Classification of Segmented Milkfish Eyes using Cosine K-Nearest Neighbor

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***Abstract*— The classification of milkfish freshness based on the eyes is supported by the results of correct fish eye segmentation. Generally, the problems faced by segmentation results are many objects with similar characters and similar gray intensity. Segmentation with K-Means produces K layers of binary image according to the selected K cluster. As a result, many objects appear as the result of segmentation. Among all objects appear, the fish eye has a special character, where it is round black. The problem faced by classic K-Nearest Neighbor (KNN) in classification is sensitive to noise when using low K while using high K the classification performance falls to the most class that shouldn't as the result. We propose Cosine KNN (CosKNN) to solve the classic KNN problem where the classification results aren't taken from the most class of nearest neighbor. CosKNN gives soft value that represents the belonging level of each class to the testing data. To evaluate the performance of CosKNN, we use precision and recall. The experiment result shows that the CosKNN achieves performance both precision and recall of 97.93% and 91.15%, respectively, all with shape features. Especially on precision performance, CosKNN achieves the highest performance compared to other methods, CosKNN, classic KNN and K-SVNN achieve 97.93%, 96.20%, and 95.77%. While in recall performance, KNN achieves the highest performance compared to other methods, CosKNN, classic KNN and K-SVNN achieve 91.15%, 92.10%, and 90.76%, respectively, all with shape features.**

Keywords*— *segmentation, eye fish, milkfish, classification, K-Nearest Neighbor, shape feature, color feature

I. Introduction

The classification of milkfish freshness based on the eyes is supported by the results of correct fish eye segmentation. Current research on [1] fish freshness is conducted by using digital image processing to determine the freshness quality and shelf life span of the three most consumed fish in the Philippines. The detected fish are milkfish (*Chanos chanos*), round scad (*Decapterus maruadsi*) and short mackerel scad (*Rastrelliger brachysoma*). By using support vector machine (SVM), this research classifies the redness of the fish's eyes and gills as a measure of the fish freshness quality level. The number images of fish are 1680 images, include 720 images for milkfish, 480 images for round scad, and 480 images for short mackerel scad. The captured image are classified to 4 freshness levels and achieve 98% accuracy. In this study, the segmentation method used is a combination of histogram equalization and binary thresholding. Segmentation results still raise some noise objects in the binary image results. The next research in [2] classifies the freshness of the fish from level 1 (stale) to level 5 (fresh) based on RGB values of the eyes and gills. By using 800 images each of the eyes and gills, the system achieves 90% accuracy for milkfish. The system uses a mask to get segmented eye fish. Segmentation results do not clearly give eye segmentation results.

Good segmentation is expected to support good results recognition, such as research by [3], segment mango leaves using Otsu's thresholding in the HSV and YCbCr color spaces. The results of the study show that Cr band is more suitable for mango leaf segmentation with precision and recall of 0.995 and 0.971, respectively. The problem faced in the segmentation of milkfish eyes is many objects with similar characters and similar gray intensity. Research conducted by [4] segments the milkfish using a spatial filter to get segmented eye milkfish in the HSV color space. The results of segmentation are compared to the ground truth to get the success rate, precision achieved by 84.04% while recall was achieved by 43.08%. The problem faced by K-Nearest Neighbor is sensitive to noise especially when using low K while using high K the classification performance falls to the most class that shouldn't as the result. We propose Cosine KNN where the classification results aren't taken from the most class of nearest neighbor. We give soft value that represents the belonging level of each class to testing data. These values start from 0 to infinity according to K used.

In this research paper, the framework for segmenting milkfish eyes using K-Means Clustering and Cosinus K-Nearest Neighbor (CosKNN) classification is presented to explain how we conduct the segmentation. K-Means segmentation produces K layers of the binary image according to the selected K cluster. As the result, many objects appear as a result of segmentation. Among all the objects that appear, the fish eye has a special character, where it is round black. Based on these different characters, the authors use a classification approach to recognize the object of the correct fish eye. In this paper, we propose Cosine K-Nearest Neighbor (CosKNN) as the classification method to deal with the classic KNN problem.

