

CLLOUD-BASED PREDICTIVE MOBILE APPLICATION FOR ASSESSING HONEY PURITY FROM STINGLESS BEES

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Abstract

Honey bees have various types and characteristics, one of which is the stingless bee. This type has limitations in producing honey, the selling value of its nest is quite expensive, and the water content in the honey produced is relatively high. The high water content affects the shelf life of this type of honey product, making it a challenge for honey farmers in marketing it. In addition, the dominant sour taste also makes its market increasingly limited or vulnerable to falsification of its purity by irresponsible producers. The use of spectrophotometers is increasingly developing in the food sector, especially in detecting the purity of a food product. The portable type of spectrophotometer also makes it easier to obtain spectrum data for a particular product. A simpler technique that is directly connected to a computer device allows it to be developed into a cloud-based application by providing minimal raw data processing (pre-processing). This study produces an android-based application and a simple cloud-based application architecture, which aims to facilitate the application of a honey purity prediction model from stingless bees. The Android-based application was successfully created by applying 'raw' spectrum data processing from the results of scanning a portable spectrophotometer, and data experiments with the SVM classification model produced an accuracy of 95%. The application of PCA techniques to cloud-based mobile application architecture results in efficient preprocessing of spectrum data.

Key words: Cloud-Based, Honey, Mobile, Portable spectrophotometer, Spectrum data.

INTRODUCTION

The development of technology has entered all fields including food products that are prone to misuse. Assessing the purity of a food product is important in today's era, the increasing needs and market demand are increasing, but the situation on the side of food production is not good. One of them is the condition of the development of honey

production which tends to be stagnant or very little attention, thus affecting the increase in its activists. Honey from stingless bees has an attractive market segment from the perspective of cultivators and just consumption. Bees with friendly characteristics with humans, namely with a smaller size than other types of bees, do not have a sting that is dangerous to humans, a flight range of only 200 meters, and produce

honey and propolis with better properties than other types of bees. Cultivators of this type of honey generally run it as a side business and are placed in the yard or garden around the house which is a residential area. This shows that the maintenance of this type of bee does not interfere with human activities.

The body becomes prime and healthy, and is efficacious in curing several diseases is one of the benefits of honey from stingless bees. Botany or food sources for stingless bees that are different for each type are also research parameters. There are 4 locations for taking honey samples from stingless bees in this study. Lampung, Bogor, Sukabumi and Rangkas Bitung are the target sample locations that have different geographical characteristics and different bee cultivation models and techniques. Nectar and pollen are types of food that bees get from various types of flowers and plant sap in certain vegetation. Nectar is a source of carbohydrates and pollen is a source of protein, fat, vitamins and minerals.

Table 1. Honey Samples from Stingless Bees

| No. | Types of Stingless Bees | Nectar (Vegetasi) | Harvest time |
|-----|-------------------------|--|--|
| 1. | Tetragonula Biroi | Antigonon, Batavia, Euphorbia, Mango tree sap, Jackfruit tree sap. | ± 3 Months, 1 Kg directly - 1 Ton/Year (stock) (depending on rainfall) |
| 2. | Tetragonula Laeviceps | Antigonon, Batavia, Kalendra, Star fruit flower, Mango tree sap, Jackfruit tree sap. | ± 3 Months, Display for Edu park |
| 3. | Heterotrigona itama | Dominant Acacia Mangium | ± 3 Months, ± 10 Kg directly (depending on rainfall) |
| 4. | Tetragonula Laeviceps | Antigonon, Kalendra, Mango and Jackfruit tree sap | ± 3 Months, ± 1 Kg, there are ±100 stops, residential scale |

Table 1 shows that each type of stingless bee used as a research sample has almost the same nectar and harvest period. According to information obtained from farmers at the sample location, overall they have the same harvest period, which is around 3 months. The geographical origin of bees located close to settlements is dominated by the nectar of the antigonon and batavia types as the main nectar sources. While the dominant acacia mangium for the geographical location of origin in the forest, samples were taken from the Lampung Way Kanan forest.

