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Classification of Gamebird Images Using Color Histogram Intersection

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Abstract – *Gamebirds and cockfighting is a multi-billion industry in the Philippines and is a viable research area. This study explores the classification of gamebird images using color histogram intersection. The dataset of gamebird images was taken from Pangasinan Breeders' Cup 2018 derby fights and are classified into dom, grey, red, and white classes. Color histograms were extracted from these images and experiments on the number of models and channels to be utilized were conducted, then the performance of the method was assessed. The results show that the classification of gamebird images using color histogram intersection performed best in the single model using all channels set-up with sensitivity of 89.75%, specificity of 96.58%, and accuracy of 94.88%.*

Keywords – Color Histogram Intersection, Image Classification, Gamebird, Cockfighting

INTRODUCTION

Gamebirds and cockfighting are part of the Filipino culture and history. It is continuously flourishing and is believed to be a 50 billion peso industry as of today [1]. Cockfighting events called derbies are common almost anywhere in the country. Derbies can be video recorded and/or live streamed so that cockfighting enthusiasts can enjoy the fights even when they are not physically present in the coliseum where the derbies are held.

Large number of derbies translate to a huge amount of video data that can be used for computing researches. Unfortunately, to the best of researchers' knowledge and simple research, only a handful computing investigations venture on this subject.

Color Histogram Intersection

Color histogram is a representation of the distribution of colors in an image. It shows the different colors that appear in an image together with their respective number of pixels [2]. Color histogram is usually presented similar to a bar graph or line graph where the x-axis represents the color/value of the pixel and y-axis as the number of appearances of that color/value of the pixel in the image. It is also common that ranges of colors/values are counted together instead of counting for each discrete color/value. These ranges or discrete values that divide the color space representing the image in a histogram are called bins.

The construction of a color histogram is done by counting the number of pixels for each scale in any of the channels of a particular color space representation, e.g., RGB, and plotting it on a graph. If the color space is large, it is first divided into intervals (bins). By counting the number of pixels belonging to each of the bins, the color histogram of the image is generated.

Since color information of an image is embedded in the color histogram, it can be used to estimate image identity particularly when color is a strong predictor of this identity [3]. This can be done by histogram intersection, a simple classification method. Figure 1 illustrates histogram intersection.

Image Classification

Geometrical cues, for example, shape, are the most reliable way to estimate an object's identity but color can also be used to analyze complex images effectively. However, dealing with colors may increase computational complexity, but there are techniques that are fast and simple but will still yield good results [4].

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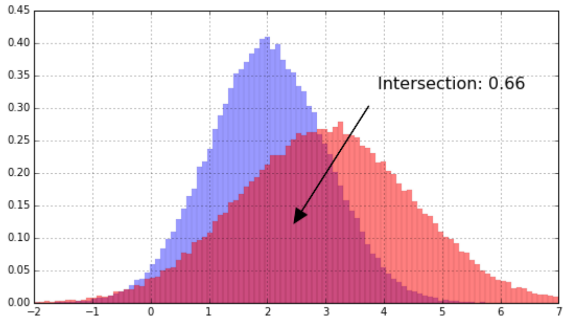

Figure 1. Histogram Intersection (*http://blog.datadive.net/histogram-intersection-for-change-detection/*)

In an article by Swain and Ballard [4], an algorithm called histogram intersection algorithm was proposed. This algorithm was particularly reliable when the color is a strong predictor of the object identity. Swain and Ballard applied histogram intersection algorithm in identifying children shirts, cereal boxes, cleaning detergents. Their method yielded an accuracy of 90%.

