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Original Article

Comb Color Analysis of Broilers Through the Video Surveillance System of a Poultry House

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ABSTRACT

Livestock and poultry production are critical agricultural industries. Intelligence in the poultry industry has received increasing attention in recent years. An intelligent monitoring system was implemented to manage the poultry house and improve its feeding conditions. Experts can remotely diagnose the health of chickens using a monitor screen. An intelligent video surveillance system was used in this study to evaluate the physical appearance of broilers in a poultry house. Comb color was studied during the long chicken growth phase, and color changes were statistically analyzed. The video surveillance system includes meticulously color-calibrated cameras with an additional YOLOv4 algorithm for comb detection and color recovery. The image data was stored for up to 90 days and then analyzed to understand comb color behavior during growth. This study develops a technique for automatically extracting comb colors that can assist professionals in making color-related broiler health diagnoses in the future.

INTRODUCTION

The poultry industry is an important agricultural sector in Taiwan. It entails keeping a large number of broilers in enclosed spaces (poultry houses). However, poultry farmers face challenges such as a shortage of workforce and incomplete data collection in management, which hinders uniformity and traceability. During the last few decades, there has been an increasing need for information digitalization in the poultry industry. Traditional manual management makes visually identifying abnormal conditions in many domestic fowls difficult. A video surveillance system with intelligent features is the most convenient solution for the remote monitoring of poultry houses. Poor health in domestic fowls is often manifested through external signs such as changes in comb and wattle color, claw appearance, anal status, and feather texture (Bakar *et al.*, 2023). To minimize pathogen cross-contamination, unnecessary interaction between poultry and farmers should be avoided. Therefore, poultry houses frequently use monitoring systems.

Color is an important indication in agriculture for intuitively identifying distinct conditions in plants and animals. Accurate color measurement and calibration are required to provide meaningful applications. Intelligent features based on imaging technologies have gained popularity during the last decade. Designing an appropriate and representative color checker might effectively improve the performance of agricultural crop images (Sunoj *et al.*, 2018).

Drone-captured aerial photos of large-scale crops help measure plant growth. Color analysis considers the most critical color factors, such as specific channels in various color spaces. This analysis may also recognize or separate different crops in an image (Zhou *et al.*, 2019; Fernandez-Gallego *et al.*, 2019). The hue angle is a component of the HSI color space and is used as an index to differentiate between different hues. Retrieving the pixel numbers of specific hue values can produce a crop senescence index for monitoring agricultural crop's growth status (Sarkar *et al.*, 2021).

Similarly, spectral scans at different wavelengths provide valuable information for identifying wheat crops' unseen and susceptible features (Sala *et al.*, 2020). These methodologies have validated a common conclusion: color analysis through crop images can save significant labor and allow timely crop growth monitoring. Despite its success in crops, color analysis is still limited by the limitations of color image sensors.

In contrast to the relatively static landscape of crops, monitoring animals is challenging because of the dynamic nature of the objects, which brings up tracking issues. In this study, we focused on broiler chickens in a poultry house. All chickens were obtained from free-range farms and a specific house. Although tracking individuals using an imaging system helps to identify abnormal chickens, instantly removing them from a poultry house is problematic. However, intelligent imaging systems do provide valuable information.

There are two main changes in the comb of broiler chickens when there are health issues (Swayne *et al.*, 2020). One is a change in the shape of the comb, making it lose vitality and be unable to stand erect. The other characteristic is the overall color change of the comb. When broiler chickens decrease their activity, the comb is an essential indicator in determining the type of disease, as its color can be used to identify some common poultry diseases (Cherian, 2007). Many diseases affect the color of the comb; therefore, timely detection of poultry diseases and the implementation of isolation measures until a veterinary specialist can confirm the diagnosis are essential issues in the poultry industry.

Artificial intelligence (AI) was used in this study to distinguish chicken combs. AI refers to systems and machines that exhibit humanlike intelligence, which assist in recognizing objects as human beings would (LeCun *et al.*, 2015). You Only Look Once (YOLO) is an object identification deep learning algorithm that can predict many items' positions and classes in an image in a single pass, while also displaying prediction confidence levels (Redmon *et al.*, 2016). This algorithm accelerates recognition while maintaining high accuracy, enabling real-time image recognition. The detection of mating, standing, eating, spreading, fighting, and drinking in broiler chickens using YOLOv3 has been successfully implemented by Wang *et al.* (2020) with an accuracy rate of up to 92%. Since 2020, YOLO has progressed from version 3 to version 7. Several valuable features and capacities, as well as overall performance, have been substantially improved by it (Bochkovskiy *et al.*, 2020, Li *et al.*, 2022; Wang *et al.*, 2022).

