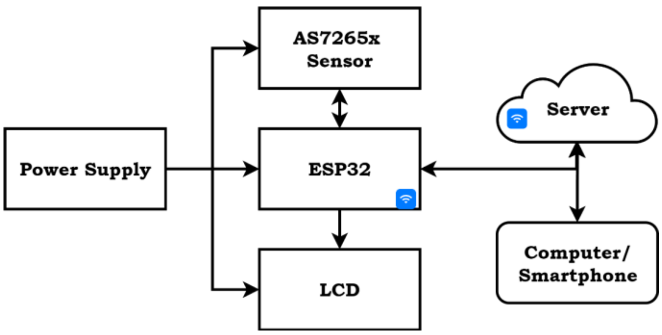


Figure 1. Block diagram of the IoT-based honey classification system using AS7265X multispectral sensor and ESP32 microcontroller.

To support direct user interaction, the system features a 3.2-inch TFT LCD touchscreen, enabling intuitive control of the measurement process and immediate visualization of results. All electronic components are housed within a custom 3D-printed enclosure, designed to ensure light isolation in the measurement chamber and to protect the internal circuitry during field use.

The system is powered by a rechargeable 18650 Li-Ion battery, managed by a TP4056 charging module, and stabilized by a DC-DC converter to provide a consistent 5 V supply to all electronic components. The complete electronic circuit, as depicted in the schematic in **Figure 2**, is housed within a custom-designed case fabricated using 3D printing technology. This enclosure not only protects the internal components but also features a light-sealed measurement chamber, which minimizes interference from ambient light during spectral data acquisition. The detailed technical specifications of the device are presented in **Table 1**.

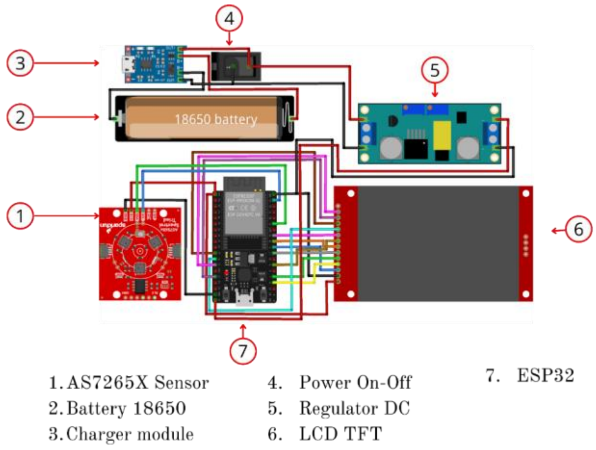


Figure 2. Electronic circuit schematic of a honey-type classification device.

In this system, the ILI9341 TFT LCD communicates with the ESP32 using the Serial Peripheral Interface (SPI). The Serial Clock (SCK) line is connected to GPIO 18, Master Out Slave In (MOSI) to GPIO 27, and Master In Slave Out (MISO) to GPIO 19. The Data/Command (DC) control signal is assigned to GPIO 2, the Chip Select (CS) line to GPIO 5, the reset line to the ESP32 EN pin, and the backlight is driven through GPIO 4. The XPT2046 touch controller shares the same SPI bus but uses different GPIO assignments: the clock line on GPIO 14, Data Input (DIN/MOSI) on GPIO 13, Data Output (DOUT/MISO) on GPIO 12, and Chip Select (CS) on GPIO 27. Meanwhile, the AS7265X multispectral sensor operates via the I²C protocol, with the Serial Data (SDA) line connected to GPIO 21 and the Serial Clock (SCL) line connected to GPIO 22.

