6. AIP 2023_Design and performance test of portable

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Design and Performance Test of Portable Spectrometer Using AS7265x Multispectral Sensor for Detection of Adulterated Cane Sugar in Granulated Coconut Sugar

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Abstract. Cane sugar is frequently added into coconut sap during heating to trigger the sugar granulation despite negative consequences to economic value. The purpose of this study was to design a portable spectrometer to detect the adulteration of cane sugar in granulated coconut sugar. The developed portable spectrometer utilized AS7265x multispectral sensor as the main component. This sensor was equipped with two LEDs as the light source and had 18 channels to read the light reflectance of the coconut sugar in a range from visible to near infrared. We employed two types of neural network with different output to determine the purity of coconut sugar and to classify the level of cane sugar added. The developed neural network consisted of 18 output channels of the instrument as the predictors in the input layer and one hidden layer with 30 nodes. To calibrate the instrument, six treatments were prepared with the ratio of cane sugar and coconut sap of 0%, 10%, 20%, 30%, 40%, and 50% (w/v). The results showed that the portable spectrometer worked normally and can read the light reflectance of the coconut sugar. Furthermore, the developed neural network algorithm had an accuracy of 100% to classify 300 and 1500 samples of pure and adulterated coconut sugar, respectively. In addition, the average accuracy of the neural network to classify the intensity of cane sugar added to coconut sugar was more than 90%. The developed portable spectrometer and neural network algorithm can successfully detect cane sugar added to granulated coconut sugar.

INTRODUCTION

Granulated coconut sugar is a type of processed coconut sap product. The granulated coconut sugar has much higher economic value compared to the either of solidified coconut sugar or white cane sugar. The quality of coconut sap is strongly influenced by the length of time of tapping, weather and season. Haryanti et al. reported that tapping at night resulted in lower sucrose levels of coconut sap than tapping during the day [1]. So that in practice coconut sugar farmers mix the sap from the tapping day and night to be further processed into coconut sugar. In rainy weather, coconut sap has a high reducing sugar content. Consequently, when the sap is processed it will produce sap that is difficult to granulize. Some coconut sugar producers are trying to increase the amount of production by adding sugar from other cheaper sources. Refined sugars such as cane sucrose are often used for this purpose because they are more readily available year-round and less expensive. It is common practice to add a small amount of cane sugar to coconut sugar during its production. Cane sugar can be used for seed crystallization on coconut sugar crystals [2]. Tanjung et al. suggested that the addition of 12% cane sucrose resulted in the highest quality palm sugar [3]. The addition of

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30% granulated sugar at a temperature of 120°C is the best treatment for palm sugar processing [4]. Although it contains sucrose sugar, it is suspected that the characteristics of coconut sugar produced will be different both chemical and sensory characteristics compared to coconut sugar without adulteration [6]. The practice of adding cane sugar is undesirable in export quality of granulated coconut sugar. The quality requirements for export quality of granulated coconut sugar are that apart from being organic, the sucrosecontent only comes from coconut sap sucrose without mixing sucrose from other sources.

Manual detection of adulteration in coconut sugar with the human eyes is very difficult to do because the appearance of pure granulated coconut sugar is relatively almost the same as that of adulterated coconut sugar. In fact, the difference between palm sugar and sugar from other sources can be seen from the molecular structure using Carbon Stable Isotope Analysis (CSIA). Palm sugar has the characteristic C3 carbon isotope typical for carbohydrates of plant origin that utilize the Calvin photosynthesis pathway to bind carbon dioxide. The mean value of δ13C ‰ for C3 derived sugars is about -25 ‰, while that for cane or corn sugar or syrup (including high fructose corn syrup) is about -10 ‰. Less negative signs of isotopic carbon are seen in corn and cane sugar since they are produced by the Hatch & Slack (C4) photosynthetic pathway, which does not cleave carbon dioxide to the same extent as the Calvin (C3) pathway [2]. Detecting the purity of coconut sugar using the Carbon SIA method, however, requires a highcost.