Observing animal behavior using monitoring systems has long been an essential technological research indicator in the livestock and poultry industries, particularly in the case of applications involving broiler chickens. Marıa *et al.* (2003) developed an automated system for environmental regulation and feeding in chicken houses to achieve automation in poultry farming. Researchers have also begun using cameras to monitor real-time feeding, behavior, and physiological changes in broiler chickens (Marıa *et al.*, 2003). With the maturation of machine-learning technologies, they have been widely applied in various livestock and poultry farming areas. In 2011, Kristensen and Cornou (2011) developed a model that automatically recorded broiler chicken activity to monitor deviations in activity as the chickens grew. This model developed into an automatic monitoring system that alerts farmers when the activity of a broiler flock deviates from the expected values. Pereira *et al.* (2013) developed a behavior classification tree to identify white broilers and distinguish them from the background. Abdanan *et al.* (2015) integrated image analysis algorithms with high-speed cameras to investigate the relationship between beak and head movements in broiler chickens while feeding. They successfully established the relevant biological variables related to broiler feeding behavior.

Over the last decade, image analysis using state-of-the-art machine learning has been investigated for determining chicken health status. Zhuang *et al.* (2018) used postural analysis to classify the health status of broiler chickens. Zhang *et al.* (2020) developed a residual network to identify diseases and illnesses. The recognition rate was of 93.7% after training with 5 thousand images.

This study focuses on the long-term monitoring of the red-feathered gallus and native Taiwanese chickens. These chickens have bright red combs that are large and easy to recognize. They are typically sent to the market at around 14 to 16 weeks of age. By implementing a surveillance system, real-time information can be obtained from videos and audio, including the chicken activity status in poultry houses, thus assisting experts in quickly responding to any health condition. To do so, we installed a surveillance system with a 4K pan-tilt-zoom camera and four HD cameras based on 5G wireless communication. All cameras were calibrated to ensure accurate color measurement performance. Moreover, in order to process many video images, we utilized the deep-learning object recognition tool YOLO (You Only Look Once) to automatically retrieve comb colors in a poultry house. The CIE color space $L^*a^*b^*$ was used to examine how comb appearance changes with age, temperature, and abnormal health.

MATERIAL AND METHODS

The experimental farm was owned by Leadray Co. Ltd. And was located in Huwei Township, Yunlin County, Taiwan. The poultry house is oriented north-south, with sunlight illuminating from the east and west during sunrise and sunset. It measured approximately 120 m in length and 12 m in breadth. The rearing cycle of chickens in this poultry house was of approximately 90 days. During this period, we installed cameras, color patterns, and network devices at the center of the poultry house.

Setup of the surveillance system

The surveillance system consisted of four HD cameras, one 4K PTZ camera, an Ethernet router, and a network-attached storage (NAS). WiFi-6 connected all HD cameras with prime lenses while a wired Giga-ethernet was used to link and control the 4K PTZ camera. To achieve a latency of less than 2 s in the 5^{th} generation wireless system (5G) framework on the Internet, two protocols were implemented and tested: the hypertext transmission protocol (HTTP) and the real-time streaming protocol (RTSP). The AXIS Q6128E 4K PTZ camera (AXIS Communications, Lund, Sweden) had pan and tilt capabilities of up to 360 and 90 degrees, respectively. It had a 12x zoom lens and a working distance of 20 m. Owing to the active and lively nature of red junglefowl, understanding the activity of broiler chickens is complex, and the limited range of cameras makes it a challenging task. In this study, the imaging equipment was installed in an area near the center of the poultry house. The working area was approximately 8 m in length and 7.5 m in width. An additional network-attached storage (NAS) system was used to collect images for long-term analysis. The NAS could store videos for up to 180 days. Only images from the 4K camera were used for the color analysis of the broiler crest during growth. This framework was designed for real-time remote monitoring.

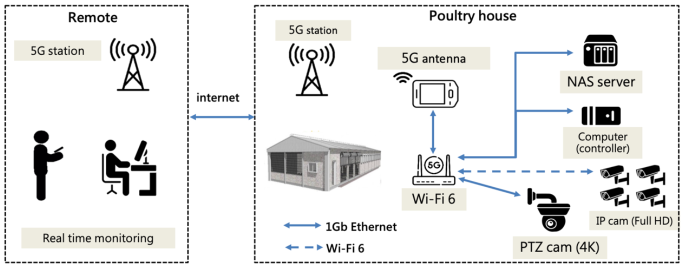


Figure 1 – The overall framework of our surveillance system.