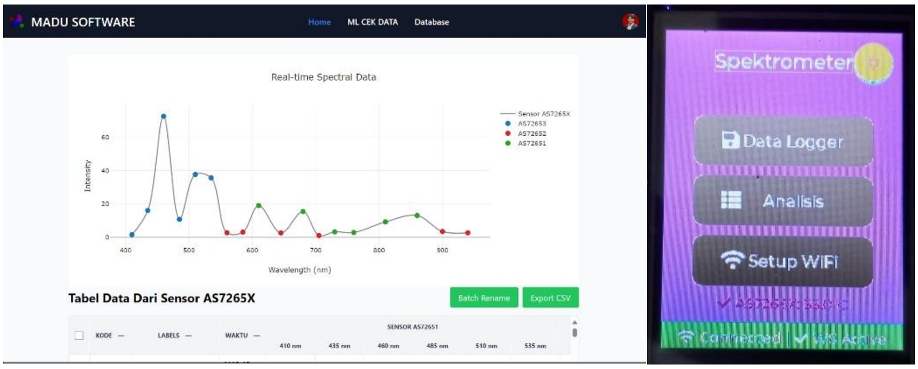
Table 1. Technical specifications of tools

Characteristics	Specifications
Sensor	AMS AS7265x (Triad)
Spectral Channel	18
Wavelength Range	410 nm - 940 nm
FWHM	20 nm
Microcontroller	ESP32
Communication	I²C, Wi-Fi
User Interface (UI)	3.2" TFT Touch Screen, Web Dashboard
Power Source	18650 Li-Ion Battery
Dimensions	150×110×100 mm

2.2 IoT System and User Interface

The IoT architecture is designed to support real-time monitoring, remote data access, and structured data management. When a measurement process begins, the ESP32 microcontroller communicates with the AS7265X multispectral sensor via an I²C interface to capture spectral intensity values across all 18 channels (410–940 nm). Each channel reading is acquired in a calibrated digital format, and the ESP32 then performs preprocessing such as averaging multiple readings to reduce noise and normalizing the values to minimize variations caused by ambient light conditions. Each data set is provided with a timestamp and device ID to ensure data integrity and traceability. The processed data is then serialized into JavaScript Object Notation (JSON) format and sent to a backend server via a persistent WebSocket connection, chosen for its low-latency, two-way communication, enabling near-real-time updates. On the server side, a Django-based backend receives the incoming JSON data, validates it, and stores it in a PostgreSQL database. Each record contains metadata such as sample type, measurement time, sensor ID, and processed spectral values, ensuring structured and reliable storage for long-term use.

The system features two primary user interfaces. The first is a local interface embedded in the device's 3.2-inch LCD touchscreen, which allows users to configure Wi-Fi connectivity, perform screen calibration, and initiate the spectral acquisition process. The second is a web-based dashboard accessible via any internet-connected device, including smartphones and computers. This dashboard allows users to monitor system status, visualize real-time spectral responses, and manage stored data, including exporting datasets for external analysis and documentation purposes.



(a) (b)

Figure 3. UI design of honey type classification tool (a) website dashboard, (b) LCD UI of the tool.

2.3 Honey Samples and Spectral Data Acquisition

This study used a diverse sample of native Indonesian honey grouped into three main categories, as detailed in Table 2. These categories included wild honey from four different regions, farmed honey from three different sources of floral nectar, and Stingless bee honey from two different species of stingless bees.

Table 2. Honey Sample Details

Main Categories	Number of Samples (N)
Wild Honey	93
Farmed Honey	93
Stingless Bee Honey	93

The data acquisition protocol was standardized to ensure consistency and reproducibility of the results. For each measurement, 4 mL of the honey sample was placed in a sterile petri dish. The petri dish was then placed inside the device at the optimized distance. Based on preliminary experiments evaluating the effect of distance on signal intensity and stability, the optimal measurement distance between the sensor and the sample surface was set at 30 mm. This distance provides the best balance between sufficient signal strength and high measurement reproducibility.