The management of this type of honey also has a number of challenges, ranging from weather factors that affect food/vegetation conditions, limited markets, to predators that are always lurking. However, the productivity of honey from stingless bees is always lower than the productivity of honey from stinging honey bees. Honey counterfeiting is a critical problem because the nutritional value of honey from fresh honey or pure harvest honey is reduced, this is due to the addition of sweeteners that can have an impact on consumer health conditions [2]. From these several things, it is hoped that innovation opportunities on the downstream side will be able to help significantly in meeting the need for stingless honey products whose purity is maintained. One of them is the need to apply a prediction model with a mobile-based application.

In general, honey product entrepreneurs in Indonesia routinely conduct composition analysis and physical property assessments, but this analysis activity takes time. This method requires sample preparation and considerable analytical capabilities, in addition to paying attention to the quality and safety of honey products. Therefore, a much more efficient solution is to take advantage of the current digital era, where everyone can easily access mobile applications.

Traditionally, the use of UV-Vis spectroscopy is intended for analysis based on the height and position of characteristic peaks. In several studies in this field, there is an average spectrum value that gets a peak value, namely in the range of 200 - 800 nm, 220 - 310 nm, and 270 - 300 nm. In this study, the peak value was obtained in the range of 350 - 450 nm, with pure honey samples from stingless bees [1]. The use of NIRS (Near Infrared Spectroscopy) technology has

comprehensively tried to play a role in honey quality detection. Sample presentation, spectral data acquisition, raw data treatment to prediction modeling are precisely carried out by the NIRS spectroscopy method. However, there are still obstacles to implementation on the user side, both on a personal and industrial scale.

In previous studies, spectral acquisition was carried out at room temperature, and using three different preprocessing algorithm approaches. Moving Average Smoothing (MAS), with 11 points, Mean Normalization (MN), and Savitzky–Golay first derivative with 11 points, and second-order polynomial fitting (order 2) (SG 1d) were used to improve the raw data collected simultaneously [2]. A similar approach in this study is the preprocessing stage with the implementation of the Probability Principal Component Analysis (PPCA) and Expectation Maximization (EM) algorithms with the result of an optimally reduced dataset. Furthermore, the dataset is placed on a cloud-based web service. The research output obtained is a simple infrastructure that can facilitate the application of honey purity prediction models from the perspective of farmers and producers.

Every application developer must ensure that the application developed is user-friendly and not difficult to understand and can be operated by anyone. In addition, it is also relatively easy to modify to add new functionality [3]. Expansion of new research areas, one of which is a smartphone-based spectrophotometer. In the field of sensor development integrated with smartphone-based applications, among others, a portable bilirubin detection device by combining a handheld fluorescence sensor and UV lamp and a smartphone for image capture [4]. Near Independent Reflectance (NIR) is based on the absorption value of solid objects of sambok honey watermelon seeds, carried out on images by extracting them into spectrum data to classify and detect seeds that contain viruses or not.

Florentin et al. have combined spectroscopic approaches with traditional chromatography techniques to streamline the sample testing process in the laboratory. Samples that have their spectrum values detected using a certain type of spectrophotometer are then subjected to clinical tests to determine their content. The method offered is a combination of the two sample testing techniques to obtain fast and

real-time results in the field [5]. In line with that, this study combines the technique of scanning honey products from stingless bees and clinical testing from the laboratory into a faster and more efficient honey purity detection method approach. Cloud technology allows the acquired dataset to be stored reliably and validly, so that the accuracy value of the implemented prediction model becomes more reliable.

The next focus of research is on portable smartphone sensing devices that are low-cost and have real-time testing results, but still rely on handheld UV lamps and dark environmental conditions [6]. In this study, the development of a smartphone application with the integration of a portable spectrophotometer based on cloud technology is focused on simplifying the pre-processing stage. So that the initial spectrum data is obtained in real time, although it still relies on the standard condition treatment of the spectral data measuring device

MATERIAL AND METHODS

Computing technology is developing very rapidly, one of which is in the field of artificial intelligence which can make computers take information from image objects for the purpose of object recognition or object classification automatically [7].

