Effectiveness of Webcam Visible Spectrometer (WeViSpec) technology dissemination at Kolej Dato' Onn Jaafar Living Lab as an Applied Research Facility

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Abstract. Adulteration of honey with starch-based sweeteners is a global challenge that requires reliable yet affordable detection technology. This research disseminates the Webcam Visible Spectrometer (WeViSpec), a low-cost (USD 30.93) spectroscopy instrument that integrates off-the-shelf components with artificial intelligence, at the Kolej Dato' Onn Jaafar (KDOJ) Living Lab, Universiti Teknologi Malaysia (UTM). This instrument is designed using a 1080p HD webcam sensor and a diffraction grating from old DVD disks with a single-channel inverted optical system. Data analysis was conducted thru differential absorbance feature engineering and the use of a Variational Autoencoder (VAE) model for dimensionality reduction, as well as a Bayesian Neural Network (BNN) for predicting adulterant concentrations. The test results show that WeViSpec has high wavelength accuracy with an average error of 2.93 nm and a spectral resolution of ~5 nm. The developed AI model successfully classified the types of sweeteners with 100% accuracy and predicted concentrations with high precision (R2=0.9978) and a Limit of Detection (LOD) of 6.66% v/v. The dissemination program involving 20 participants showed very high effectiveness with an average score of 4.68 out of 5.00, confirming the successful transfer of WeViSpec technology as a functional field screening tool in the living lab ecosystem.

1 Introduction

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Food security and sustainable natural resource management are increasingly urgent global challenges in the 21st century. Rapid population growth, urbanization, and climate change have significantly impacted the productivity of the agriculture and forestry sectors, including the decline in bee populations as natural pollinators. Bees play a crucial role in maintaining the balance of the global ecosystem thru pollination, which contributes to about 75% of the world's food crop production. However, bee populations continue to decline due to deforestation, excessive pesticide use, and the climate crisis [1]. This condition directly affects the availability of honey as a natural product with very high nutritional and economic value.

Honey has long been recognized as a highly nutritious product that offers various health benefits for humans. In addition to containing easily absorbed carbohydrates such as fructose and glucose, honey is also rich in vitamins, minerals, enzymes, and bioactive compounds that function as antioxidants [2]. As global awareness of a healthy lifestyle increases, the demand for honey continues to soar. However, this high demand has triggered a surge in food fraud practices thru product adulteration, mixing pure honey with starch-based sweeteners [3]. This adulteration not only undermines the economic integrity of the product but also poses a risk to consumer health [4].

In the global market, honey quality monitoring is often ineffective due to limited access to reliable yet affordable detection technology. Various advanced laboratory techniques have been developed, such as chromatography and biosensors [5]. Although these techniques are accurate, the high cost of the instruments limits their use in the field [6]. As a solution, the development of low-cost spectrometers based on off-the-shelf components such as webcams and DVD diffraction gratings is being extensively tested [7][8].

The proposing team disseminated the WeViSpec, which integrates simple optics with artificial intelligence [9]. The use of Variational Autoencoder (VAE) allows for the reduction of complex spectral data dimensions into a meaningful latent space [10]. This dissemination was carried out at the Kolej Dato' Onn Jaafar (KDOJ) Living Lab, an open innovation ecosystem that emphasizes co-creation between developers and users [11]. Based on these conditions, this research aims to answer: How effective is the dissemination and application of the WeViSpec technology based on deep learning as a rapid screening instrument for detecting honey adulteration in the environment of the Kolej Dato' Onn Jaafar Living Lab?

2 Methods

2.1 Spectrometer Design and Hardware Fabrication

The development of the WeViSpec instrument follows the design principle of a single-beam reverse optics spectrophotometer, where the sample cuvette is placed before the light dispersion stage by the diffraction grating [9]. This device is designed with compact external dimensions (17.8 × 8 × 7 cm) to support portability in the field. The instrument enclosure is designed using Blender software and fabricated using an FDM 3D printer with PETG filament due to its high durability and flexibility.