2.4. Data Processing and Machine Learning Models

The data analysis and machine learning workflow is illustrated in **Figure 4.**

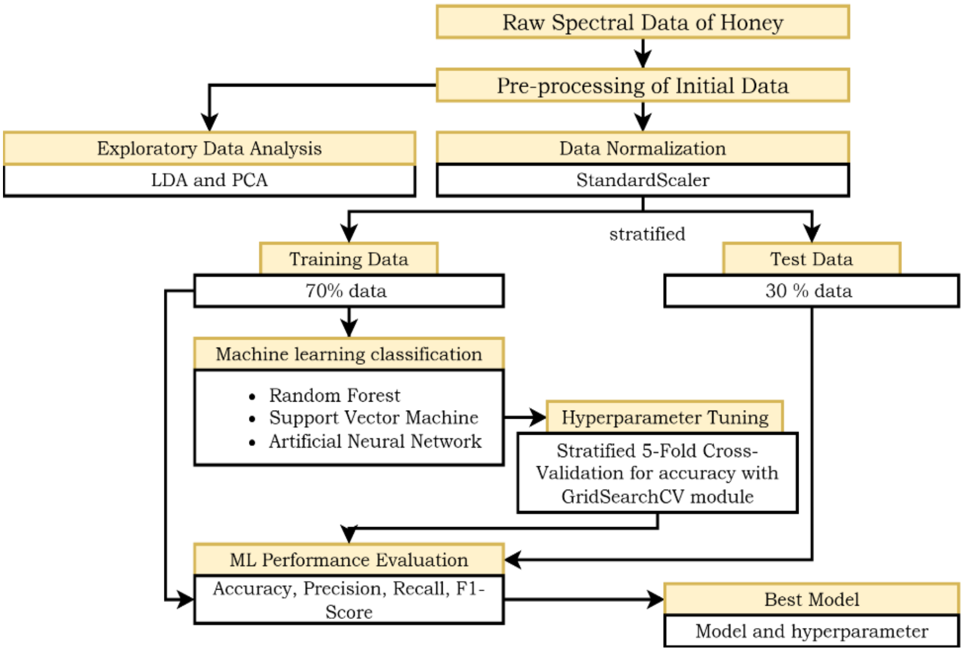


Figure 4. Model development diagram for honey type classification.

The data analysis and machine learning workflows were designed to develop robust and reliable classification models.

1. Exploratory Data Analysis.
   Prior to modeling, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were applied to the spectral dataset. PCA, an unsupervised technique, was employed to visualize the intrinsic variance within the data and to identify potential natural groupings. In contrast, LDA, a supervised method, was used to assess the linear separability of the predefined honey classes by maximizing the ratio of between-class to within-class variance.
2. Pre-processing and Data Sharing
   The entire dataset was normalized using StandardScaler to rescale all 18 spectral features to a uniform range (mean 0, standard deviation 1). Finally, the processed data was divided into a training dataset (70%) and a test dataset (30%) using a stratified split to ensure the proportion of each class was maintained in both sets.
3. Training Machine Learning
   Models such as Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) were evaluated in this study. Extensive hyperparameter tuning was performed using the GridSearchCV method with stratified 5-fold cross-validation on the training dataset to identify the optimal configuration of each model. This approach enables the systematic testing of various hyperparameter combinations to identify the settings that yield the best performance. The hyperparameter search space and the optimal values found for each model are summarized in **Table 3**.

Table 3. Hyperparameter Search Space of machine learning models.

Algorithm	Hyperparameter	Tuning Range / Value
ANN	hidden layer size	(58), (116), (58,10), (116,10), (58,58), (116,58), (58,58,58), (116,116,116)
	solver	lbfgs, sgd
	activation	identity, tanh, relu
	Alpha	0.0001, 0.001, 0.01
RF	n_estimators	100, 200, 300, 400, 500
	max_depth	None, 10, 20, 30
SVM	kernel	linear, rbf, poly
	C_Values	0.1, 1, 10, 100, 1000
	Gamma	1, 0.1, 0.01, 0.001

2.5. Model Evaluation

The performance of each classification model was evaluated using a confusion matrix, which compares predicted class labels against the true class labels. From the confusion matrix, several key performance metrics were derived, including accuracy, sensitivity (recall), specificity, and the F1-score. Accuracy represents the overall proportion of correct predictions across all classes. Sensitivity (or recall) measures the model's ability to correctly identify positive instances, while specificity quantifies its ability to identify negative instances correctly. The F1-score provides a harmonic mean of precision and recall, offering a balanced metric that is particularly useful in scenarios with class imbalance. These metrics collectively provide a comprehensive assessment of model performance across various aspects of classification quality.