In classification using histogram intersection, given a set of classes, C = $\{c_1, c_2, c_3, \ldots, c_n\}$ and input image *I*, a class c_k is assigned to the image *I*. In this method, each class has a model image *M*. Histograms *h*(*I*) and *h*(*M*) are extracted from images *I* and *M* respectively and their intersection will be computed with the formula in Eq. 1 where *n* is the number of bins in each histogram and min function takes the jth bin of *h*(*I*) and *h*(*M*) and return the smallest value between the two.

$$\sum_{j=1}^{n} \min\left(h(I)_j, h(M)_j\right) \qquad (1)$$

This value is then normalized by dividing it with the total number of pixels in *h*(*M*). The result of the intersection is the number of pixels from the model that have corresponding pixels of the same colors in the input image *I*. The intersection is computed for all model images *M*. Image *I* is then assigned to the class of the model *M* that maximizes the normalized Eq. 1.

REVIEW OF RELATED STUDIES

There are several studies that utilize histogram intersection in a classification method. In a research by Erkang Cheng, Nianchua Xie, Habin Ling, Pedrang R. Bakic, Andrew D.A. Maidment, and Vasileios Megalooikonomou (2010), histogram intersection was used to classifying mammographic images [5]. Their method of combining histogram intersection and support vector machine was able to classify mammographic images, if they have radiological findings, with an accuracy of 80.7%.

Hanbin Xi and Tiantian Chang (2015) in their research entitled Image Classification using Histogram Intersection Kernel, classified 590 different images into 59 classes [6]. Their results show that histogram intersection kernel outperformed radial basis function kernel by a margin of up to 5.83%.

In another research, histogram intersection was also applied in face recognition application [7]. Jiang Qiangrong and Gao Yuan (2009) experimented on recognizing faces of 40 subjects. They extracted histograms of these face images and integrated it with support vector machine. This method performed with an accuracy of 91% to 92%.

OBJECTIVES OF THE STUDY

The main objective of this study is to classify gamebird images into their color class using color histogram intersection and to assess the performance of the classification based on accuracy, sensitivity and specificity.

METHODOLOGY

This section describes the process of classifying gamebirds according to its color using histogram intersection. A diagram showing this process is depicted in Figure 2.

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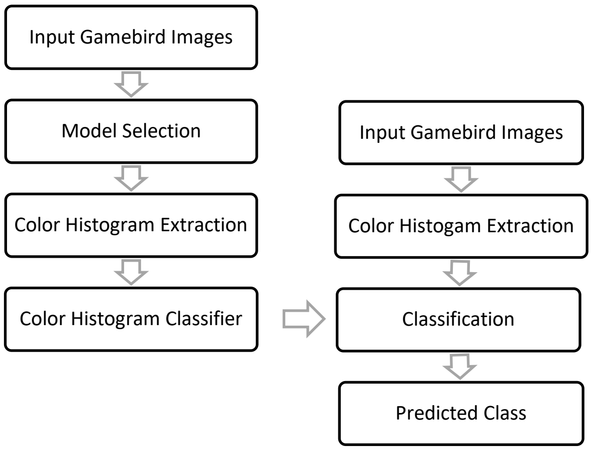

Figure 2. Process flow of the classification method

Input Gamebird Images

Images of gamebirds were extracted from derby fight videos of Pangasinan Breeders' Cup (PBC) 2018. A total of 400 images were collected consisting of 100 images for each feather class namely dom, grey, red, and white. These images were then cropped into a two by two image, and the background was removed to focus solely on the gamebird. The images have a resolution of 200 by 200 pixels. Figure 3 shows the sample input gamebird images.

Figure 3. Sample Input Gamebird Images *(from top row to bottom: dom, grey, red, white)*

Model Image Selection

Model images for each feather class were chosen from the preprocessed dataset. Selection method is by expert's choice. Single and multiple model images for each class were also considered. Figure 4 shows the model images for each class.

Figure 4. Model for each class (*from left to right, dom, grey, red and white)*

Color Histogram Extraction

Images are read in BGR format. The histogram for each channel was extracted using 64 bins. The results were then normalized. In this research, classification is based on single color channel or a combination of all channels. For the combination of all channels, each normalized color histograms per channel were concatenated together forming a single histogram. Color histograms for all models are kept to be used for classifying input images. Figure 5 shows the green channel histogram of models from Figure 4.