Technically, WeViSpec consists of seven main component groups: (1) Webcam Sensor using a USB 1080p HD web camera as a spectral detector; (2) Diffraction Grating made from pieces of old DVD optical media transformed into a transmission grating; (3) Light Source in the form of a 2.5 V tungsten lamp; (4) Convex Optical Lens to focus the polychromatic light beam; (5) 3D-printed Enclosure; (6) Supporting Electronics such as a toggle switch and MB-102 power supply module; and (7) Accessories in the form of a plastic cuvette [9]. The user interface (GUI) was developed using the Python programming language with the Tkinter and OpenCV libraries for real-time data acquisition, ROI (Region of Interest) adjustment, and Ambient Light Canceling.

2.2 Sample Preparation and Measurement Protocol

The sample preparation procedure was carried out systematically to simulate adulteration conditions in the real world. Four categories of samples were prepared: pure honey (100%) and honey mixed with three types of syrup (orange, cane, and palm) with concentrations ranging from 5% to 45% in 5% increments (Suhendar et al., 2025;). Each mixture was measured at 5 mL, mixed homogeneously, and allowed to stand for 10–20 minutes to eliminate air bubbles that could interfere with light transmission. Absorbance measurements were performed using the Beer-Lambert law, where the instrument captures the intensity spectrum without the sample (I_0) and the intensity spectrum after the sample is placed in the cuvette (I) to then calculate the absorbance value.

2.3 Computational Framework and Deep Learning Models

Data analysis begins with the extraction of spectral absorbance features and their first derivative (differential absorbance) to enhance the separation of features between different types of sweeteners [9][12]. The Variational Autoencoder (VAE) model is used for non-linear dimensionality reduction. The VAE architecture consists of an encoder network with three conventional 1D layers that compress spectral data (1280 vector elements) into a two-dimensional latent space, as well as a decoder network that reconstructs the original spectrum [9]. For concentration prediction, a Bayesian Neural Network (BNN) is used with the VAE latent space features and prediction labels from a Support Vector Machine (SVM) as input [9]. The BNN model integrates dropout properties (p=0.1) to estimate Bayesian inference thru 500 iterations of Monte Carlo inference to obtain concentration prediction values while also calculating the uncertainty quantification.

2.4 Dissemination Framework at KDOJ Living Lab

The implementation of the WeViSpec dissemination program at KDOJ Living Lab follows an open innovation approach that positions users as active partners [13]. The dissemination stages are designed to ensure sustainable technology transfer thru five main phases as shown in Figure 1.

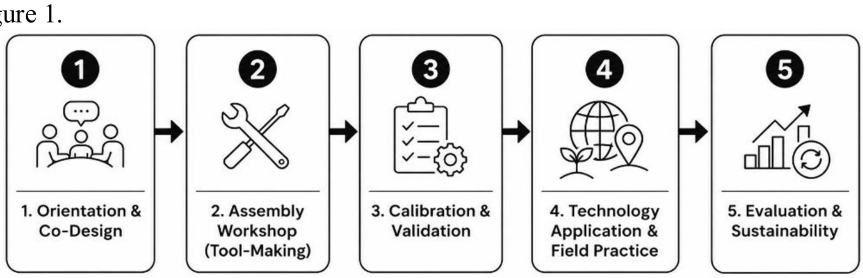


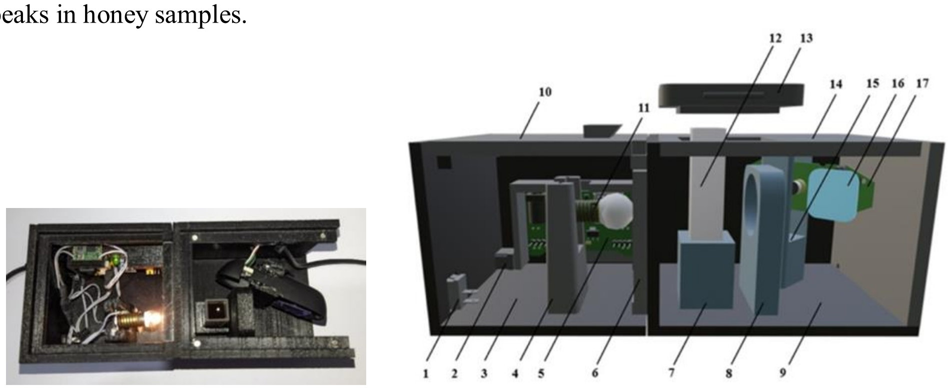
Fig. 1. Flow of dissemination implementation

