A New Approach to the Quality Determination of Used Palm Cooking Oil using Supervised Learning based on Electronic Sensors

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ABSTRACT

As discarding used palm oil in nature is very dangerous, a processing mechanism is needed to utilize it according to needs. This utilization depends on the palm oil used, so the sorting process becomes important. This study proposes a new classification approach for the quality of used palm oil using Self-Organizing Map (SOM), Linear Vector Quantization (LVQ), and K-means, based on electronic sensors. This study included hardware design, software development, data collection, and training and testing processes. Based on the experimental results, the proposed system performed well using 13 parameters consisting of e-nose data, color, viscosity, and turbidity. The accuracy of SOM was 91.11%, LVQ achieved 95.56%, and K-Means obtained an accuracy of 98.89%. This system can be used as a decision support system in the automatic recognition of used palm oil to classify its quality.

Keywords-used oil; palm; SOM; LVQ; k-means

I. INTRODUCTION

The amount of used cooking oil worldwide cannot be determined, but between 2019 and 2020, 203,910 tonnes of used cooking oil were processed [1]. Other data from the Indonesian Central Bureau of Statistics state that the average household consumption of palm oil per capita per year reached 11.58 l in 2020. In 2015, the amount of oil cooking used per capita was 10.33 l. The consumption of palm cooking oil at the household level in Indonesia during the period 2015-2020 increased by 2.32% per year. The potential for used cooking oil in the five major cities of Java and Bali from the RT sector is 2,847.07 Kl/month, while the potential for used cooking oil from micro-businesses is 1,509.64 Kl/month [2]. This fact requires follow-up action to reduce the amount of cooking oil waste by reprocessing it to benefit society.

The reuse of used palm oil aims to reduce hazardous waste in the environment. Used palm oil that is discarded with municipal waste or directly through the drain causes waste [3]. Used palm oil can currently be used as raw material for biolubricants, biofuels, bisabolene, liquid detergents, plasticizers, dishwashing soap and aromatherapy candles, polyurethane foam, surfactants, and also asphalt rejuvenation

[4]. In addition, it can be used as a lubricant, wei polymers, plasticizers, biosurfactants, microbial lipids, biomaterials, and others [5]. Glycerol, which is a byproduct of used palm oil processing, can be used as a cosurfactant in the production of nanocreams [6]. The large amount of used cooking oil waste produced worldwide has prompted researchers to reuse it to benefit humans and the environment. Used palm oil can be used as fuel (biodiesel), which is a sustainable alternative to fossil fuels because it can be biodegraded. This utilization is very feasible because the cost is lower than for other materials [7]. The processing of used cooking oil into biodiesel can be carried out through various catalyst processes, such as a series of bifunctional strontium-zinc-aluminum mixed oxides [8] or heterogeneous catalysts made from chicken bones [9]. Biodiesel from used palm oil can also be produced through alkali catalysts [10] or a CaO catalyst modified with ZnO and TiO_2 [11]. Before further processing, a mechanism is needed to determine the quality of used palm oil according to its intended use and subsequent processes. So far, used palm oil is classified manually based on its color, odor, and viscosity. This manual sorting process poses a health risk to sorting workers, as it can contain hazardous substances [12]. Meanwhile, sensor technology has been developed to support electronic nose research [13-15], color detection [16-18], and liquid viscosity determination [19]. On the other hand, the development of artificial intelligence is growing rapidly and has been applied in various fields [20-23]. Several supervised learning methods, such as Self Organizing Map (SOM) [24], Linear Vector Quantization (LVQ) [25], and K-Means [26], have been applied in many fields.

This study proposes an approach to determine the quality of used palm cooking oil using supervised learning based on electronic sensors. The sensors used were: TGS 2620, MQ 4, MQ 2, viscosity sensor, and TCS 230. The TGS 2620, MQ 4, and MQ 2 sensors represent odor information (e-nose), and the TCS 230 sensor is used to determine the color information of used palm oil. This study uses these sensors because they have been used in various previous studies, such as using TGS 2620 to detect COPD and lung cancer [27], MQ 4 to determine the decrease in methane gas in waste [28], MQ 2 to measure the viscosity of a liquid [29], and TCS 230 to determine the level of glucose content [16]. This study aims to help design a decision support system to classify used palm oil so that it can be reused and further processed according to its quality. In addition, the proposed automatic sorting process can reduce the health risks of sorting workers.