K-Means as an image segmentation method is also effective to use, such as research [5] recognize plant diseased leaf, K-Means is used to segment the lesion image from each super-pixel. By using pyramid of histograms of orientation gradients (PHOG) descriptor from three color band of each segmented lesion image and its grayscale image, the system provides a feasible solution for plant diseased leaf image segmentation and plant disease recognition. K-Means clustering also used by [6] with neutrosophy to deal with indeterminacy factor of image pixels. The approach is to transform the image into the neutrosophic set by calculating truth, falsity and indeterminacy values of pixels and then, the clustering technique based on neutrosophic set is used for image segmentation. The cluster results are then refined to be more suitable for the segmentation. This algorithm provides better results than only K-means clustering approach. In research [7] combine K-Means and mathematical morphology to conduct fish image segmentation. The best number of clusters is determined by the number of gray histogram peaks and the cluster center data is filtered by comparing the mean with the threshold by Otsu. To get the contour of the fish body, the research uses mathematical morphology especially opening and closing. The result of the experiment, system achieves good result in separation between the fish image and the background with complex backgrounds.

To measure the validity of segmentation results, the authors conduct several tests by comparing the parameters used during segmentation, namely K from CosKNN. K-Means also uses K as the number of clusters that would produces K layer of the segmented image, where the greater the K the more objects will be produced by K-Means. In this study, we use K = 3 as the number of clusters. The features used in K-Means are Red, Green and Blue bands from the RGB color space. The K of CosKNN affects the classification results where the selection of K neighbors is a difficult problem. In the classic K-NN, if the K is too small, the prediction results will be sensitive to the presence of noise. On the other hand, if K is too large, then the closest neighbor chosen may be too much from another class which is actually irrelevant because of the distance too far [8]. The number of fish eye objects on the results of segmentation is far less than other objects, and attention to fish eyes is more important than not fish eyes, so performance measurements can't use accuracy, in this study the authors use precision and recall as evaluation metrics. The authors also conduct tests by comparing between CosKNN and the other methods, as follows: classic KNN and K-Support Vector Nearest Neighbor (K-SVNN). This test is used to prove that CosKNN achieved better performance rather than other methods.

The authors use 71 images of fish eyes with varying sizes ranging from 180x180 pixels to 655x655 pixels. The image of the fish eye has gone through the crop stage of all parts of the fish body. The image is taken in a normal environment in the morning and evening. At night there is no other lighting except the room lights. Image taking distance is 20-30 cm with normal image effects.

II. Research Methodology

A. *Segmentation Framework*

The segmentation framework is presented in Figure 1. The framework for segmentation of milkfish eyes using K-Means and CosKNN is explained as follows:

1. Extract Red, Green and Blue band of RGB color space

   In this first step, the authors separate Red, Green and Blue bands from RGB images. The three bands will be used as clustering features with K-Means.

2. Arrange R, G, B band to be K-Means dataset

   Each band R, G and B is one layer images, so the authors arrange for each band to act as a feature on K-Means. Suppose that [r, c] is the size of the row and column of the band, so we change the size of each band into the matrix [rxc, 1]. By combining the three band matrices into the matrix [rxc, 3] then we get the K-Means dataset with rxc data and 3 features.

3. Clustering with K-Means

   In this step, we do clustering with K-Means. The distance used to measure the similarity is Euclidean, while the number of clusters used during this study is 3 clusters.

4. Reshape K cluster to be K layer image

   The K cluster as a result of K-Means clustering will be K layer image. Each layer must be reshape into the original rxc image.

5. Morphological operation

   At each layer, the image is treated by morphological operations to reduce small and useless objects. The morphological operations used are closing and opening using strel disk with a radius of 1 pixel.