Several studies have been conducted to detect the purity of agricultural commodities using the reflectance method of visible and near infrared (Vis-NIR) light [6, 7]. However, the studiesthat have been carried out generally utilize a laboratory-scale Vis-NIR spectrometer. Although the results are more accurate, the use of this tool has several drawbacks. The laboratory-scale Vis-NIR spectrometer is very expensive (USD 8,000-10,000) and its dimension is quite large, so it is not easily movable. In addition, the operation of the deviceis complicated and special skills are needed to use it. For this reason, it is necessary to develop an instrument capableof detecting the purity of granulated coconut sugar at a relatively more affordable cost, easier to use, and accurate results. The AS7265x sensor is a multispectral sensor consisting of three optical sensors, namely: the AS72651, AS72652 and AS72653 sensors. The combination of these three sensors is able to capture the reflectance of 18 spectrums of the Vis-NIR with wavelength ranging from 410 to 940 nm [8]. With these specifications, the AS7265x sensor has the potential to be applied in agriculture for quality evaluation with a more affordable equipment investment cost.

To determine the effectiveness of the designed instrument, a pattern recognition algorithm was developed. A neural network-based pattern recognition was employed to classify the impurity level of the granulated coconut sugar as well as to determine the accuracy of the detection. The application of neural network for pattern recognition has been successfully proofed in many classification problems [9-12].

The aim of this research was to design a portable spectrometer to detect the adulteration of cane sugar in granulated coconut sugar. The developed portable spectrometer utilized AS7265x multispectral sensor as the main component. A backpropagation neural network (BPNN) was established to perform the classification of coconut sugar pureness with output values of the portable spectrometer as the predictors in the input layer of the network.

MATERIAL AND METHODS

This research was conducted through several steps, i.e., design of portable spectrometer, initial experiment, main experiment, and data analysis. Each step will be explained in more detail in the next sub-section.

Design of Portable Spectrometer

The main components to build the portable Vis-NIR spectrometer were AS7265x chipset (**Fig. 1**), Arduino Uno, jumper cables, USB 2.0 A-to-B device cable, and switches. **Fig. 2** shows the interaction between the developed instrument and the coconut sugar sample as the observed object. The AS7265x multispectral sensor is able to capture light reflectance from 18 wavelengths in the visible to infrared light range which is represented in 18 channels as shown in **TABLE 1**.

To operate the developed portable spectrometer, the procedures were as follows. A weight of 5 gram of sugar sample was put into a small black bowl (**Fig. 3a**). The funnel of the instrument was brought close to the sugar sample, then the measuring instrument was turned on (**Fig. 3b**). When the measuring instrument was on, the LEDs subsequently emitted light to the sugar sample. When the light hit the sugar sample, some portions of the Vis- NIR light were reflected and captured by the sensors. The captured light will then be processed using an Arduino- based program and the output value will be displayed on the computer (**Fig. 3c**).

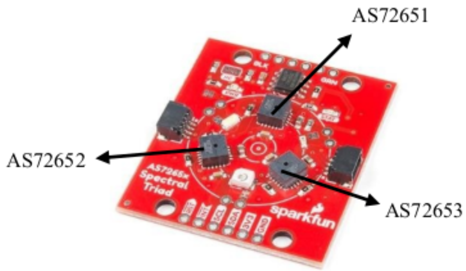


FIGURE 1. The AS7265x chipset with a combination of three sensors (AS72651, AS72652 and AS72653).

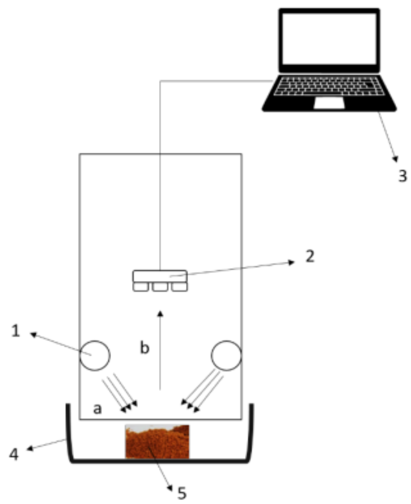


Figure description:
1. LEDs, 2. Sensor array, 3. Personal Computer,
4. Sample dish, 5. Sugar sample.

a. LEDs emit lights to sugar sample.
b. Reflectance of the Vis-NIR is captured bythe sensors.

FIGURE 2. A schematic design of the developed instrument.

(a) (b) (c)

FIGURE 3. Data acquisition of granulated coconut sugar.

TABLE 1. Channels and wavelengths captured by the AS7265x multispectral sensor.