3. Results and Discussions

3.1 Prototype spectral Multichannel System

The final prototype is a fully functional, portable device housed in a 3D-printed enclosure with dimensions of 150 × 110 × 100 mm, as illustrated in **Figure 5.** It integrates all major components, including the ESP32 microcontroller, the AS7265X multispectral sensor, and a 3.2-inch LCD touchscreen for user interaction. The system is powered by a Li-ion battery, enabling standalone and portable use in the field. The prototype design includes a light-tight measurement chamber and a customizable sample platform, ensuring consistency and accuracy in the data acquisition process. Functional testing of the integrated system showed fast response times, averaging 1-2 seconds from the start of the scan until the spectral results are displayed on the web-based IoT dashboard. This speed is one of the main advantages over conventional laboratory methods, which generally require hours to days of analysis time (Biswas & Chaudhari, 2024; Chotimah et al., 2024).The practical implications of this system are considerable. Its ability to provide fast and accurate on-site analysis supports a wide range of stakeholders in the honey value chain. Beekeepers, honey collectors, and regulatory agencies can efficiently perform timely quality control and classify honey types. This, in turn, enhances consumer trust and elevates the commercial value of local honey products. The development aligns with the broader goals of food sensor innovation—namely, delivering rapid, portable, cost-effective, and non-destructive analytical tools.

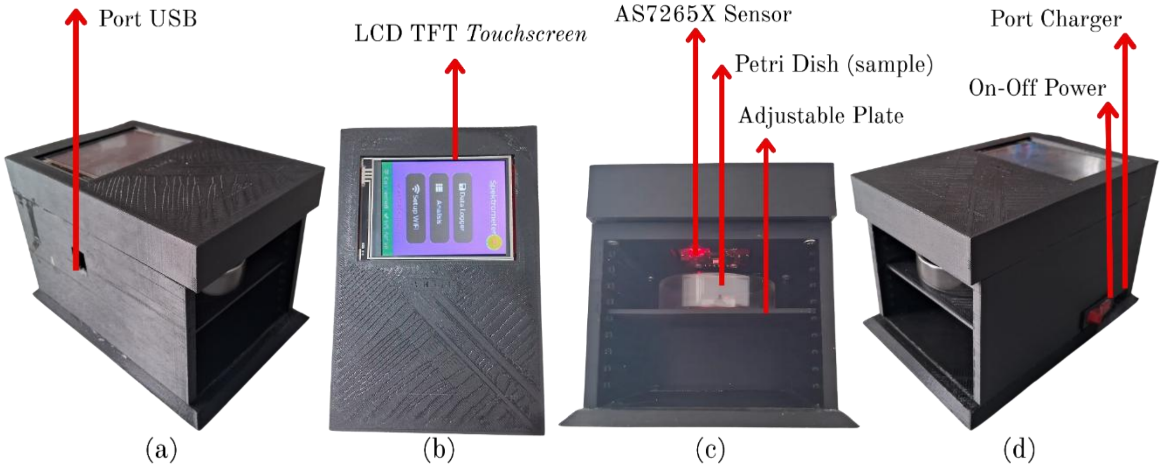


Figure 5. Tool with 3D printing packaging, (a) left side view, (b) top view, (c) front view, and (d) right side view.