6. Shape and color features extraction

   In this step, we extract the shape and color features. In the shape feature, the authors extract circularity, major and minor axis objects, eccentricity, and major axis ratios with image width. In the color feature, the authors extract the mean and standard deviation from the gray image of each object.

7. Cosine K-Nearest Neighbor (CosKNN) classification

   This step is the final step of segmentation where extracted features are classified using CosKNN. In this study we used many variations of K, as explained in the next section.

B. *The Dataset*

We generated 71 images of fish eyes that have gone through the cropping stage of all parts of the fish body, the image size varies from 180x180 pixels to 655x655 pixels. The image is captured in the normal morning and night environment. At night there is no help from other lights besides the room lights. Image capturing distance is 20-30 cm with normal image effects. The environment of image taking in this study is adjusted to the situation when the application would be used in a normal environment. In all images there is only one fish eye object. Examples of fish eye images used in this study are presented in Figure 2 (a) - (c).

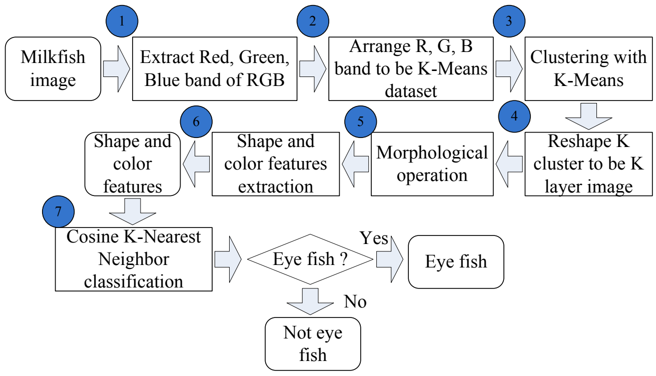


Fig. 1. Framework for milkfish segmentation using K-Means and CosKNN

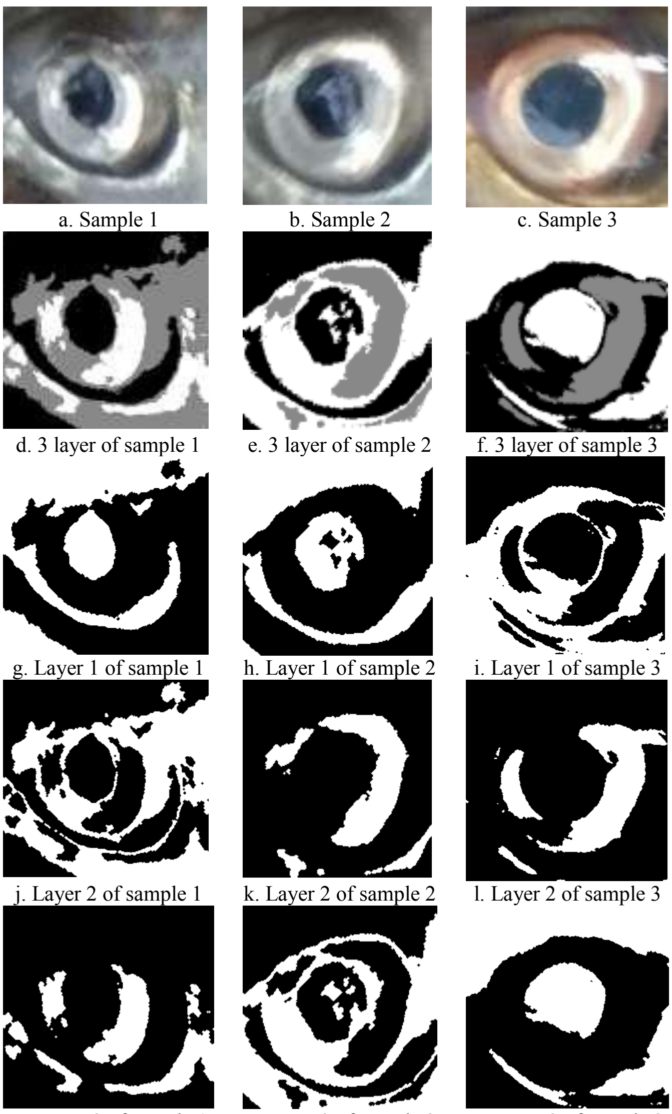


Fig. 2. Milkfish eye images and the result of K-Means clustering with 3 cluster

C. Cosine K-Nearest Neighbor (CosKNN)

In the classic K-NN, if the K is too small, the prediction results will be sensitive to the presence of noise. On the other hand, if K is too large, then the closest neighbor chosen may be too much from another class which is actually irrelevant because of the distance too far [8]. To solve this problem we propose Cosine KNN where we use soft values that represent ownership of each class to the test data. This soft value is highly dependent on the distance between the test data and the K nearest neighbor. To get a Cosine value for each nearest neighbor, we involve a pair of two neighbors. So, for the 3 closest neighbors, we will get 3 pairs of neighbors. For example the 3-NN is x_1, x_2, and x_3. Then the pair is: x_1x_2, x_1x_3, x_2x_3. Furthermore, each pair will have 2 cosine values according to the data pair. The cosine values are then added together according to each class.