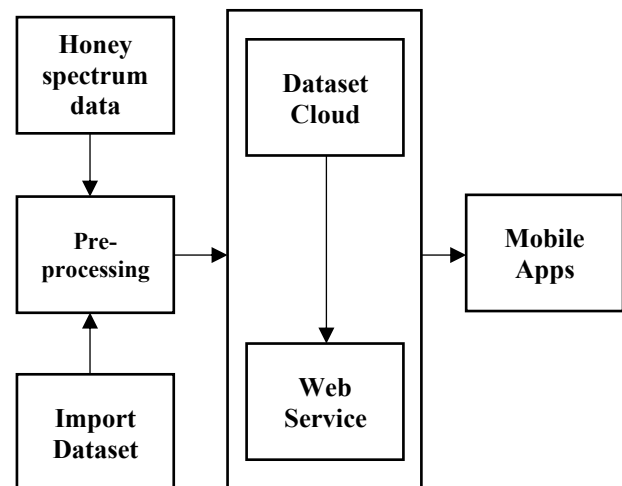


Fig. 1 Application development stages

Furthermore, artificial intelligence through the area of machine learning facilitates the development of predictive models with the approach of using spectrum data. There are several stages of implementing the development of cloud-based smartphone

applications for the predictive model. Figure 1, shows the stages of smartphone application development for stingless honey detection based on cloud technology. The first is the processing of spectrum data at the pre-processing stage, the second is the development of a web service for dataset management, and the development of mobile applications.

| | WaterContent | Diastase | Hydroxymethylfurfural | Reducing Sugar | Saccharose | Acidity | 357 | 357.5 | 358 | 358.5 | ... |
|----|--------------|----------|-----------------------|----------------|------------|-----------|------|-------|------|-------|-----|
| 0 | 30.100000 | 0.000000 | 3.240000 | 67.460000 | 69.700000 | 18.270000 | 24.9 | 24.2 | 24.9 | 27.7 | ... |
| 1 | 30.249573 | 0.163651 | 3.494071 | 67.292515 | 69.086837 | 18.049679 | 32.5 | 32.6 | 33.1 | 36.7 | ... |
| 2 | 30.187093 | 0.206429 | 3.489143 | 67.329906 | 69.181418 | 18.090128 | 34.7 | 35.5 | 35.4 | 39.6 | ... |
| 3 | 30.384793 | 0.267841 | 3.453478 | 67.230139 | 68.971269 | 17.990812 | 37.0 | 37.0 | 36.9 | 41.6 | ... |
| 4 | 30.294006 | 0.147358 | 3.245851 | 67.215891 | 68.960656 | 18.189460 | 38.8 | 38.5 | 38.9 | 43.1 | ... |
| -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | ... |

Fig 2. Dataset acquisition

The first stage focuses on pre-processing, which consists of honey spectrum data collection with minimum standards of fluorescence-based data collection process. Environmental conditions are positioned in a box with a curtain cover to ensure darkness without light interference. The portable spectrometer measuring device is set in the box and then the Exposure value is set at 2000, Gain 2, Number of cycles 10 and Delay 100 to obtain standard spectrum value scan results.

The combination of data collection methods, namely, non-destructive methods for honey spectrum data and clinical tests to obtain standard content values from honey. Figure 2 is the acquisition data generated in this study. The dataset has specifications of 6 columns of clinical honey characteristics according to SNI 8664: 2018 and SNI 3743: 2021 standards and 1 column of sample origin labels and several wavelength columns of honey spectrum data results at 357 - 725.5 nm.

In addition, the dataset import process is also a stage carried out to support easier and simpler pre-processing in providing datasets. then in the second stage the dataset is set to be managed by a web service with a cloud technology approach. At the end of this application development stage, the kotlin implementation is used to provide an application interface display according to needs.

Pre-processing

The wavelength used in this study was 357 - 725.5 nm. Each pure honey sample was prepared by giving standard treatment before the spectrum data was taken. Such as dilution with a ratio of 1:10 and heating and mixing with each process following the process rules in time. The spectrum data obtained from each sample is 400 data columns. The specifications and characteristics of the samples are detailed in table 1. Each spectrum data obtained from the scan results, is transposed and then collected into honey spectrum data from stingless bees.

Web Service

Web service development uses a web framework written in python, namely flask. It is a type of microframework, used as an application framework and display of an application. The flexibility of flask can be seen in the application behavior settings that are easier, and basically flask does not require a specific tool or library. This framework is very suitable for the needs of simple application development in this study. In addition, the development needs on the web service side are also appropriate and to implement the programming language used is also in accordance with the language used when creating the prediction model. This is because flask has quite high flexibility and scalability compared to other frameworks.