Starting with the socialization and co-design phase between the team from Universitas Negeri Jakarta (UNJ) and KDOJ Living Lab to align needs, workshop schedules, and standardize instrument kit components. This stage is followed by an intensive tool-making workshop involving 20 participants to independently assemble the mechanical, optical, and electronic components of WeViSpec in small groups. To ensure measurement accuracy, each group performs wavelength calibration and validation using three laser sources (red, green, and UV) to validate the instrument assembly results and ensure the reliability of spectral readings before using them for sample testing. In the technology application and field practice phase, participants independently acquire data from pure and adulterated honey samples using the assembled kit, and run a Python notebook to process spectral data and predict honey purity levels based on the developed AI model. The program concludes with an evaluation and sustainability phase that includes the handover of WeViSpec kit grants to partners, an audit of the quality of participants' measurement data, and the development of an equipment maintenance plan. The integration of these systematic procedures aims to ensure that the WeViSpec technology innovation can function sustainably as an applied research facility and a permanent learning resource in the living lab environment.

3 Result and Discussion

3.1 Spectrometer Performance and Cost Analysis

The developed WeViSpec spectrometer shows competitive optical performance for the category of low-cost instruments. Based on the calibration results using three different laser sources [red (650 nm), green (532 nm), and ultraviolet (405 nm)], this instrument achieves high wavelength accuracy with an average error of only 2.93 nm and a maximum error of 3.43 nm. These results are well below the standard tolerance threshold of ±10 nm, proving that the integration of a webcam and DVD diffraction grating can produce precise spectral data. In addition, the spectral resolution measured thru Full Width at Half Maximum (FWHM) reaches approximately 5 nm, allowing for the identification of sharp absorbance peaks in honey samples.



(a) (b)

Fig. 2. (a) The WeViSpec's internal view. (b) Detailed setup of the WeViSpec component: 1-switch, 2-female connector, 3-light source enclosure, 4-light source holder, 5-power supply, 6-light blocker with slit, 7-cuvette holder, 8-lense holder, 9-sample and camera enclosure, 10-lamp enclosure cover, 11-light source, 12-cuvette, 13-cuvette cover, 14-sample and camera enclosure, 15-camera holder, 16-grating, 17-camera.

From an economic perspective, WeViSpec offers a significant cost disruption advantage for the research community in a living lab environment. Based on the cost analysis in Table 1, the total material cost for one unit of the instrument as figure 2 is only USD 30,93. For comparison, commercial spectrometers like the Hamamatsu C12880MA are priced around USD 170 with a lower resolution, approximately 15 nm [14]. This affordability is made possible by the use of off-the-shelf components and the utilization of recycled optical media, which is crucial in ensuring the sustainability of the dissemination program at the KDOJ Living Lab, as partners can replicate it independently with minimal investment.

Table 1. Details of the WeViSpec component costs based on groups (10 Units).

No	Component Group	Component Name	Price (USD)
1	Webcam Sensor	Web Camera (1080p HD)	167,10
2	Diffraction Grating	Grating (DVD Cut)	5,60
3	Light Source	E10 bulb	2,80
4	Optical Lens	Focusing Lens (Convex)	27,90
5	Enclosure	3D-printed Parts (Enclosure and Holders)	44,60
6	Supporting Electronics	Adaptor 12V 1A, Step Down Voltage, Switch and Connectors	16,70
7	Cuvette	Cuvette and Cover	44,60
TOTAL			**309,30**