Suppose the class of the data set is C=c_1, c_2, …, c_n, where n is the number of classes. While $X = x_1, x_2, x_i, \ldots, x_k$ is the nearest neighbor chosen from the training data, k is the number of nearest neighbor. Then for the nearest neighboring pair x_i and x_j will have the cosine value as follows:

$$Cos(x_i x_j) = 1 - \frac{d_i}{\sqrt{d_i^2 + d_j^2}} \qquad (1)$$

$$Cos(x_j x_i) = 1 - \frac{d_j}{\sqrt{d_i^2 + d_j^2}}$$

Where d is the distance of training data to test data. $Cos(x_1 x_2)$ will belong to the c_i class according to the class owned by x_1. For example, the pair of closest neighboring and class as follows: (x_1,c_1), (x_2,c_2), (x_3,c_1). Then the cosine value for the pair x_1x_2 is:

$Cos(x_1 x_2) = 1 - \frac{d_1}{\sqrt{d_1^2 + d_2^2}}$ will belong to the class c_1, and

$Cos(x_2 x_1) = 1 - \frac{d_2}{\sqrt{d_1^2 + d_2^2}}$ will belong to the class c_2.

Next, to accumulate all cosine values of the R test data in the class c_j , we use (2):

$$SumofCos(\mathrm{R}, c_j) = \sum_{i=1}^{n} Cos(x_i), c_i = c_j, j = 1, \ldots, n \qquad (2)$$

The $SumofCos(\mathrm{R}, c_j)$ is a soft value that ranges in [0,∞]. A value of zero (0) means that none of the nearest neighbors has a class c_j. The greater K used, the greater this value corresponds to the number of cosines calculated.

III. Results and Discussions

We apply testing the CosKNN by classifying 71 segmented fish eye images with K-Means clustering, we use K-fold Cross Validation with K = 3, meaning that 2/3 part of the data is used as training data while 1/3 part as the testing data. For CosKNN classification, we use varies of K as follows: 3, 5, 7, 9, 11, 13, 15, 17 and 19. In each K, we evaluate using precision and recall. Next, we get the average precision and recall from all of them.

The segmented image with K-Means clustering is presented in Figure 2 (d) - (o), the clustering result of sample

1 is presented by image (d), while each layer is presented by Figure 2 (g), (j) and (m). In Figure 2(d) we present code of layer 1, 2 and 3 by black, grey and white respectively. Then, each code is presented by binary image in Figure 2 (d), (j) and (m). Similarly for samples 2 and 3.