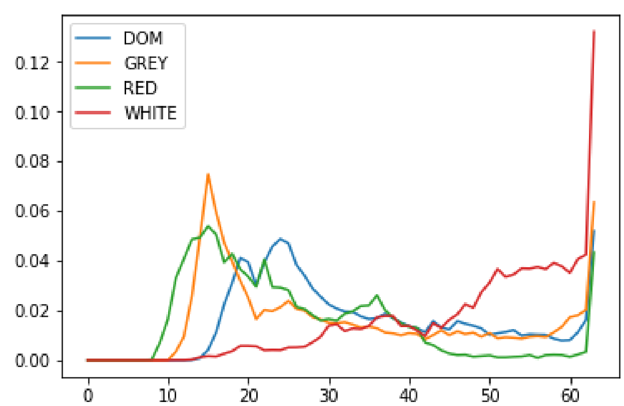

Figure 5. Histogram of Model Images for Single Model Using Green Channel

Color Histogram Classifier

Color histograms of model images will be the reference of the classification process.

Color histograms of input images will be compared for each color histogram of model images using histogram intersection method. Overlaps of the model and input image will be computed and recorded. Each corresponding image will be assigned to the class of the model of which their respective histograms have the largest intersection value.

Image Classification

The dataset (400 images, 100 images for each class) were fed to the classifier and their predicted class was tallied. This is done for each number of models and either single channel or combination of all three channels. Predicted class was compared to the input image's ground truth class. The performance of the classification was then assessed based on its accuracy, sensitivity, and specificity.

RESULTS AND DISCUSSION

Sensitivity, specificity, and accuracy are the main performance evaluation factors of the classification process [8]. Computations of these factors are from true positive (TP), true negative (TN), false negative (FN) and false positive (FP) values. If an image is classified as class A and has a ground truth of class A, then the classification is considered TP. The classification of an image as not class A and is indeed not of class A, is reflected as TN. If an image is classified as of class A but is actually not of class A, then the classification is deemed FP. Accordingly, if an image is classified as not of class A but is actually of class A, will be considered as FN classification [9].

Sensitivity is defined to be the probability of correctly predicting an image to be of class A given that it is indeed of class A. This shows how good the classifier is in predicting an image to be of particular class. Eq. 2 shows the equation for sensitivity.

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

Specificity is the probability of correctly predicting an image to be not of class A given that it is indeed not of class A. This shows how good the classifier is in excluding images to be of particular class. Eq. 3 shows the equation for specificity.

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

Accuracy is the proportion of true results (both TP and TN) among the total number of images examined. Eq. 4 shows the equation for accuracy.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{4}$$

Single Image Model and Single Channel

In this experiment, only one image model was used as template for each class. Classification was also based on each single channel only, i.e., blue, green, or red. Table 1 to Table 3 shows the confusion matrix of this experiment. Rows indicate the actual number of inputs per class, while columns are the number of predicted images per class.

Table 1. Confusion Matrix of Single Model using Blue Channel

Class	Dom	Grey	Red	White	Total
Dom	76	10	12	2	100
Grey	12	61	25	2	100
Red	3	0	97	0	100
White	0	3	0	97	100
Total	91	74	134	101	

Table 2. Confusion Matrix of Single Model using Green Channel

Class	Dom	Grey	Red	White	Total
Dom	80	9	8	3	100
Grey	7	82	9	2	100
Red	3	3	94	0	100
White	1	0	0	99	100
Total	91	94	111	104	

Table 3. Confusion Matrix of Single Model using Red Channel

Class	Dom	Grey	Red	White	Total
Dom	80	8	10	2	100
Grey	8	65	27	0	100
Red	3	6	91	0	100
White	8	0	0	92	100

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Total	99	79	128	94

The performance of single model single channel in classifying gamebird images into dom, grey, red, and white classes was computed from their respective confusion matrices as shown in Tables 4, 5, and 6. The average sensitivity, specificity, and accuracy of single model using blue channel are 82.75%, 94.08% and 91.31% respectively, single model using green channel has 88.75%, 96.25%, and 94.37%, while single model using red channel has 82.00%, 94.00%, and 91.00%.