3.2 Sensor Stability

To ensure data reliability, the stability of the AS7265X multispectral sensor was evaluated using two complementary approaches: (1) temporal monitoring during 30 minutes of continuous operation, and (2) statistical analysis of signal consistency based on the Coefficient of Variation (CV) for each spectral channel.

The temporal stability test results (**Figure 6**) indicate that the sensor maintains a consistent signal throughout the observation period, with no evidence of significant drift. In addition, recorded fluctuations in ambient temperature did not exhibit a meaningful correlation with signal variation, suggesting that the device demonstrates strong environmental robustness. These results confirm that the sensor is suitable for extended operation in field conditions, providing reliable and consistent spectral data for downstream analysis.

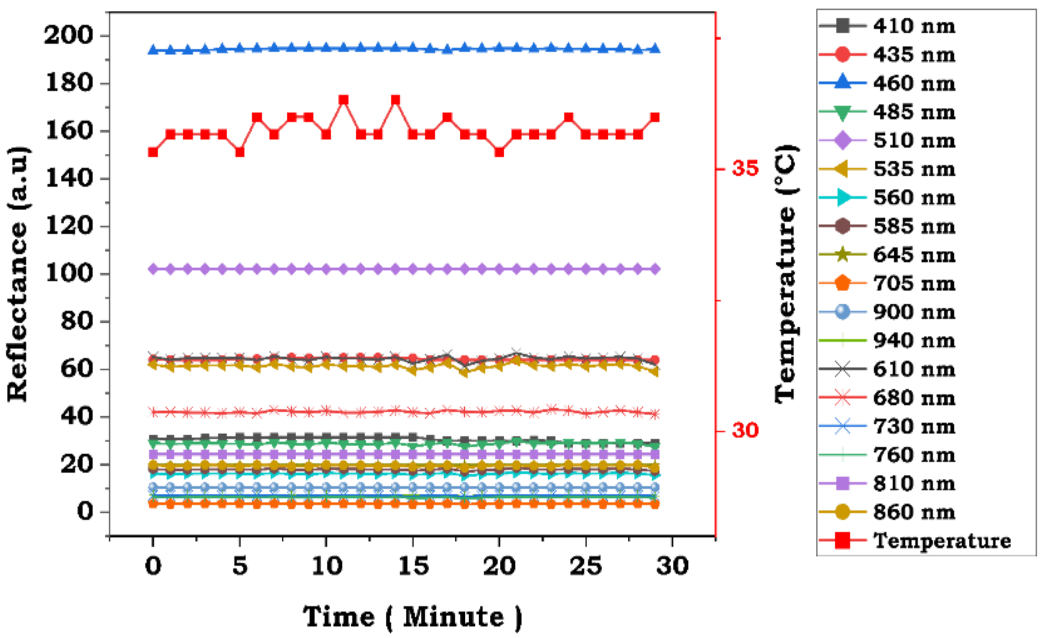


Figure 6. Sensor stability over time.

The CV analysis, as displayed in Figure 7, shows the variation in signal stability levels across wavelength channels. The 410 nm channel exhibits the highest variability (CV ≈ 3.2%), suggesting potential noise at this wavelength. In contrast, the 510 nm, 645 nm, 810 nm, and 900 nm channels show excellent signal stability, with CV values below 0.001%, indicating a precise and consistent signal. Despite the differences between channels, all CV values are still below the acceptable tolerance threshold in spectral measurements (Yang et al., 2020. Thus, these results confirm that the AS7265X sensor is overall capable of producing stable and reliable data for use in developing robust and accurate machine learning classification models.

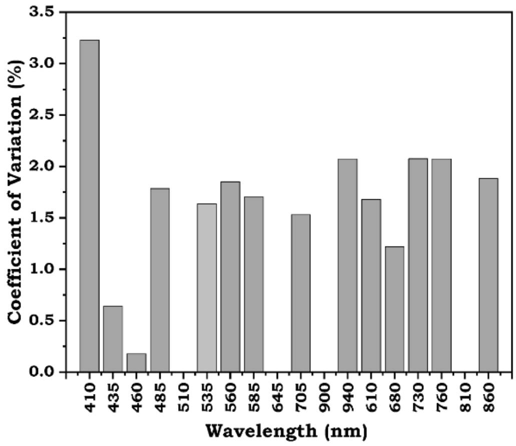


Figure 7. Coefficient of Variation multispectral sensor.