The results of the CosKNN classification on sample 1 images are presented in Table I. The RM2M column is the ratio of Minor Axis Length and Major Axis Length. Real Label is a sign whether the object is a fish eye or not (1 means eye fish, 0 means not). The Result column is the classification result by CosKNN with selected features, we divide it into 3 types as follows: S (Shape feature), C (color feature), and S + C (Shape and Color feature). There are 25 objects divided into 3 clusters, fish eye objects is attended to cluster 1, on all types of features, all predict as fish eyes correctly both shape, color and shape + color. There are no objects other than fish eyes that are recognized as fish eyes. So, all segmentation results are perfect.

The results achieved by the image sample 2 are presented in Table II, there are 16 objects divided into 3 clusters, the fish eye object is attended to cluster 1, on all feature options, shape features and shape and color combinations successfully predict correctly. While the color feature is failed to predict as a fish eye (zero value). The color feature also incorrectly predicts two object as a fish eye. So, the results of this segmentation only succeed in the shape and combination of shape and color features.

TABLE I. THE RESULT OF COSKNN CLASSIFICATION FOR IMAGE SAMPLE 1

No.	Cluster	Circularity	RM2M	Eccentricity	RM2W	Average	Stadev	Real Label	Result		
									S	C	S+C
1	1	0.11	0.92	0.39	1.14	83.67	23.24	0	0	0	0
2	1	0.48	0.51	0.86	0.36	75.71	19.39	0	0	0	0
3	1	0.85	0.74	0.67	0.32	70.75	22.27	1	1	1	1
4	1	0.53	0.54	0.84	0.11	112.86	5.03	0	0	0	0
5	2	0.42	0.40	0.92	0.18	189.18	25.98	0	0	0	0
6	2	0.75	0.88	0.47	0.07	183.42	11.58	0	0	0	0
7	2	0.30	0.31	0.95	0.30	189.96	11.27	0	0	0	0
8	2	0.37	0.48	0.88	0.25	197.55	16.92	0	0	0	0
9	2	1.99	1.00	0.00	0.01	173.34	1.68	0	0	0	0
10	2	1.99	1.00	0.00	0.01	169.12	2.44	0	0	0	0
11	2	0.94	0.54	0.84	0.05	177.27	2.32	0	0	0	0
12	2	0.32	0.43	0.90	0.52	219.10	26.77	0	0	0	0
13	2	0.21	0.37	0.93	0.57	201.16	27.24	0	0	0	0
14	2	1.99	1.00	0.00	0.01	158.77	5.83	0	0	0	0
15	2	0.27	0.38	0.92	0.18	184.10	9.80	0	0	0	0
16	2	1.64	0.68	0.73	0.02	161.04	3.58	0	0	0	0
17	2	0.89	0.57	0.82	0.02	173.55	4.93	0	0	0	0
18	2	2.39	0.68	0.73	0.01	100.49	8.00	0	0	0	0
19	3	0.09	0.24	0.97	1.30	149.52	24.10	0	0	0	0
20	3	0.25	0.62	0.79	1.01	147.99	47.00	0	0	0	0
21	3	0.70	0.28	0.96	0.04	150.13	9.24	0	0	0	0
22	3	1.93	0.84	0.55	0.01	151.69	12.86	0	0	0	0
23	3	1.07	0.44	0.90	0.03	154.22	11.69	0	0	0	0
24	3	1.22	0.79	0.62	0.02	98.86	3.44	0	0	0	0
25	3	0.13	0.24	0.97	0.36	148.14	17.54	0	0	0	0