No.	Channel	Wavelengths (nm)	No.	Channel	Wavelengths (nm)
1.	A	410	10.	J	705
2.	B	435	11.	K	900
3.	C	460	12.	L	940
4.	D	485	13.	R	610
5.	E	510	14.	S	680
6.	F	535	15.	T	730
7.	G	560	16.	U	760
8.	H	585	17.	V	810
9.	I	645	18.	W	860

Initial Experiment

To find out how well the work of the developed instrument, initial experiment was conducted by taking samples of granulated coconut sugar and cane sugar from market. This procedure was also to figure out if there was a difference between the Vis-NIR reflectance of both sugar types. At this initial stage, we also made both pure and adulterated granulated coconut sugar to ensure that the adulterated coconut sugar had no difference in appearance compared to the pure one. The cane sugar was added when the coconut sap was heating, which was more precisely when the coconut sap reached its initial boiling point. The addition of cane sugar at this stage was 150 g into 3000 mL (= 3 L) of sap, or in a ratio of 5% (w/v). This ratio was based on the common practice conducted by coconut sugar producers by adding 1.5 kg of granulated sugar into 30 L of sap. Therefore, in this research the concentration of 5% (w/v) was assigned as the maximum concentration of cane sugar added into coconut sap.

Main Experiment

In this stage, an experiment was carried out by making six treatments of granulated sugar with a variation of cane sugar concentration as presented in **TABLE 2**. The percentage of sugar added was the ratio between the weight of cane sugar (g) and the volume of coconut sap (mL). Each treatment produced about 450 g of granulated coconut sugar. We took a sample of 300 g of the produced coconut sugar for measuring its light reflectance while the rest was for chemical analysis. The sample was then divided and put into small black bowl in which each bowl contained 5 g of coconut sugar. Thus, the number of samples for each treatment was 60 samples. In total there was 360 samples for sixtreatments.

TABLE 2. Six treatments with different cane sugar concentration.

Treatment	Concentration of cane sugar in coconut sap (w/v)	Weight of cane sugar (g)	Volume of coconut sap (mL)
P0-control	0%	0	3000
P1	1%	30	3000
P2	2%	60	3000
P3	3%	90	3000
P4	4%	120	3000
P5	5%	150	3000

After producing coconut sugar, the next step was Vis-NIR reflectance measurement using the developed portable spectrometer. Each sample of granulated coconut sugar was measured its reflectance five times. Therefore, we collected 300 light reflectance data for each treatment, or 1800 data for all treatments. All of these data were then arranged into a dataset which comprised 18 inputs from Vis-NIR channels (see **TABLE 1**) and one output that represented coconut sugar purity class.

In this study, we conducted two types of purity classification. Firstly, we classified the granulated coconut sugar into two classes, i.e., pure and impure (adulterated). According to **TABLE 2**, the pure sugar class was resulted from treatment P0, while the sugar produced from P1-P5 was categorized as impure (adulterated). In the second classification, we classified the coconut sugar into six classes based on the concentration of cane sugar added into the coconut sap during heating. The two types of datasets developed for coconut sugar classification can be seen in **TABLE3** and **TABLE 4**.

TABLE 3. Dataset for classification of coconut sugar purity with Vis-NIR reflectance as the inputs.

Sample	Inputs																		Output		Class
	A	B	C	D	E	F	G	H	I	J	K	L	R	S	T	U	W	V			
1																			1	0	Pure
2																			1	0	Pure
…																			1	0	Pure
300																			1	0	Pure
301																			0	1	Impure
302																			0	1	Impure
…																			0	1	Impure
1800																			0	1	Impure

TABLE 4. Dataset for classification of cane sugar concentration added into coconut sap with Vis-NIR reflectance as the inputs.

Sample	Inputs																		Output						Class
	A	B	C	D	E	F	G	H	I	J	K	L	R	S	T	U	W	V							
1																			1	0	0	0	0	0	0%
2																			1	0	0	0	0	0	0%
…																			1	0	0	0	0	0	0%
300																			1	0	0	0	0	0	0%
301																			0	1	0	0	0	0	1%
302																			0	1	0	0	0	0	1%
…																			0	1	0	0	0	0	1%
600																			0	1	0	0	0	0	1%
601																			0	0	1	0	0	0	2%
602																			0	0	1	0	0	0	2%
…																			0	0	1	0	0	0	2%
900																			0	0	1	0	0	0	2%
901																			0	0	0	1	0	0	3%
902																			0	0	0	1	0	0	3%
…																			0	0	0	1	0	0	3%
1200																			0	0	0	1	0	0	3%
1201																			0	0	0	0	1	0	4%
1202																			0	0	0	0	1	0	4%
…																			0	0	0	0	1	0	4%
1500																			0	0	0	0	1	0	4%
1501																			0	0	0	0	0	1	5%
1502																			0	0	0	0	0	1	5%
…																			0	0	0	0	0	1	5%
1800																			0	0	0	0	0	1	5%