The recording period for the surveillance system began on December 8, 2021. No evident combs were observed in the initial period. On January 3, 2022, when broilers reached four weeks of age, the combs on their heads started to grow. Broilers were culled on March 2, 2022, after completing a rearing period of 80 days (approximately 11 weeks). The recorded data were retrieved from the NAS for additional color calibration and analysis.

Environmental color and color calibration

The 4K surveillance camera was set to operate at 30 frames per second (fps) with an 8 Mbps transmission bit rate to balance the transmission payload and image quality. A bitrate value of 8 Mbps was verified in advance through various tests in a poultry house. Furthermore, standard environmental colors were chosen as reference targets for the camera color calibration. To this end, the camera's image color, brightness, and sharpness were fixed at their default values and did not vary during the shooting process. Its exposure was set to automatic mode, allowing it to adjust to variations in light to capture the fine details of broiler chickens during daylight hours. In addition, the camera's white balance function was fixed at a specific color temperature to ensure consistency with the color calibration status. Color correction from measured to reference RGB values was accomplished by using polynomial regression (Hong *et al.*, 2000). Based on earlier work, the calibration equation of the 3 × 10 matrix was used, as it previously displayed the least amount of fitting error (Wei *et al.*, 2022). In (1), the calibration matrix M can be constructed using the least-squares method by collecting at least ten samples; where $[r_i, g_i, b_i]$ denotes the *i*-th measurement value from the image. Moreover, $[R_i, G_i, B_i]$ is the reference value converted from the commercial Topcon SR-UL1R spectroradiometer (Taiwan Denkei Solution Co. Ltd., Taipei, Taiwan). Equation (1) can be rewritten as (2), and the matrix M can be solved using (3). In practice, CIE XYZ color space data were acquired from the device and then converted into the CIE $L^*a^*b^*$

and sRGB color domains under a specific illumination temperature. Both domains were normalized to [0, 1], and the reference color temperature was 6500 K.

$$\begin{bmatrix} R_1 & R_2 & \cdots & R_n \\ G_1 & G_2 & \cdots & G_n \\ B_1 & B_2 & & B_n \end{bmatrix} = \mathbf{M} \begin{bmatrix} r_1^2 & g_1^2 & b_1^2 & r_1 g_1 & g_1 b_1 & r_1 b_1 & r_1 & g_1 & b_1 & 1 \\ r_2^2 & g_2^2 & b_2^2 & r_2 g_2 & g_2 b_2 & r_2 b_2 & r_2 & g_2 & b_2 & 1 \\ & & & & \cdots & & & & & \\ r_n^2 & g_n^2 & b_n^2 & r_n g_n & g_n b_n & r_n b_n & r_n & g_n & b_n & 1 \end{bmatrix}^{T} \quad (1)$$

$$\mathbf{A} = \mathbf{M}\mathbf{b}^{T} \quad (2)$$

$$\mathbf{M} = \mathbf{A}\mathbf{b}(\mathbf{b}^{T}\mathbf{b})^{-1} \quad (3)$$

Off-the-shelf color calibration palettes such as the Macbeth Color Checker (McCamy *et al.*, 1976) are designed for outdoor landscape scenes. Environmental colors and some of the standard colors were included in the reference palette to improve color calibration accuracy. We classified the colors into primary, environmental, and chicken. These are listed as sets-1 to 3 in Table 1. The primary colors and set-1 were obtained directly from the Macbeth Color Checker. Set-2 was selected from colors that usually appear in the environment. Colors of set-3 were initially obtained from the RGB values of specific targets in the images of the poultry house and chicken. These colors were then printed on a poster. Finally, the poster's L*a*b* and RGB values were determined using a spectroradiometer. A series of CH1 to CH4 reactions often occur in chickens. Similarly, the colors GD1–GD3 are common in poultry houses. Finally, color palettes were glued onto the pillars and feed tubes for camera color calibration (Figure 2).

Figure 2 – Color palettes on the pillar and feed tubes were used for color calibration.

Table 1 – Selected colors for camera color calibration.