TABLE II. THE RESULT OF COSKNN CLASSIFICATION FOR IMAGE SAMPLE 2

No.	Cluster	Circularity	RM2M	Eccentricity	RM2W	Average	Stadev	Real Label	Result		
									S	C	S+C
1	1	0.34	0.29	0.96	1.22	76.82	22.54	0	0	1	0
2	1	0.14	0.34	0.94	1.37	98.80	15.69	0	0	0	0
3	1	0.64	0.56	0.83	0.11	78.39	22.92	0	0	1	0
4	1	0.64	0.81	0.59	0.41	82.94	25.08	1	1	0	1
5	1	1.99	1.00	0.00	0.01	127.67	1.13	0	0	0	0
6	2	0.56	0.77	0.64	0.98	159.00	52.68	0	0	0	0
7	2	0.10	0.24	0.97	1.34	145.89	27.80	0	0	0	0
8	2	0.20	0.11	0.99	0.24	138.27	37.37	0	0	0	0
9	3	0.39	0.33	0.94	0.32	201.81	11.11	0	0	0	0
10	3	0.52	0.51	0.86	0.18	193.10	20.67	0	0	0	0
11	3	1.99	1.00	0.00	0.01	185.63	0.67	0	0	0	0
12	3	1.05	0.73	0.68	0.03	180.10	4.52	0	0	0	0
13	3	1.23	0.89	0.46	0.04	173.02	13.38	0	0	0	0
14	3	0.27	0.45	0.89	0.86	225.52	20.34	0	0	0	0
15	3	0.43	0.22	0.98	0.11	173.98	10.05	0	0	0	0
16	3	0.36	0.27	0.96	0.34	198.01	22.69	0	0	0	0

TABLE III. THE RESULT OF COSKNN CLASSIFICATION FOR IMAGE SAMPLE 3

No.	Cluster	Circularity	RM2M	Eccentricity	RM2W	Average	Stadev	Real Label	Result		
									S	C	S+C
1	1	0.06	0.83	0.56	1.18	157.60	23.84	0	0	0	0
2	1	1.41	0.62	0.79	0.01	105.91	0.43	0	0	0	0
3	1	1.41	0.62	0.79	0.01	161.84	8.98	0	0	0	0
4	1	1.99	1.00	0.00	0.01	99.82	1.44	0	0	0	0
5	1	1.69	0.81	0.59	0.01	110.65	2.03	0	0	0	0
6	2	1.23	0.61	0.79	0.02	133.68	22.35	0	0	0	0
7	2	0.91	0.50	0.87	0.02	191.00	1.13	0	0	0	0
8	2	0.49	0.31	0.95	0.05	192.15	1.53	0	0	0	0
9	2	1.99	1.00	0.00	0.01	191.10	0.21	0	0	0	0
10	2	0.34	0.16	0.99	0.25	207.85	8.40	0	0	0	0
11	2	0.41	0.37	0.93	0.38	212.21	11.46	0	0	0	0
12	2	1.34	0.58	0.81	0.02	192.63	0.37	0	0	0	0
13	2	0.65	0.40	0.92	0.04	193.19	0.56	0	0	0	0
14	2	0.19	0.42	0.91	0.84	232.54	19.31	0	0	0	0
15	2	0.47	0.17	0.98	0.05	104.61	8.13	0	0	0	0
16	2	0.78	0.28	0.96	0.03	86.59	18.03	0	0	0	0
17	3	0.33	0.27	0.96	1.28	75.87	16.00	0	0	0	0
18	3	0.18	0.13	0.99	0.50	117.00	7.20	0	0	0	0
19	3	0.61	0.84	0.54	0.40	82.72	15.83	1	1	0	1
20	3	0.66	0.43	0.90	0.04	125.83	1.28	0	0	0	0
21	3	1.93	0.84	0.55	0.01	136.92	5.54	0	0	0	0
22	3	1.40	0.75	0.67	0.02	105.57	13.88	0	0	0	0
23	3	1.10	0.50	0.87	0.02	83.22	11.66	0	0	0	0
24	3	0.29	0.48	0.88	0.52	93.80	17.36	0	0	0	0
25	3	1.25	0.53	0.85	0.02	131.25	1.12	0	0	0	0
26	3	0.72	0.49	0.87	0.03	131.29	3.06	0	0	0	0
27	3	1.03	0.47	0.88	0.02	97.35	15.27	0	0	0	0

The results achieved by the image sample 3 are presented in Table III, there are 27 objects divided into 3 clusters, the fish eye object is attended to cluster 3, on all feature choices, shape features and shape and color combinations successfully predict correctly. While the color feature is failed to predict as fish eye (zero value). There are no objects other than fish eyes that are detected as fish eyes. So, the results of this segmentation only succeed in the shape and combination of shape and color features.