3.2 Spectral Analysis and Feature Engineering

Analysis of pure honey samples shows a dominant absorbance peak in the range of 470–500 nm, which is a natural optical characteristic of honey composition. However, when honey is mixed with sweetener syrup, the absorbance profile undergoes gradual modifications. Mixing with cane syrup causes a decrease in the intensity of the primary peak due to the dilution effect, while the darker-colored palm syrup produces a wider absorbance band at wavelengths of 680–700 nm. To enhance the detection sensitivity to subtle spectral changes, this study applies differential absorbance (the first derivative of the absorbance spectrum). This technique has been proven to significantly enhance feature separation, particularly in distinguishing pure honey from honey adulterated with orange syrup, which was previously difficult to differentiate in the raw absorbance spectrum. This is reinforced by the increased silhouette coefficient value from 0.54 in PCA absorbance to 0.63 in PCA differential absorbance, confirming that feature engineering is crucial before the data is input into the deep learning model.

3.3 Deep Learning Model Effectiveness

The application of the Variational Autoencoder (VAE) model provides an advantage in mapping high-dimensional spectral data (1280 vectors) into a continuous and structured two-dimensional latent space. Unlike linear methods such as PCA, the probabilistic nature of VAE allows the model to capture complex non-linear relationships and reconstruct the spectrum with a very low error rate (Mean Absolute Error) of 0.00635 on previously unseen test data. Visualization of the latent space shows very clear clustering based on the type of sweetener, where separation using Support Vector Machine (SVM) in the latent space achieved 100% accuracy in 5-fold cross-validation. Furthermore, the Bayesian Neural Network (BNN) model with the Monte Carlo Dropout method successfully provided highly accurate predictions of sweetener concentrations with an R2 value reaching 0.9978. In addition to accuracy, the BNN is capable of providing uncertainty estimates for each prediction, which allows the system to determine a Limit of Detection (LOD) of 6.66% v/v. This capability provides a higher level of confidence for users in the living lab to distinguish pure honey from samples with low levels of adulteration.

3.4 Impact of Dissemination at KDOJ Living Lab

The effectiveness of dissemination at the KDOJ Living Lab is evident from the success of 20 participants in mastering the entire technology usage cycle, from mechanical assembly to the interpretation of AI prediction results. The living lab approach, which emphasizes co-creation, ensures that the training modules and SOPs developed are tailored to the needs of local partners. Thru the provision of 10 WeViSpec kits, this program has transformed laboratory prototypes into functional field screening tools, which are now part of the permanent applied research facilities at KDOJ Living Lab UTM. Additionally, the effectiveness of the dissemination program was measured using a quantitative approach with a questionnaire involving 20 participants (N=20). This questionnaire is designed to evaluate five critical aspects in the technology transfer cycle: module clarity, technical skills, operational ease, understanding of AI-based data analysis, and perception of instrument utility (Table 2). The use of this evaluation instrument aims to ensure that each stage in the dissemination process, from socialization to sustainability, has achieved the established performance indicators.

The results of the questionnaire analysis show a very high level of effectiveness with an average score of 4.68 out of 5.00 (Figure 3). The highest score of 5.00 in the utility aspect indicates very good acceptance from international partners toward the WeViSpec technology as a sustainable applied research asset. The high scores in assembly skills (4.65) and calibration (4.70) validate that the compact instrument design and standardized procedures facilitate the replication of the tool even by non-experts.

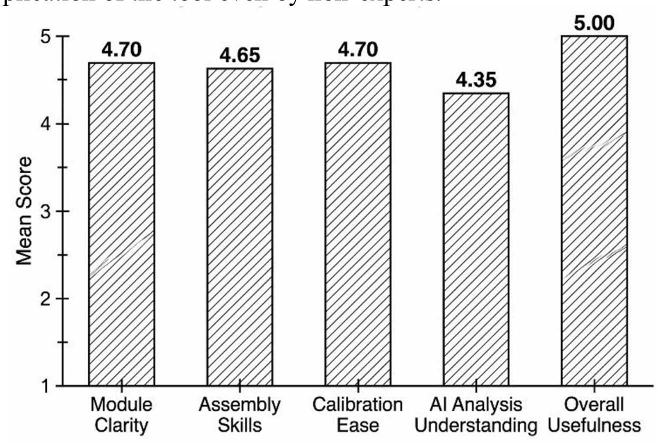


Fig. 3. Average value for each aspect.