Data Analysis

After creating two datasets, we developed two feedforward neural networks with backpropagation learning. Both neural networks had 18 neurons in input layer which represented output values of 18 channels of the designed spectrometer. In the meanwhile, the binary codes which represented the coconut sugar classes, as seen in **TABLE 3** and **TABLE 4**, were assigned as the output layer of the first and second backpropagation neural networks (BPNN-1 and BPNN-2), respectively. Thus, BPNN-1 and BPNN-2 had two and six neurons in the hidden layer, respectively. As for the hidden layer, we set up only one hidden layer with number of hidden nodes following this equation:

$$Nh = \frac{Ni + No}{2} + \sqrt{Np}$$

where Ni, Nh, and No are the number of inputs, hidden and output layer nodes, respectively, while Np is the number of samples in dataset.

According to Eq. (1), the number of hidden layer nodes for BPNN-1 and BPNN-2 were 52 and 54 nodes, respectively, with the number of samples in dataset was 1800 in total. From 1800 data, we divided the data for train, validation and test with data composition of 70%, 15% and 15%, respectively. The architecture of developed BPNN-1 and BPNN-2 can be seen in **Fig. 4**.

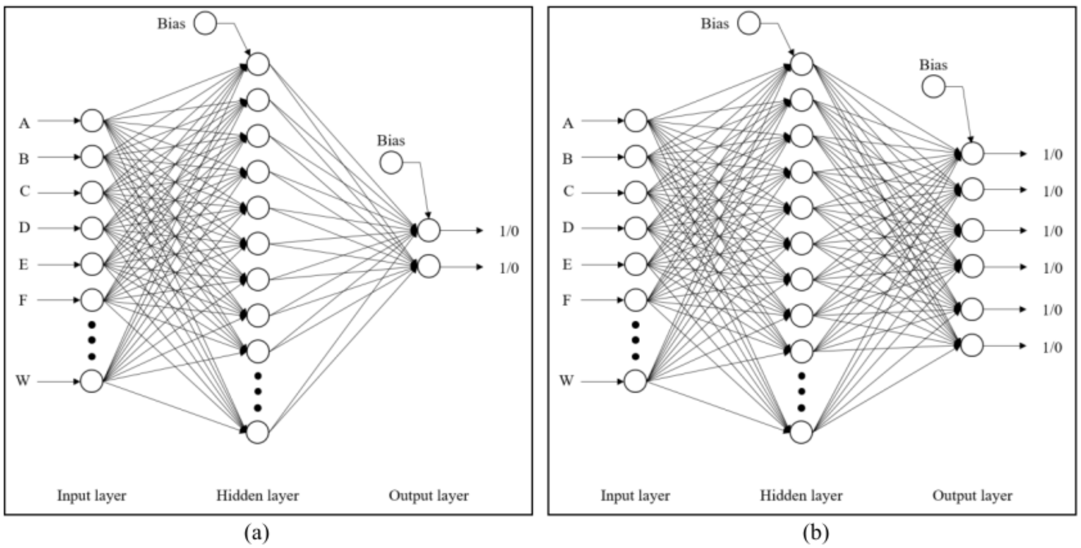


FIGURE 4. The architecture of the developed (a) BPNN-1 and (b) BPNN-2 for coconut sugar classification.

After training the neural networks, the next step was calculating the accuracy level of classification. The accuracy can be determined by using this following equation:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

RESULTS AND DISCUSSION

The portable spectrometer using AS7265x multispectral sensor has been created and successfully tested through several experiments. The spectrometer output values of cane sugar and pure granulated coconut sugar were significantly different on some channels as seen in **Fig. 5**. The difference of spectral responses of these two types of sugar was served as the basis for detecting the contamination of cane sugar in granulated coconut sugar.