3.3 Spectral Characteristics of Honey Samples

Figure 8 presents the average spectral profiles of the three honey categories: Wild Honey, Farmed Honey, and Stingless Bee Honey. Distinct differences are observed, particularly around 460 nm, 510–535 nm, and 610 nm within the visible (VIS) spectrum. These variations are likely attributable to differences in the concentration and composition of natural pigments such as flavonoids and carotenoids, which influence the color and chemical properties of honey (Labsvards et al., 2023). In the near-infrared (NIR) region, especially near 940 nm, additional spectral variations are evident. These are associated with overtone vibrations of O–H molecular bonds, primarily arising from water and sugar content—the major constituents of honey. This finding is consistent with existing NIR spectroscopy literature, where interactions with O–H and C–H bonds are frequently used to assess composition and authenticity (Biswas & Chaudhari, 2024).

Despite the observed mean differences, significant intra-class variability was present, leading to overlap between the spectral profiles of different honey types. This complexity indicates that simple threshold-based or rule-based classification approaches are inadequate. Therefore, machine learning methods are required to identify and model subtle, high-dimensional patterns across the spectrum to enable accurate and reliable honey classification.

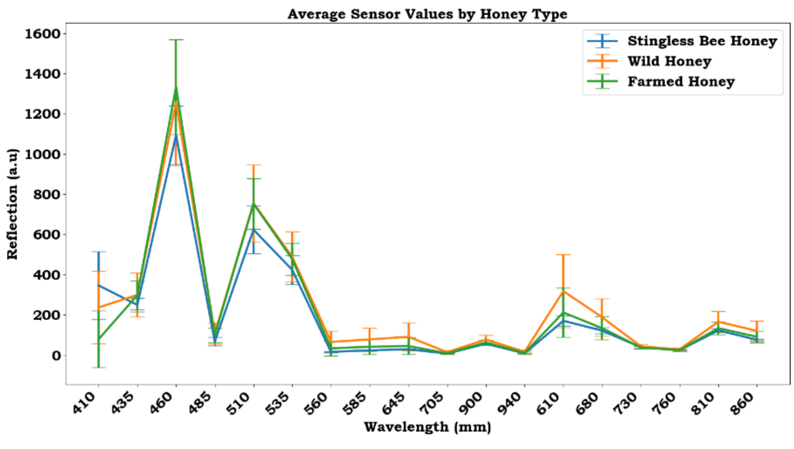


Figure 8. Average sensor value for each type of honey.

3.4. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA)

To visualize the structure of the data and assess the potential for class separation, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were applied to the spectral dataset. These chemometric techniques are widely used in sensor-based systems, including electronic nose (e-nose) and spectroscopy applications, to reduce dimensionality and reveal underlying data patterns(Biswas & Chaudhari, 2024; Chotimah et al., 2024; Ihsan et al., 2025).

The PCA results (**Figure 9**) show that the three honey categories—Wild Honey, Farmed Honey, and Stingless Bee Honey—form relatively distinct clusters in the space defined by the first two principal components. PC1 and PC2 together account for over 85% of the total variance, with individual contributions of 73% and 12%, respectively. This high variance capture suggests that the major sources of variation in the data may be attributed to differences in water content, sugar profile, or other chemical constituents among the honey types.