II. METHODS

The stages of this study included hardware design, software development, data collection, and training and testing. Figure 1 shows the hardware design of the proposed system. The sensors used are TGS 2620, MQ 4, MQ 2, a viscosity sensor, and TCS 230. Previously, the quality of used cooking oil was determined using the sense of smell, viscosity, and eye testing. These sensors were used to determine the physical properties of used cooking oil. TGS 2600, MQ 4, and MQ 2 sensors represent the sense of smell and viscosity sensors, and TCS 230 is used to determine the color.

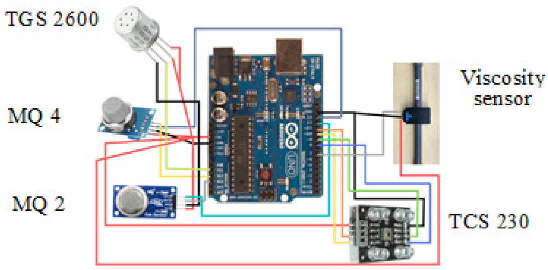

Fig. 1. Hardware design.

Data collection was carried out quantitatively through observation. The observations were the output of each sensor (TGS 2600, MQ 4, MQ 2, viscosity sensor, and TCS 230), which were used to determine the quality of the used cooking oil. The data was divided into training and testing sets. The training set was used to train SOM, LVQ, and K-means, and the testing set was used to test them. Data processing was carried out by experimenting with each sample 10 times and monitoring how each sensor reacted. Sampling was divided into three chambers. The first chamber of cooking oil was heated to 150°C, and the heated steam was captured by the TGS 2600, MQ 4, and MQ 2 sensors. The reactions read by the sensors were then graphed and the response of each sensor for each sample was analyzed. In the second chamber, butter was added to used palm cooking oil samples to determine the reaction of the TCS 230 sensor and the level of toxicity of the cooking oil samples. The reaction read by the sensor was then graphed, and the response of each sensor for each sample was analyzed. Table I describes the data to be analyzed. The third chamber measured the viscosity of cooking oil.

TABLE I. REACTION OF THE TCS 230 SENSOR

No	Type of cooking oil	TCS 230 sensor reaction	Observation results using the human eye
1	Palm cooking oil before using for frying	Color remains/does not change	Color remains/does not change
2	Used palm cooking oil (used for frying once)	Becomes redder than the original color	Becomes redder than the original color
3	Used palm cooking oil (used for frying more than once)	Becomes redder than the original color	Becomes redder than the original color

The initial stage of the training process was to determine the gold standard for each cluster: oil before being used for frying, oil that has been used for frying once, and oil that has been used for frying more than once. The training process was carried out using SOM, LVQ, and K-means. The algorithm of SOM is as follows [30]:

- Input vector initialization process.
- Determine the target for each input.
- Determine the initial weight (gold standard) for each cluster.
- Determine the learning rate (between 0.1 to 0.9).
- Repeat steps until reaching the specified epoch.
- The training process starts with data learning.

- Find the shortest distance from each cluster using the Euclidian distance formula.
- Compare the results of the shortest distance to each cluster. If the calculated cluster matches the specified target, then the weight remains. If it is different, a new weight calculation is carried out as in (1).

$$w_{ij}(t+1) = w_{ij}(t) + \propto(t)\left[x_{ij} - w_{ij}(t)\right] \quad (1)$$

- Update the weights.
- Save the new weight.

The LVQ method was also used, which is described as follows:

- Initialize the input vector.
- Determine the target for each input.
- Determine the initial weight (gold standard) for each cluster.
- Determining the learning rate (between 0.1 to 0.9).
- Repeat steps until reaching the specified epoch.
- Start the training process.
- Find the shortest distance from each cluster using the Euclidian distance formula.
- Compare the results of the shortest distance to each cluster. If the cluster calculation results match the specified target, (2) is used.

$$w_{ij}(t+1) = w_{ij}(t) + \propto(t)\left[x_{ij} - w_{ij}(t)\right] \quad (2)$$

- If it is different, a new weight calculation is carried out by:

$$w_{ij}(t+1) = w_{ij}(t) - \propto(t)\left[x_{ij} - w_{ij}(t)\right] \quad (3)$$

- Update the weights.
- Save the new weight.