Mobile Apps

The development of smartphone-based applications in this study focuses on the integration of datasets that are directly read by the device with fluorescence sensors. The application developed is a simple interface for managing spectrum data that has become a predictive modeling dataset. The cloud technology used in building the model dataset is integrated into an Android-based mobile application. The results of the spectrophotometer scan produce fluorescence-based spectrum data that needs to be adjusted for the rows and columns according to the dataset in the model. For this reason, the import of the data obtained is translated by Kotlin into a standardized cloud dataset. Furthermore, the prediction process is carried out in the web services area and then the model results are displayed on the mobile application interface.

RESULT AND DISCUSSION

Laboratory experiments were conducted in a study to identify some physicochemical properties and their quantities in various types of research objects [8] (honey from stingless bees). This study used primary data samples, namely 4 geographical locations of origin, 3 types of stingless bees and botanical or vegetation variants as feed. The results of sample collection, then the process of dataset acquisition in the form of spectrum data from various types of honey was carried out. To then form a model as a prediction tool for the quality of purity of honey from stingless bees. The next stage which is the main content of this article is the creation of an Android smartphone application based on cloud technology.

Data acquisition input

Incomplete clinical trial data based on the number of samples, from 4 honey samples with 100 repetitions, there should be 4 x 100 repetitions of clinical trials. Due to research limitations, only 4 x 2 repetitions of clinical trials were obtained. Synthetic Minority Oversampling (SMOTE) was used, smote was used to complete incomplete clinical trial data. In handling unbalanced data, there are several approaches in programming implementation, one of which is imputable. Other studies of this smote method are only applied to training datasets to produce minority class data into several majority data [9]. However, in this study smote with imputable is used to fill in majority data based on primary data which is a minority (oversampling).

Machine learning methods cannot replace linear statistical approaches [10]. The state of the data before entering the model is taken into account, which is essentially a statistical problem. However, with proper sampling taken from the statistical distribution of metabolites [10]. The idea of this concept is applied by determining the composition of the important or main standard content in the purity of honey products from stingless bee species.

Figure 2 shows the application architecture that will be developed using a 3 layer approach. The application layer consists of using the spectrolab application on laptop media and developing android-based applications. The next layer is related to application development services, in this case using excel, python and kotlin applications. The final layer is the data

layer which is planned to be part of the integration of desktop and android-based application development. Fluorescence-based spectrum data files can be accommodated in local storage media. The data file is managed with simple excel to get .csv. Integration is carried out to obtain modeling results based on data processing in excel.

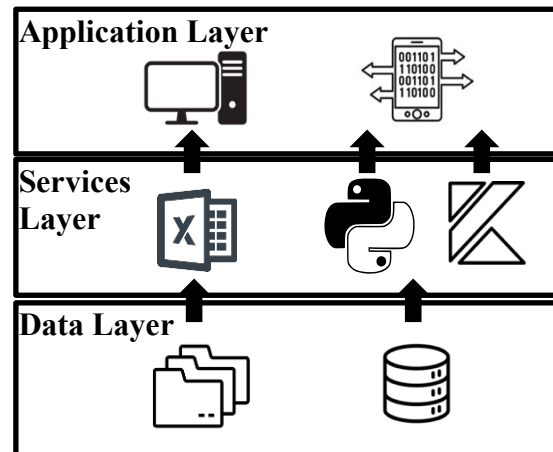


Fig. 2 Application arcahitecture

The concept of training networks using large and diverse datasets remains a promising direction, although each method will continue to evolve [11]. Not to mention the development of infrastructure that accommodates datasets, increasingly diverse and quickly adapting to the needs of lightweight and efficient systems. The combination of data collection methods before acquisition becomes more efficient with the implementation of mobile-based applications with web services in the data layer.

Cloud Based Web Service

The test results of a study on CPU usage on a facial recognition system with conditions of changes in the amount of data in the database were obtained ranging from 35% to 41% [12]. This shows that CPU usage on a system that works in real time will not significantly reduce its workload if it only reduces the amount of data. Therefore, this study offers cloud technology that shifts the huge computing workload with web service packaging in the cloud area.