The PCA results **(Figure 9)** show that the three main honey categories-Wild Honey, Farmed Honey, and Stingless Bee Honey-form relatively separate groups in the space of the two principal components. The first (PC1) and second

(PC2) principal components cumulatively explained more than 85% of the total data variance, with contributions of 73% and 12%, respectively. This indicates a dominant difference between honey types, which is most likely related to differences in water content, sugar composition, or other chemical compounds. This finding is consistent with the results of (Mateo et al., 2021), who demonstrated that PCA is effective in classifying honey based on its botanical sources. Thus, PCA proved to be a powerful initial method for identifying key patterns and structures in honey spectral data, while providing a solid foundation for the next stage of classification using machine learning algorithms.

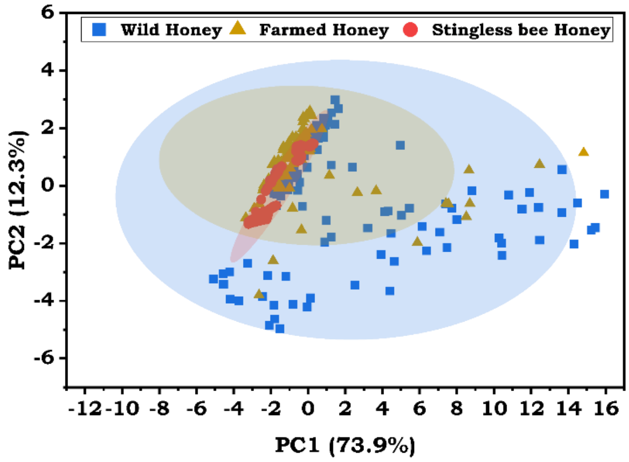


Figure 9. PCA analysis of honey spectral data.

To improve the separation between classes identified through PCA, the supervised Linear Discriminant Analysis (LDA) method was applied to the spectral data. The visualization results in **Figure 10** show a much sharper class separation, where the two principal components of LDA (LD1 and LD2) cumulatively explain more than 99% of the discriminative variance between classes. This shows that LDA successfully optimizes the ratio of between-class to within-class variance, resulting in highly informative data projections for classification purposes.

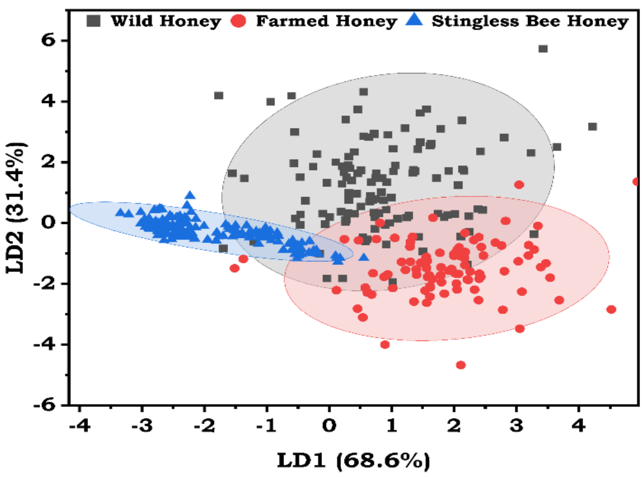


Figure 10. LDA analysis on honey spectral data.

3.5 Performance Classification

Table 4 presents the optimal parameter values obtained using GridSearchCV for each machine learning model in the honey type main category classification. The performance of the three machine learning models was evaluated using the test dataset.

Table 4. Tuned Hyperparameters for Each Classification Model.

Model	Hyperparameter
ANN	activation: tanh, alpha: 0.01, hidden_layer_sizes: (58), solver: lbfgs
RF	max_depth: None, n_estimators: 300
SVM	C: 10, gamma: 1, kernel: linear