Table 4. Performance of Single Model Using Blue Channel

Class	Sensitivity	Specificity	Accuracy
Dom	76.00%	95.00%	90.00%
Grey	61.00%	95.67%	87.00%
Red	97.00%	87.00%	90.00%
White	97.00%	98.67%	98.25%
Average	82.75%	94.08%	91.31%

Table 5. Performance of Single Model Using Green Channel

Class	Sensitivity	Specificity	Accuracy
Dom	80.00%	96.33%	92.25%
Grey	82.00%	96.00%	92.50%
Red	94.00%	94.33%	94.25%
White	99.00%	98.33%	98.50%
Average	88.75%	96.25%	94.37%

Table 6. Performance of Single Model Using Red Channel

Class	Sensitivity	Specificity	Accuracy
Dom	80.00%	93.67%	90.25%
Grey	65.00%	95.33%	87.75%
Red	91.00%	87.67%	88.50%
White	92.00%	99.33%	97.50%
Average	82.00%	94.00%	91.00%

Single Image Model and Combination of All Channels

In this experiment, again, only one image model was used as template for each class. Classification was also based on all channels, blue, green, and red, concatenated in a single histogram. Table 7 shows the confusion matrix.

Table 7. Confusion Matrix of Single Model using All Channels

Class	Dom	Grey	Red	White	Total
Dom	84	11	4	1	100
Grey	5	81	12	2	100
Red	3	2	95	0	100
White	1	0	0	99	100
Total	93	94	111	102	

The performance of single model using all channels appears on Table 8. This shows that the average sensitivity is 89.75%, average specificity is 96.58%, and average accuracy is at 94.88%.

Table 8. Performance of Single Model Using All Channels

Class	Sensitivity	Specificity	Accuracy
Dom	84.00%	97.00%	93.75%
Grey	81.00%	95.67%	92.00%
Red	95.00%	94.67%	94.75%
White	99.00%	99.00%	99.00%
Average	89.75%	96.58%	94.88%

Double Image Model and Single Channel

In this experiment, two image models were used for each class. Classification was also on based on each single channel only, e.g., blue, green, and red. Table 9 to Table 11 shows the results.

Table 9. Confusion Matrix of Double Model using Blue Channel

Class	Dom	Grey	Red	White	Total
Dom	62	22	15	1	100
Grey	10	78	10	2	100
Red	0	2	98	0	100
White	12	1	0	87	100
Total	84	103	123	90	

Table 10. Confusion Matrix of Double Model using Green Channel

Class	Dom	Grey	Red	White	Total
Dom	67	27	5	1	100
Grey	9	85	6	0	100
Red	1	3	96	0	100
White	5	0	0	95	100
Total	82	115	107	96	

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Table 11. Confusion Matrix of Double Model using Red Channel

Class	Dom	Grey	Red	White	Total
Dom	65	29	5	1	100
Grey	8	73	19	0	100
Red	2	15	83	0	100
White	9	0	0	91	100
Total	84	117	107	92	

The performance of double model using single channel is shown in Tables 12, 13, and 14. The average sensitivity, specificity, and accuracy of double model using blue channel are 76.25%, 93.75%, and 90.62%, double model using green channel has 85.75%, 95.25%, and 92.88%, while double model using red channel has 78.00%, 92.67%, and 88.75% respectively.