According to Riccardo, et al., there are two types of point cloud considerations. The first is the density of points and similar regularity as in the training set, and the second is on non-uniform random sampling [13].

Applications are supported by web services technology in integrating datasets obtained from portable spectrophotometers. Input data from the spectrophotometer is processed automatically with the resulting CSV file. The application interface is still the result of a general score from modeling with a dataset obtained from 4 sample data locations. Lampung, Bogor, Sukabumi and Rangkas Bitung are the sampling areas determined in this research. Prediction results from the model can be implemented into applications precisely and appropriately.

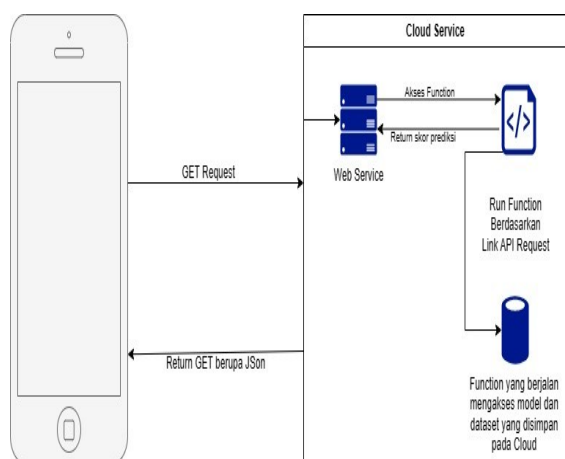


Fig. 3 Web service flow

Simple Mobile Apps Integration

The integration of spectrum data that has been stored and processed on the data layer, on the application layer is implemented using cloud technology. The cloud computing layer has a network, firewall and server that are outside the virtual cloud environment in the middle position. The cloud management and virtualization platform has a part to ensure that the virtualization infrastructure is hosted on the server and storage is well managed [14].

In previous studies, to obtain information about the content of impurities or those that interfere with the purity of a product, as well as the physical and chemical properties of samples that have been standardized, a multivariate analysis such as PCA (principal component analysis) analysis was needed [15]. This study uses PPCA (Probabilistic Principal Component Analysis) and EM (Expectation Maximization) analysis in the pre-processing stage. Dimension reduction is carried out using PPCA and EM Algorithms to obtain the probability value as an initial estimate. Furthermore, using the

Gaussian mixture approach to confirm the determination of the number of principle components (PC) obtained from the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC).

However, this article explains the implementation of the results of the spectrum data analysis to the formation of a prediction model. In this case, the prediction model is used to provide recommendations for the purity of honey from stingless bees. Figure 4 shows two buttons, standard scalar and minmax scalar, where each button shows a different function. standard scalar shows the results of data processing with PPCA analysis without being given EM algorithm treatment. While minmax scalar is the result of the maximum estimated value of the EM algorithm.

Modeling is done with the Support Vector Machine (SVM) algorithm without using additional kernel functions or parameters that make the accuracy value better. The SVM prediction model is used as an effective pre-processing stage test to obtain better prediction accuracy values. The prediction accuracy value is shown from each of the button actions.

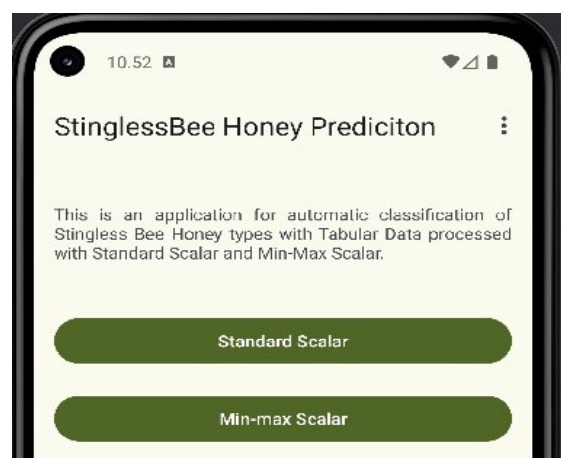


Fig. 4 Prediction view

A similar case in the use of Gaussian mixture models takes data from a number of specific respondent subjects, then using principal component analysis reduces the dimensionality of the features of the data [16].