The training and evaluation results of the machine learning models are summarized in Table 5. Among the models tested, the **ANN** achieved the highest performance on the test dataset, with an **accuracy of 94.05%** and an **F1-score of 93.95%**. Both **SVM** and **RF** also demonstrated strong classification abilities, yielding accuracies of **92.86%** and **89.29%**, respectively. The superior performance of the ANN model in this study is consistent with findings from previous work by (Faal et al., 2019), which showed that ANN outperformed SVM in predicting the physicochemical properties of honey using electronic nose (e-nose) data. Furthermore, the accuracy obtained by the proposed system is highly competitive when compared to similar classification systems for other food products. For instance, (Al-Awadhi & Deshmukh, 2023) achieved 96.67% accuracy in detecting adulteration in 10 types of honey using Vis-NIR reflectance spectroscopy combined with OSWR-LDA-KNN feature selection method.(Ihsan et al., 2025) reported 93% accuracy to distinguish luwak and non-luwak coffee using e-nose with an optimized LDA model with polynomial feature extraction.

Table 5. Model Performance for Honey Type Classification

Model	Metrics	Test Data
ANN	Accuracy	94.05%
	F1-Score	93.95%
RF	Accuracy	89.29%
	F1-Score	89.00%
SVM	Accuracy	92.86%
	F1-Score	92.82%

The confusion matrix (**Figure 11**) revealed that, despite high performance, some misclassifications still occurred between Forest Honey and Cattle Honey, indicating an overlap in spectral characteristics between the two. This is a common challenge in the analysis of natural products that have high compositional variability. On the other hand, all three models accurately identified 100% of the Klanceng Honey samples, indicating that Klanceng Honey has a distinct spectral "fingerprint" that is unique from the other two categories.

It is important to note that achieving this high accuracy depends not only on the quality of the sensor but also on the overall data processing flow, especially the pre-processing stage. In this study, normalization using StandardScaler was applied to homogenize the scale of the features. The importance of this stage is also emphasized by (Al-Awadhi & Deshmukh, 2023), who found that pre-processing using Standard Normal Variate (SNV) was a crucial step that significantly improved the accuracy of their model in honey counterfeit detection. This highlights that the combination of reliable sensors and meticulous data processing is crucial to success in developing machine learning-based classification systems.

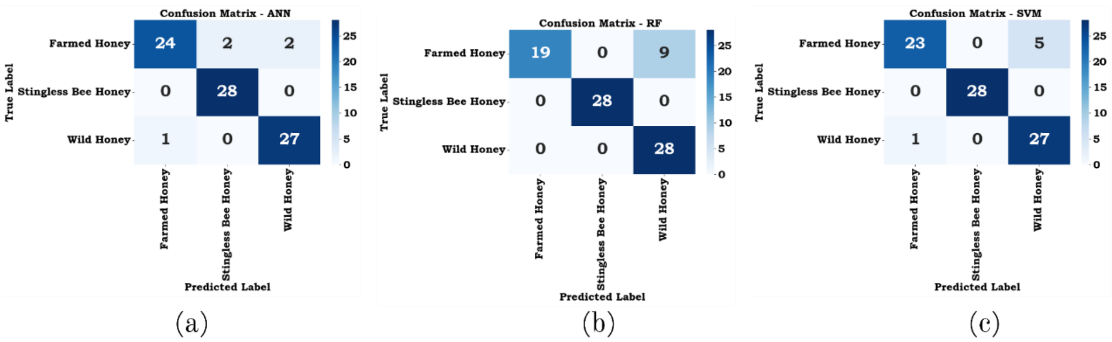


Figure 11. Confusion matrix of honey type classification results: (a) ANN, (b) RF, and (c) SVM.

4. Conclusion

This research successfully developed a low-cost, portable honey classification prototype that utilizes the AS7265X multispectral sensor, integrated with machine learning algorithms. Among the evaluated models, the ANN demonstrated the highest performance, achieving a classification accuracy of 94.05%. The system is also supported by a responsive IoT architecture, with an average response time of 1–2 seconds. The proposed device shows strong potential as a practical, fast, accurate, and efficient tool for honey classification, particularly for small-scale producers, quality inspectors, and end consumers. Its combination of affordability, portability, and real-time data accessibility positions it as a viable alternative to conventional laboratory-based methods.

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