Table 12. Performance of Double Model Using Blue Channel

Class	Sensitivity	Specificity	Accuracy
Dom	62.00%	92.67%	85.00%
Grey	78.00%	91.67%	88.25%
Red	98.00%	91.67%	93.25%
White	87.00%	99.00%	96.00%
Average	76.25%	93.75%	90.62%

Table 13. Performance of Double Model Using Green Channel

Class	Sensitivity	Specificity	Accuracy
Dom	67.00%	95.00%	88.00%
Grey	85.00%	90.00%	88.75%
Red	96.00%	96.33%	96.25%
White	95.00%	99.67%	98.50%
Average	85.75%	95.25%	92.88%

Table 14. Performance of Double Model Using Red Channel

Class	Sensitivity	Specificity	Accuracy
Dom	65.00%	93.67%	86.50%
Grey	73.00%	85.33%	82.25%
Red	83.00%	92.00%	89.75%
White	91.00%	99.67%	97.50%
Average	78.00%	92.67%	88.75%

Double Image Model and Combination of All Channels

In this experiment, again, two image models were used as template for each class. Classification was also based on all channels, blue, green, and red, concatenated in a single histogram. The confusion matrix and performance matrix of this experiment appears in Tale 15 and Table 16.

Table 15. Confusion Matrix of Double Model using All Channels

Class	Dom	Grey	Red	White	Total
Dom	69	24	6	1	100
Grey	7	84	8	1	100
Red	1	3	96	0	100
White	6	0	0	94	100
Total	83	111	110	96	

Table 16. Performance of Double Model Using All Channels

Class	Sensitivity	Specificity	Accuracy
Dom	69.00%	95.33%	88.75%
Grey	84.00%	91.00%	89.25%
Red	96.00%	95.33%	95.50%
White	94.00%	99.33%	98.00%
Average	85.75%	95.25%	92.88%

The performance of double model using all channels shows that the average sensitivity is 85.75%, average specificity is 95.25%, and average accuracy is at 92.88%.

ANALYSIS ON MISCLASSIFICATIONS

The confusion matrices show that misclassifications are usually among the classes dom, grey, and red. This might be because of the resemblance of their histograms, which are skewed towards the low value bins. Inspection of other misclassified images also show that the orientation of the gamebird in these images is different from the model images, thereby, histogram extracted will have a different proportion of pixels with their respective models, thus, the misclassification.

Table 17 shows some of the misclassified images in the single model all channel experiment. The column Score shows the

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histogram intersection of the image with each model. It can be noticed that the score for the predicted class and the actual class have small margins. Results from the single model all channel experiment actually shows that 85.37% of the misclassified images have the actual class as the second highest score in the classification.

Table 17. Sample misclassified images.

Image	Predicted Class (PC)	Actual Class (AC)	Score [dom, grey, red, white]
	white 	dom 	[25.24, 24.09, 15.97, 34.68]
	red 	dom 	[27.32, 27.12, 30.46, 15.10]
	grey 	dom 	[28.03, 29.66, 27.78, 14.51]
	dom 	grey 	[28.20 28.10, 24.12, 19.58]
	red 	grey 	[24.03, 28.20, 32.63, 15.13]
	grey 	red 	[29.18, 27.73, 27.69, 15.40]
	grey 	red 	[25.29, 30.87, 30.52, 13.32]
	dom 	white 	[27.82, 26.83, 20.02, 25.32]

CONCLUSION AND RECOMMENDATION

Results show that classification using color histogram intersection can be used to classify gamebird images into their color classes. This method performed best using single model and utilizing all channels where sensitivity, specificity, and accuracy was computed to be at 89.75%, 96.58%, and 94.88% respectively. Based on the experiments, green channel performed best among the color channels in this classification method, and therefore, should be the top choice if only one channel will be used due to computational speed consideration.

In future researches, one may consider better methods on selecting what model image to use other than just simply by expert's choice or perhaps automate this step. The dataset must also be increased and the image resolution be improved in order to achieve better performance. Other image features can also be considered and other methods of classifications may also be investigated.

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