Quantitatively assessing the performance of a framework, using stratified random sampling of the classification results. The same pooled samples are used across products, to assess performance. Overall accuracy (OA), user accuracy (UA), manufacturer accuracy (PA),

and F1 (harmonic mean of PA and UA) are generated from the error matrix [17]. The accuracy of the model on the developed application is assessed using the same test sample based on Manufacturer Accuracy (PA), User Accuracy (UA), and Overall Accuracy (OA) [18]. However, in this study, overall accuracy is used to show the prediction value with the confusion matrix. The results obtained are shown in Table 1.

Table 1. Confusion Matrix

| value | precision | recall | f1-score |
|--------------|-----------|--------|----------|
| macro avg | 0.95 | 0.94 | 0.95 |
| weighted avg | 0.95 | 0.95 | 0.95 |

Table 1 shows the average macro and weight values of each class data. Both values are used to overcome dataset imbalance by looking at the average of each class and its data distribution. Both values are obtained based on the accuracy of the positive values obtained (precision), the extent to which the model can capture all positive data (recall) and the harmony formed from precision and recall (f1-score). The data shows that the overall average macro and weight values are at 95%, so that the model formed has good accuracy with an error rate of 0.05 or 5%.

The application is developed with spectrum data and prediction models stored in the cloud layer. Furthermore, the front end of the application receives input data from honey scans via a portable spectrophotometer via regular data transfer. In the end, the application provides prediction results for honey purity in the percentage of model accuracy.

Figure 5 shows the display of clinical test data input results that can be input in addition to the results of the spectrum data scan from the spectro tool. There are 6 clinical test parameters determined in the study, namely water content, diastase, hydroxymethylfurfural, reducing sugar, saccharose, and acidity. As input, these parameters can affect the prediction results of the purity of the honey whose purity is to be tested.

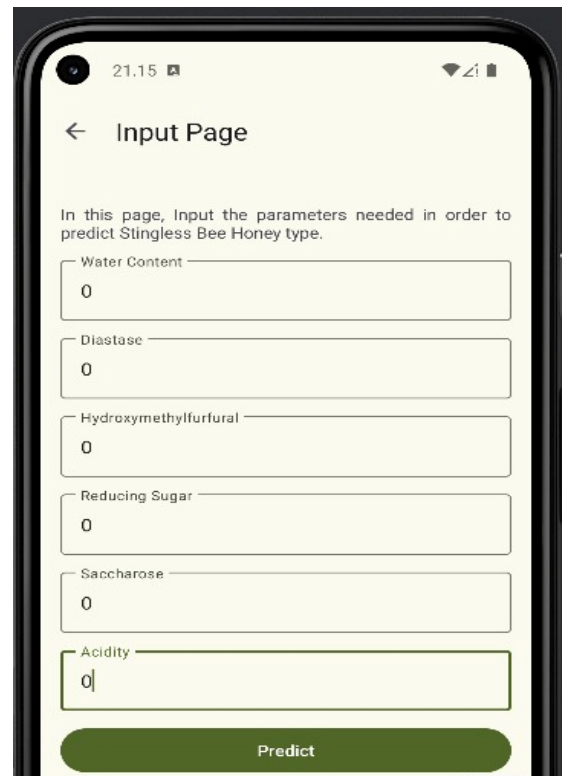


Fig. 5 Input page

In this research, cloud services are used to manage databases, APIs and web services. All running functions access models and datasets stored in cloud services. Next, the function is executed based on the API Request link. Web services are an integration for mobile applications that are built, using a JSON management interface, calculation results and scores are displayed properly and precisely.

CONCLUSION

The implementation of cloud services has succeeded in developing a honey purity prediction application based on a mobile application. The model used has an accuracy value of 95% so that in its implementation the dataset and prediction model stored in a cloud-based web service can have their accuracy values increased. In the future, cloud implementation can be maximized by measuring the computational performance of the model.

Furthermore, it can be compared to the implementation of local storage by only relying on web services as an integration of applications and data.

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ACKNOWLEDGMENT

Gratitude is expressed to all parties who support the achievement of the objectives of this study. The Indonesian Education Scholarship study completion program and the Center for Research and Community Service (P3M) of the Jakarta State Polytechnic.

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