Reference palette			CIE L*a*b*			sRGB (8 bit)		
Category	Name of color		L*	a*	b*	R	G	B
Set-1	Red		47.0	34.1	19.7	171.2	86.6	80.2
	Green		58.1	-30.7	31.5	101.4	152.6	82.4
	Blue		40.9	5.7	-34.8	63.2	96.4	153.4
	Magenta		52.8	33.2	-9.2	173.5	104.3	142.6
	Cyan		55.7	-21.6	-18.1	48.8	145.2	164.1
	Yellow		76.8	-1.7	67.2	219.6	187.5	54.1
	White		93.8	-0.1	-4.2	233.1	237.5	245.2
	Neutral 8		85.9	-3.5	1.5	209.0	216.7	211.8
	Neutral 6.5		76.7	-5.2	3.9	182.3	192.0	181.9
	Neutral 5		55.7	-3.3	5.5	131.6	134.9	123.9
	Neutral 3.5		54.7	-2.9	4.7	129.2	132.1	122.7
	Black		43.9	-1.8	2.9	102.8	104.5	98.9
Set-2	Dark skin		45.0	7.4	11.2	125.4	101.7	88.2
	Light skin		69.0	6.3	17.4	191.4	163.6	137.4
	Blue sky		56.5	-9.4	-0.9	116.3	140.4	136.7
	Blue flower		62.0	3.0	-18.8	137.2	149.5	182.9
	Moderate red		53.5	29.7	13.1	181.6	107.2	106.7
	Yellow green		71.1	-22.3	51.1	163.1	183.3	75.9
	Orange yellow		70.8	6.9	52.6	211.5	166.5	74.5
Set-3	CH1		70.1	24.8	11.0	221.0	154.5	151.3
	CH2		51.3	48.3	17.4	201.6	83.2	94.3
	CH3		67.6	13.5	7.5	193.8	156.0	150.5
	CH4		45.9	21.2	6.1	145.6	95.3	98.5
	GD1		89.4	-2.5	10.2	228.1	225.6	203.6
	GD2		87.0	-3.8	-15.0	194.5	221.4	244.2
	GD3		36.5	1.8	-2.3	87.2	85.1	88.8

The color difference of CIE1976 was used to assess color accuracy. The linear sRGB or calibrated sRGB values from the camera were converted into the CIE-XYZ color space using Eq. (4), with the illuminant assumed to be D65. The color difference, ΔE^*_{ab}, was calculated using Equations (5)–(7). In Eq (5), $[X_n, Y_n, Z_n]$ was the reference white color.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4123 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 01192 & 0.9504 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

$$\begin{aligned} L^* &= 116 f(Y/Y_n) - 16 \\ a^* &= 500\{f(X/X_n) - f(Y/Y_n)\} \\ b^* &= 200\{f(Y/Y_n) - f(Z/Z_n)\} \end{aligned} \tag{5}$$

$$\begin{aligned} f(I/I_n) &= f(I/I_n)^{1/3}, \textit{where } I/I_n < 0.008856 \\ f(I/I_n) &= 7.787(I/I_n) + 16/116, \text{where } I/I_n \le 0.008856 \end{aligned} \tag{6}$$

$$\Delta E^*_{ab} = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2} \tag{7}$$

Chicken comb recognition based on YOLOv4

We used the YOLOv4 detection model, a well-known deep-learning method, to automatically extract the comb color from a large number of images. The training data were collected from the 4K cameras set to different zoom levels, angles, and times inside the poultry house. Additionally, manual cropping operations for chicken combs based on a labeling tool named "LabelImg" were required for every image. As shown in Table 2, 860 images were captured under various lighting conditions during the day and night, and different weather conditions affected lighting and shadows. Figure 2 (a) illustrates the images captured at night, and the red rectangles with confidence values in Figure 2 (b) indicate where the combs were detected.

The comb detection findings can be divided into four categories: 1. true positives (tp), in which the chicken combs were correctly identified; 2. false positives (fp), in which non-chicken comb objects were incorrectly identified; 3. true negatives (tn), in which no chicken combs were correctly identified; and 4. false negatives (fn), in which chicken combs are present but not recognized. In performance verification, "precision" and "recall" are commonly used. Precision is defined as tp/(tp+fp) and recall as tp/(tp+fn). The higher the values of both are, the better. In this study, the YOLOv4 model had a precision of 90% and a recall of 89% for chicken comb detection. However, it should be noted that small chicken combs or those positioned too far away in the image were difficult to distinguish.