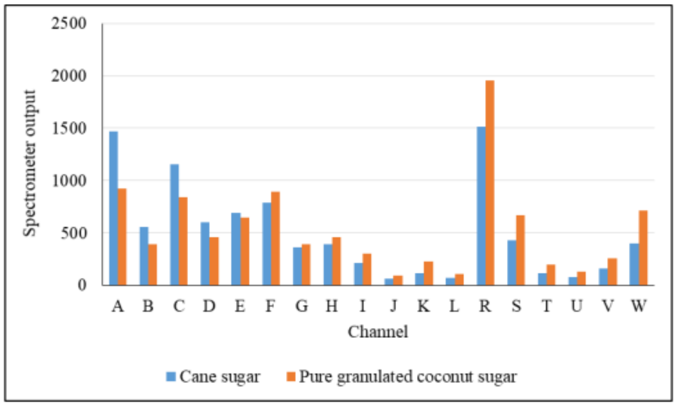
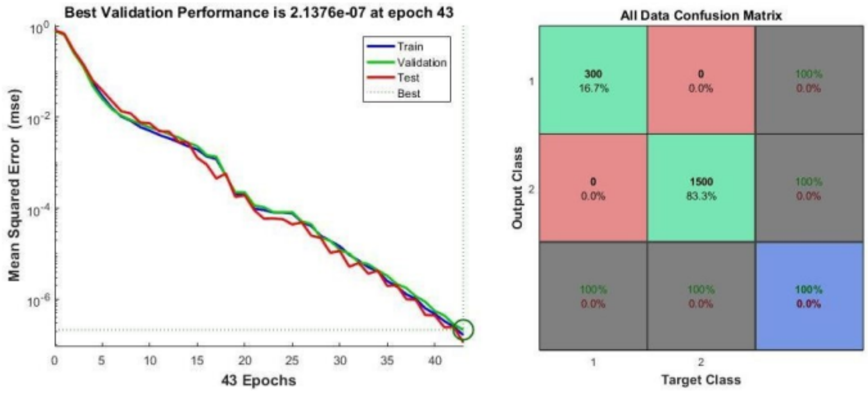


FIGURE 5. The spectrometer output values of cane sugar and pure granulated coconut sugar on each channel.

According to our experiment, the granulated coconut sugar produced with addition of cane sugar (P1-P5) had no considerable difference in appearance compared to the pure coconut sugar (P0) as seen in **Fig. 6**. This would be a very challenging task to detect adulterated coconut sugar which cannot be distinguished by human eyes. However, the developed spectrometer can be applied to tackle this problem. The Vis-NIR reflectance captured by the AS7265x sensor was able to be utilized as predictors to identify the presence of cane sugar as impurity in granulated coconut sugar. The developed BPNN-1 has successfully differentiated pure and impure coconut sugar with accuracy level of 100%. The neural network training and confusion matrix can be seen in **Fig. 7**. This very high accuracy indicates that all coconut sugar samples can be exactly classified into two categories (pure and adulterated). Meanwhile, the developed BPNN-2 has also showed good results to predict the cane sugar concentration in the granulated coconut sugar. The means of spectrometer values were different on each channel, as shown in **Fig. 8**. Although the difference was not significant on all channels, the classification can be successfully performed by the developed BPNN-2 with accuracy level of 96.6%. The BPNN-2 training, and its confusion matrix can be seen in **Fig. 9**.

(a) (b) (c) (d) (e) (f)

FIGURE 6. The appearance of granulated coconut sugar produced from six treatments of cane sugar concentration: (a) 0%, (b) 1%, (c) 2%, (d) 3%, (e) 4%, and (f) 5%.



(a) (b)

FIGURE 7. (a) BPNN-1 training to classify pure and adulterated coconut sugar and (b) confusion matrix as the result of the classification.