The following learning process is carried out using the K-means method:

- Determine the number of clusters (K),
- Determine the gold standard for each cluster.
- Calculate the distance of each data to the center of the cluster using:

$$d = |x - y|\sqrt{\textstyle\sum_{i=1}^{n}(x_i - y_i)^2} \quad (4)$$

where d is the distance calculation from the center of the cluster, x is the object coordinates point, y is the coordinate centroid, x_i is the coordinate point of the i object, and y_i is the centroid coordinate point of the i object.

- Group data into clusters with the shortest distance.
- Calculate the cluster center.
- Repeat steps 2-4 until no data moves to another cluster.

The next stage was to train and test the models. The weight results from the training process are used in the testing stage. The results of this testing process are then analyzed to calculate the system performance. Laboratory tests were carried out for each cluster to determine the levels of $KMnO_4$ 0.1 N in ml, H_2O_2, NaOH, and free fatty acids. This was done to determine the quality of each class.

III. RESULTS AND DISCUSSION

A. Hardware and Software Design

Figure 2 shows the design implementation. For each used oil sample, 13 data were taken using the e-nose (MQ-2, MQ-4, TGS2600) and the TCS 3200 sensor (red, green, blue, white), using butter and without butter, and the viscosity and turbidity sensors. The data obtained from the sensors were used as a basis for determining the quality of used oil. Used palm oil samples were examined twice. Each sample was divided into two, one to be mixed with butter and the other without. The oil sample was placed on the same color base (white paper) because the intensity of used palm oil when detected using TCS3200 needs to be conditioned (must be homogeneous).

To determine the viscosity of the used palm oil, the sample was inserted into the pipe of the viscosity sensor. The results obtained were displayed on the LCD. The turbidity sensor needs to ensure that it has completely entered the oil sample.

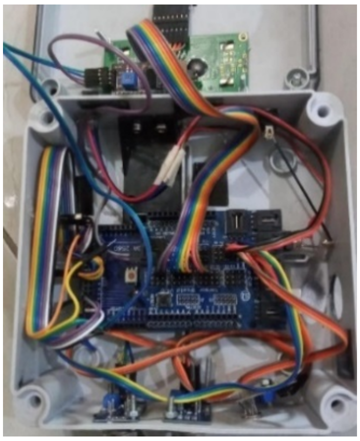

Fig. 2. Design implementation.

Data were obtained from each sensor. E-nose was detected by the TGS2600, MQ-2, and MQ-4 sensors. The MQ-4 detects methane specifically, while the MQ-2 detects hydrogen, LPG, carbon, alcohol, and propane gas. The TGS2600 is an air quality sensor that detects hydrogen and carbon monoxide. The viscosity sensor determines the viscosity of the cooking oil and the turbidity sensor determines its clarity. Then, the TCS3200 sensor detects the color of the oil.

B. System Performance Analysis

Experiments were carried out on 30 used oil samples. The data collection method was heating the cooking oil and then capturing the heated steam by the TGS 2620, MQ 4, and MQ 2 sensors. Figure 3 shows the results of the first cluster (palm oil that has not been used for frying).

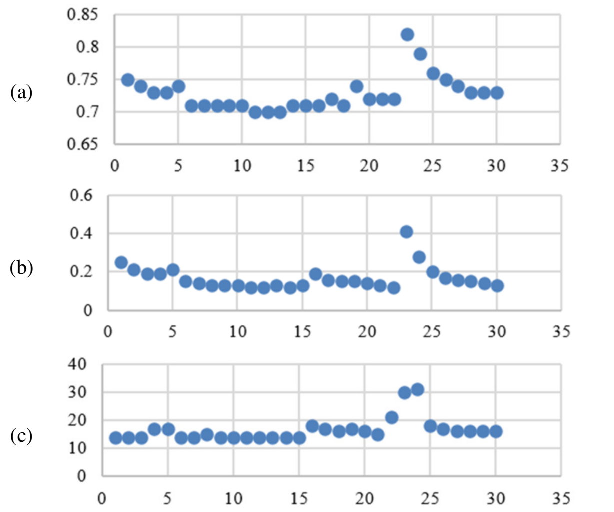

Fig. 3. First experimental results for palm cooking oil before used for frying (cluster1): (a) TGS 2620, (b) MQ 4, (c) MQ 2.