This success is inseparable from the implementation of a systematic dissemination process (Figure 1), which emphasizes the Living Lab principle thru the active involvement of participants as co-creation partners. Although the aspect of understanding Python-based data analysis (4.35) had the lowest score among the other indicators, the value still fell within the "Very Good" category, indicating that the integration of the VAE-BNN model was well understood thru intensive mentoring during the workshop. The integration of this low-cost instrument and artificial intelligence has now officially become part of the research facilities at KDOJ Living Lab to support science literacy and honey adulteration detection in Malaysia.

Table 2. Indicator for Assessing the Effectiveness of WeViSpec Dissemination

No	Aspects	Assessment Indicator
1	**Clarity of the Module**	1. The language and instructions in the technical guide are communicative and easy for participants to follow. 2. The visualizations in the module help accurately identify the 17 main components. 3. The module's structure is systematically organized, covering the stages from tool-making to AI data interpretation.
2	**Assembly Skills**	1. Ability to install mechanical components and electronic components with precision. 2. Accuracy in adjusting the focal distance between the webcam sensor and the DVD diffraction grating. 3. Proficiency in installing optical components (convex lens and slit) according to the light path.
3	**Ease of Calibration**	1. The ability to operate the calibration feature on a Python-based GUI interface independently. 2. 2. Accuracy in determining pixel coordinates for three reference laser sources (650 nm, 532 nm, and 405 nm). 3. Success in validating calibration results within a tolerance error limit of ±10 nm.Kemampuan mengoperasikan fitur kalibrasi pada antarmuka GUI berbasis Python secara mandiri.
4	**Understanding of Analysis**	1. Understanding in executing the workflow on a Python notebook from background correction to prediction. 2. Ability to interpret the position of sample clusters in the two-dimensional VAE latent space. 3. Accuracy in reading the predicted sweetener concentration values along with the uncertainty parameters.
5	**Reliability**	1. The instrument is capable of consistently capturing the characteristic absorbance peak of pure honey in the range of 470–500 nm. 2. The effectiveness of the Ambient Light Canceling feature in maintaining spectrum quality from ambient light interference. 3. The instrument's signal stability in repeated measurements (repeatability) with minimal standard deviation.
6	**Usefulness**	1. The low production cost supports the potential for independent replication by local partners. 2. The instrument functions continuously as a learning medium for optical instrumentation for students at KDOJ. 3. The spectral data generated can be contributed to the development of a honey research database in the living lab ecosystem.

4 Conclusion

This research has successfully developed and disseminated the Webcam Visible Spectrometer (WeViSpec) technology as a rapid screening solution for honey adulteration in the Kolej Dato' Onn Jaafar Living Lab environment. Technically, this instrument has proven that low-cost optical components (USD 30.93) can produce high-quality spectral data with a resolution of ~5 nm and reliable wavelength accuracy. The integration of the Variational Autoencoder (VAE) and Bayesian Neural Network (BNN) models offers a robust analytical framework, capable of not only classifying types of sweeteners with 100% accuracy but also predicting concentrations with high precision and providing crucial uncertainty quantification for field data validation.

From a community service perspective, this program has achieved its strategic goal of enhancing the technical capacity of 20 international participants thru participatory and structured training methods. The living lab approach ensures that this innovation has a long-term impact, where the donated WeViSpec kit now serves as an applied research facility and a learning medium for optical instrumentation for students and researchers at UTM partners. The success of this knowledge transfer demonstrates that AI-based appropriate technology has great potential for widespread adoption in society at minimal cost.

For future development, this research recommends expanding the dataset to include various honey varieties with different botanical and geographical origins to enhance the model's generalization. Additionally, further validation is needed using commercial honey samples from open markets to test the system's robustness in facing varying environmental conditions. Improving the device's stability against ambient light and room temperature is also an important point so that WeViSpec can be implemented as a more robust and reliable standard detection instrument in the field.

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