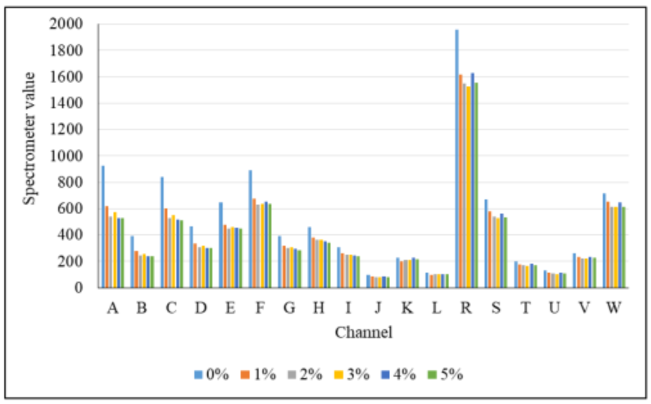
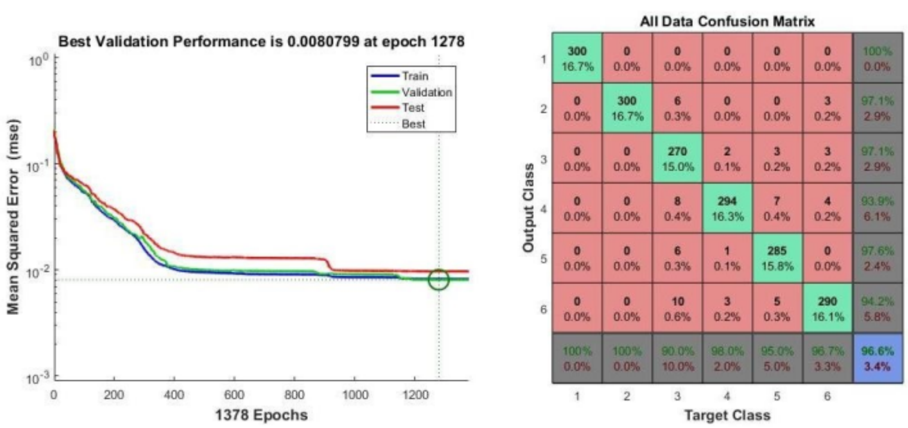


FIGURE 8. The means of spectrometer values on each channel.



(a) (b)

FIGURE 9. (a) BPNN-2 training to classify cane sugar concentration in the granulated coconut sugar and (b) confusion matrix as the result of the classification.

CONCLUSION

The developed portable spectrometer using AS7265x sensor and neural network algorithm can successfully detect cane sugar added to granulated coconut sugar. The first type of the developed neural network can identify pure and impure coconut sugar with accuracy level of 100%, while the second neural network can classify granulated coconut sugar in which cane sugar concentration added to the coconut sap up to 5% (w/v) with accuracy level of 96%.

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REFERENCES

1. P, Haryanti, Supriyadi, D. W. Marseno, U. Santoso, International Journal of Science & Technology, **5**(3), 52-59 (2017).
2. S. Kelly, "Identification of an internal isotopic reference compound in palm sugar to improve the detection of cane sugar addition," Final Report, Norwich, 2009.
3. R. A. Tanjung, T. Karo-Karo, and E. Julianti, J. Food Life Sci., **2**(2), 123 – 132 (2018).
4. G. H. Joseph and P. Layuk, Buletin Palma, **13**(1), 60 – 65 (2012).
5. J. Wiboonsirikul, Int. Food Res. J., **23**(1), 61-67 (2016).
6. C. Kumaravelu and A. Gopal, Int. J. Food Prop., **18**(9), 1930–1935 (2015).
7. N. Vanstone, A. Moore, P. Martos, and S. Neethirajan, Food Qual. Saf., **2**(4), 189–198 (2018).
8. ams, "AS7265x Smart Spectral Sensor", https://ams.com/as7265x, accessed on September 2021.
9. W. Caesarendra, M. Ariyanto, K. A. Pambudi, M. F. Amri, and A. Turnip, Internetworking Indonesia., **9**(1), 15-20 (2017).
10. R. R. Isnanto, A. Hidayatno, A. J. Zahra, Eskanesiari, A. I. Bagaskara, and R. Septiana, "Herb leaves recognition using combinations of hu's moment variants - backpropagation neural network and 2-d gabor filter-learning vector quantization (LVQ)", Proc. of 4th Int. Conf. on Information Tech., Computer, and Electrical Engineering (ICITACEE), Semarang, 2017, pp. 219-224.
11. A. P. Tindi, R. Gernowo, and O. D. Nurhayati, "Machine learning: fisher fund classification using neural network and particle swarm optimization," Proc. of International Conference on Information and Communications Technology (ICOIACT), 2018, pp. 315-320.
12. L. S. A. Putra, R. R. Isnanto, A. Triwiyatno, and V. A. Gunawan, "Identification of heart disease with iridology using backpropagation neural network," Proc. of 2nd Borneo International Conference on Applied Mathematics and Engineering (BICAME), 2018, pp. 138-142.

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