Figure 4 shows the experimental results from the TGS 2620, MQ 4, and MQ 2 sensors for the three clusters of cooking oil (not used for frying, used for frying once, and used multiple times).

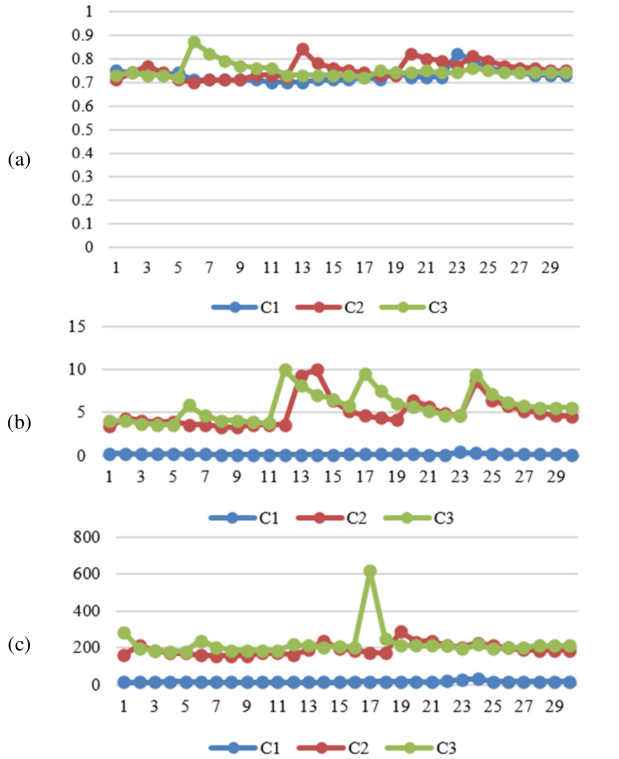

Fig. 4. Experimental reaction results from the e-nose sensors: (a) TGS 2620, (b) MQ 4, (c) MQ 2.

The second experiment involved adding butter to the cooking oil samples and then measuring the RGBW value using the TCS 230 sensor. An RGBW measurement experiment was also carried out using the same sensor for cooking oil without butter. Figures 5, 6, and 7 show the results for pure oil, for oil used for frying once, and for oil used for frying more than once.

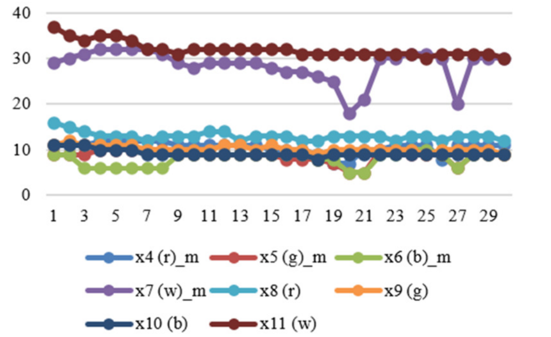

Fig. 5. RGBW results for cooking oil before being used for frying.

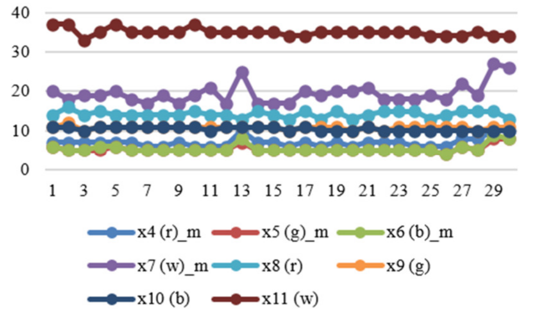

Fig. 6. RGBW results for cooking oil that has been used for frying once.

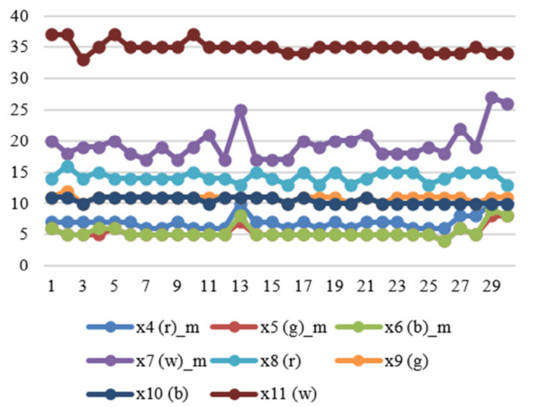

Fig. 7. RGBW results for cooking oil that has been used for frying more than once.