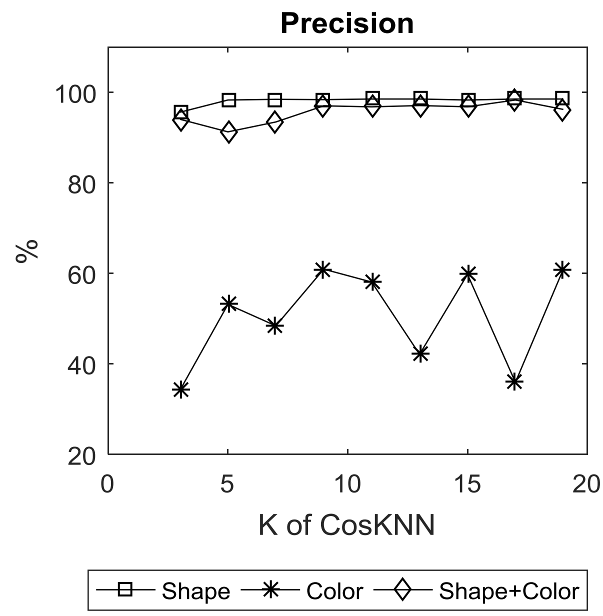
We apply testing with the K option used by CosKNN. We choose K as follows: 3,5,7,9,11,13,15,17 and 19. By testing each K option in 71 images and Cross Validation, we get precision and recall. We compare the precision and recall performance of each feature shape, color and combination of shapes and colors. The results are presented in Figure 3.

In this study, precision means the number of fish eye images objects that have been detected from all objects detected as fish eyes. Of course, one image only contains one fish eye, so the recall means that the number of the eye fish images that have been detected from all the images tested.

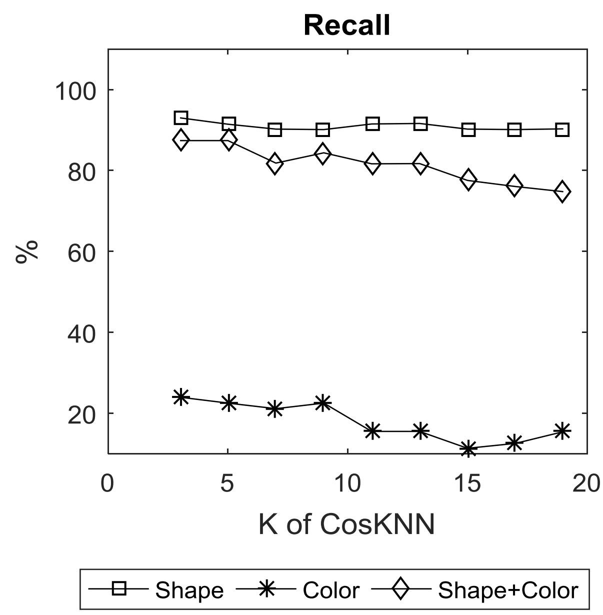
In the graph presented in Figure 3 (a), the result of segmentation with precision of shape features are always the best among all the other features, even the color features provide very low precision below 70%. Thus, the classification for recognizing eye fish can be conducted using only the shape features, without combining color features.

The recall performance also provides similar results, the shape feature successfully classifies objects with the best performance on all varies of K, where recall is always above 90%. While the combination of shape and color features achieve lower recall performance. Different results are achieved by the color feature where the recall achieved isn't up to 40%, of course this performance is very bad.