The third experiment was to measure the viscosity and clarity of the cooking oil for the same classes. The experimental results showed that the values between classes were quite close, but there were still differences. This shows that this feature can be used as a characteristic for each class.

The data obtained were standardized to ensure that all values (from x_1 to x_{13}) have values between 0 and 1. This standardization was performed using:

$$xi_i = \frac{x_i}{xmax_i} \quad (5)$$

where xi_i is the result of the standardized value for the i data, x_i is the value of the i variable, and $xmax_i$ is the maximum value of the i variable.

The quality of cooking oil was divided into three clusters. To determine the quality of cooking oil, the average of each variable (from x_1 to x_{13}) in each cluster was used as the gold standard. To identify quality clusters of cooking oil, it was necessary to calculate the initial average of the variables. Initialization was carried out for each cluster, using the following formulas:

$$xgd_i = \frac{xrata_i}{xmax_i} \quad (6)$$

$$ygd_i = \frac{yrata_i}{xmax_i} \quad (7)$$

$$zgd_i = \frac{zrata_i}{xmax_i} \quad (8)$$

where xgd_i is the gold standard for cluster1, ygd_i is the gold standard for cluster2, zgd_i is the gold standard for cluster3, $xrata_i$ is the average value of variable i for cluster1, $yrata_i$ is the average value of variable i for cluster2, $zrata_i$ is the average value of variable i for cluster3, and $xmax_i$ is the maximum value of the i variable.

The following process was used to calculate the Euclidian distance from each cluster, by subtracting the value of the variable with the gold standard from each cluster. Equation (9) was used to calculate the Euclidian distance to the gold standard in cluster 1, while (10) was used to calculate the Euclidian distance to the gold standard in cluster 2, and (11) was used to calculate the Euclidian distance to gold standard cluster 3.

$$dx = \sum_{i=1}^{i=13} |(xi_i - xgd_i)| \quad (9)$$

$$dy = \sum_{i=1}^{i=13} |(xi_i - ygd_i)| \quad (10)$$

$$dz = \sum_{i=1}^{i=13} |(xi_i - zgd_i)| \quad (11)$$

where dx is the Euclidean distance for cluster 1, dy is the Euclidean distance for cluster 2, dz is the Euclidean distance for cluster 3, xgd_i is the gold standard for cluster 1, ygd_i is the gold standard for cluster 2, zgd_i is the gold standard for cluster 3, and xi_i is the standardized data i.

The training process used a learning rate of 0.1 and epochs of 10, 100, 200, 300, 400, 500, 600, 700, 800, 900, and 1000. The training results were then tested 11 times according to the weights produced by the training process learning. Using SOM, the average system accuracy of the test results was 91.11%. The best accuracy results were achieved for 1000 epochs for the three methods. Tables II-IV show the confusion matrices for SOM, LVQ, and K-means.

TABLE II. CONFUSION MATRIX USING SOM

	Cluster 1	Cluster 2	Cluster 3
Cluster 1	280	20	0
Cluster 2	0	160	140
Cluster 3	0	0	300

TABLE III. CONFUSION MATRIX USING LVQ

	Cluster 1	Cluster 2	Cluster 3
Cluster 1	280	2	0
Cluster 2	0	160	14
Cluster 3	0	0	300

TABLE IV. CONFUSION MATRIX USING K-MEANS

	Cluster 1	Cluster 2	Cluster 3
Cluster 1	290	1	0
Cluster 2	0	300	0
Cluster 3	0	0	300

The results of K-means show that pure oil was classified as oil that was used for frying once. In addition, clusters 2 and 3 using the K-means were well identified. The accuracy, precision, recall, and F1-score results using SOM, LVQ, and K-means are shown in Tables V-VII.

TABLE V. SYSTEM PERFORMANCE USING SOM

System Performance	Value
Accuracy	0.911
Precision cluster 1	0.866
Precision cluster 2	0.900
Precision cluster 3	0.966
Precision	0.911
Recall cluster 1	0.896
Recall cluster 2	0.843
Recall cluster 3	1.000
Recall	0.913
F1 score	0.912

TABLE VI. SYSTEM PERFORMANCE USING LVQ

System Performance	Value
Accuracy	0.955
Precision cluster 1	0.966
Precision cluster 2	0.900
Precision cluster 3	1.000
Precision	0.955
Recall cluster 1	0.906
Recall cluster 2	0.964
Recall cluster 3	1.000
Recall	0.956
F1 score	0.956

TABLE VII. SYSTEM PERFORMANCE USING K-MEANS

System Performance	Value
Accuracy	0.988
Precision cluster 1	0.966
Precision cluster 2	1.000
Precision cluster 3	1.000
Precision	0.988
Recall cluster 1	1.000
Recall cluster 2	0.967
Recall cluster 3	1.000
Recall	0.989
F1 score	0.989

An analysis of H_2O_2 and free fatty acid levels was carried out for each cluster, which is shown in Table VIII. This process was carried out to determine the average volume of 0.1 N $KMnO_4$ Titration (ml), H_2O_2 content in perhydrol (%), average H_2O_2 content in meg/kg, average volume of 0.1 N NaOH titration-free fatty acid content (ml), and free fatty acid content (%) of each cluster. This test provides clearer information about each cluster.

TABLE VIII. RESULTS OF H_2O_2 AND FREE FATTY ACID LEVELS FOR EACH CLUSTER

Type of sample	No	Average volume of 0.1 N $KMnO_4$ Titration (ml)	H2O2 content in perhydrol (%)	Average H2O2 levels in meg/kg	Average volume of 0.1 N NaOH Titration free-fatty acid content (ml)	Free-fatty acid content (%)
Unused palm cooking oil	1	0.100	0.003	0.034	0.050	0.021
	2	0.100	0.003	0.034	0.100	0.128
	3	0.100	0.003	0.034	0.100	0.042
Average		0.100	0.003	0.034	0.083	0.063
Used palm cooking oil after frying once	1	0.150	0.004	0.052	0.100	0.043
	2	0.150	0.004	0.052	0.150	0.149
	3	0.130	0.004	0.045	0.200	0.085
Average		0.143	0.004	0.049	0.150	0.092
Used palm cooking oil after frying more than once	1	0.160	0.005	0.055	0.200	0.085
	2	0.200	0.006	0.069	0.250	0.171
	3	0.220	0.006	0.076	0.300	0.128
Average		0.193	0.006	0.067	0.250	0.128

The proposed system worked well using 13 parameters consisting of e-nose data, color, viscosity, and turbidity. These data were then used as input for the used oil classification system. Tests were carried out using SOM, LVQ, and K-means. The best accuracy result for SOM was 91.11%, for LVQ was 95.56%, and for K-means was 98.89%. SOM also achieved 0.911 precision, 0.913 recall, and 0.912 F1 score. LVQ achieved 0.955 precision, 0.956 recall, and 0.956 F1 score. The K-means achieved 0.989 precision, 0.989 recall, and 0.989 F1 score. These results show the superiority of K-means for this specific task compared to SOM and LVQ.

According to Table VIII, each cluster has different characteristics. Cluster 1 had free fatty acid levels in an average volume of 0.1 N NaOH titration of 0.05 ml to 0.1 ml, with an average value of 0.083 ml. Cluster 2 had higher levels of free fatty acids, between 0.1 and 0.2 ml, with an average value of 0.15 ml. Cluster 3 had the highest levels of free fatty acids, between 0.2 and 0.3 ml, with an average value of 0.25 ml. This system can be used for automatic classification of the quality of palm oil so that this cooking waste can then be utilized according to the needs.

IV. CONCLUSION

This study presented a new approach to determine the quality of used palm cooking oil using SOM, LVQ, and K-means based on electronic sensors. Based on the experimental results, the system worked well by producing 13 parameters consisting of e-nose data, color, viscosity, and turbidity. These data were used as input for the cooking oil quality classification system, testing the SOM, LVQ, and K-means models. The best accuracy result for SOM was 91.11%, LVQ achieved 95.56%, and K-Means obtained an accuracy of 98.89%. The K-means obtained the highest accuracy with a precision of 0.989, a recall of 0.989, and an F1-score of 0.989. The proposed system can be used as a decision support system to automatically determine the quality of used palm oil and reduce the health risks of the sorting workers.

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