We resume performance evaluations into average precision and recall, as presented in Table IV. We also compare the performance with the other Nearest Neighbor method: KNN, and K-SVNN. For precision, CosKNN achieves the best performance for all varies of features compared to other method, the precision for shape, color, and combination of shape and color are 97.93%, 43.86%, and 95.14% respectively. The best recall performance are achieved by KNN with the shape feature, the recall performance is 92.10%. The recall performance of CossKNN achieves the best result with the combination of shape and color feature compared to other methods, the recall performance is 82.5%.



a. Precision performance



b. Recall performance

Fig. 3. Precision and recall performance

TABLE IV. THE RESULT OF COSKNN CLASSIFICATION FOR IMAGE SAMPLE 3

Features	Precision			Recall		
	CosKNN	**KNN**	**K-SVNN**	**CosKNN**	**KNN**	**K-SVNN**
Shape	**97.93%**	96.20%	95.77%	91.15%	**92.10%**	90.76%
Color	**43.86%**	43.86%	43.00%	19.30%	20.00%	**21.44%**
Shape+ Color	**95.14%**	94.12%	95.09%	**82.55%**	82.23%	81.49%

This research also provides evidence that the color feature can't improve the system performance. This can be seen on all method used in this research that the color feature performance isn't higher than 44%. Of course, this is bad performance.

IV. CONCLUSION

From the research conducted, it can be concluded that CosKNN achieves performance both precision and recall of 97.93% and 91.15%, respectively, all with shape features. Especially on precision performance, CosKNN achieves the highest performance compared to other methods, CosKNN, classic KNN and K-SVNN achieve 97.93%, 96.20%, and 95.77%. While in recall performance, KNN achieves the highest performance compared to other methods, CosKNN, classic KNN and K-SVNN achieve 91.15%, 92.10%, and 90.76%, respectively, all with shape features. The color features are less suitable because it provides very poor precision and recall performance, even the performance of the shape features decreases when joining color features. The suggestion for the next research is to try using texture features to classify fish eye objects and try other methods such as edge detection or other region-based methods to segment milkfish eyes.

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REFERENCES

[1] L. K. S. Tolentino, Orillo, J.W.F., Aguacito, P.D., Colango1, E.J.M, Malit, J.R.H., Marcelino, J.T.G., Nadora, A.C., Odeza, A.J.D., "Fish Freshness Determination through Support Vector Machine," *Journal of Telecommunication, Electronic andComputer Engineering*, vol. 9, pp. 139-143, 2017.

[2] I. C. Navotas, Santos, C.N.V, Balderrama, E.J.M., Candido, F.E.B., Villacanas, A.J.E., Velasco, J.S., "Fish Identification And Freshness Classification Through Image Processing Using Artificial Neural Network," *ARPN Journal of Engineering and Applied Sciences*, vol. 13, pp. 4912-4922, 2018.

[3] E. Prasetyo, Adityo, R.D., Suciati, N., and Fatichah, C., "Mango Leaf Image Segmentation on HSV and YCbCr Color Spaces Using Otsu Thresholding," in *International Conference on Science and Technology*, Yogyakarta, 2017.

[4] E. Prasetyo, "Eye Black Circle of Milkfish Segmentation on HSV Color Space," *Journal of Electrical Engineering and Computer Sciences*, vol. 3, pp. 377-380, 2018.

[5] S. Zhang, Wang, H., Huang, W., You, Z., "Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG," *Optik*, vol. 157, pp. 866-872, 2018.

[6] M. N. Qureshi, Ahamad, M.V., "An Improved Method for Image Segmentation Using K-Means Clustering with Neutrosophic Logic," in *International Conference on Computational Intelligence and Data Science*, 2018, pp. 534-540.

[7] H. Yao, Duana, Q., Li, D., Wang, J., "An improved K-means clustering algorithm for fish image segmentation," *Mathematical and Computer Modelling*, vol. 58, pp. 790-798, 2013.

[8] X. Wu, Kumar, V. , *The Top Ten Algorithms in Data Mining*. Boca Raton London: CRC Press Taylor & Francis Group, 2009.