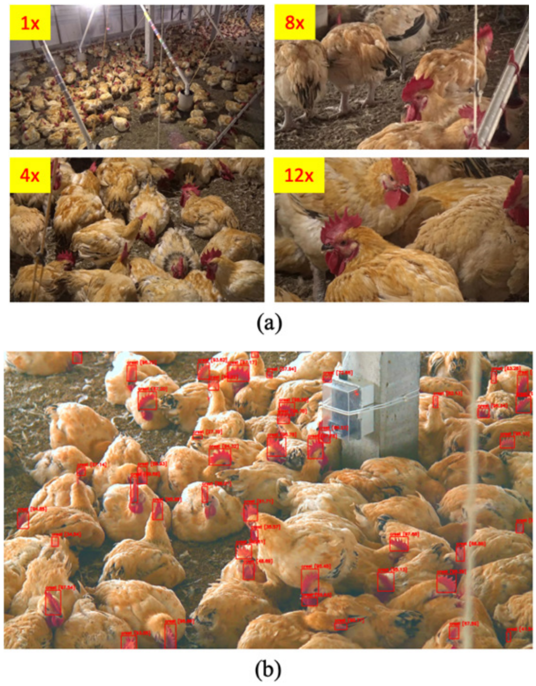


Figure 3 – (a) Selected images under different zoom level, and (b) an example of comb recognition result.

Table 2 – Number of images for training of chicken comb recognition.

Zoom level	Time	No. of images for training	
1.0x	Day Night	110 35	145
4.0x	Day Night	127 41	168
8.0x	Day Night	148 37	185
12.0x	Day Night	140 35	175
24.0x (2.0x Digital)	Day Night	150 37	187
Total			860

RESULT AND DISCUSSION

Evaluation of color calibration

In our surveillance system, NAS was used to store all images of broiler chickens during the growth period. Color calibration was accomplished using Eqs. (1)–(3) to obtain stable color analysis. The CIE $L^*a^*b^*$ values of the color palettes were used as reference targets for comparison because they were collected directly from the spectroradiometer in advance, as shown in Table 1. The estimated $L^*a^*b^*$ values were obtained from the images and converted using Eqs. (4) and (5). This experiment captured images on sunny, cloudy, and rainy days. Images captured within the same half-hour were grouped to analyze their differences during the daytime. Experimental results are illustrated in Figure

4. The color difference (ΔE^*_{ab}) was significantly reduced to 8.0 after calibration. Because of the sunlight, the errors were large in the morning and evening.

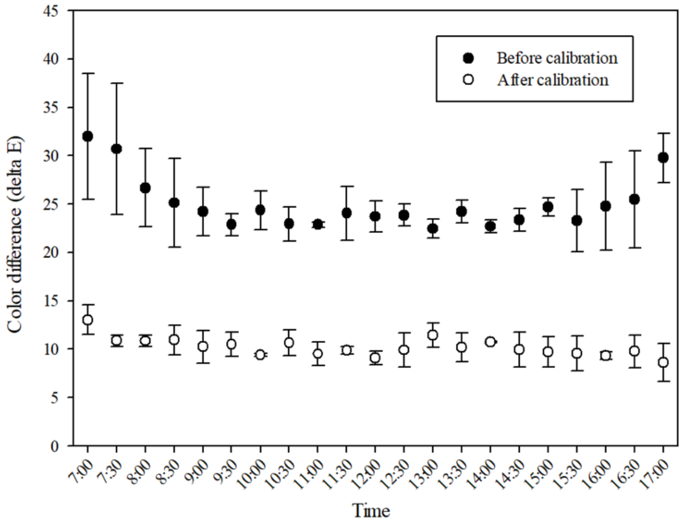
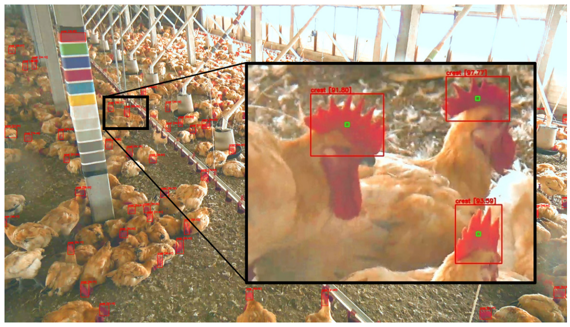


Figure 4 – Color differences before and after calibration.

Comb color changes during broiler chicken growth

Based on the results in Section 3.1, a stable calibration matrix was used for the color analysis of the long-term observations. As the comb has wrinkles and connective tissue patterns, when the outermost layer of the epidermis reflects the color of the underlying blood vessels, it results in different color variations. The color gamut of a single comb was recorded every five days in this study, beginning on day 25 and finishing on day 80 of broiler chicken age. We used a 4K camera positioned at a fixed angle toward the inside to eliminate interference from sunlight. We captured images at midday to obtain a large amount of broiler chicken comb color data. The recording method involved capturing corrected images using the same color calibration matrix and applying a comb-detection algorithm to retrieve at least 20 combs from every image. A confidence level greater than 0.60 was chosen to ensure that the number of combs was sufficient. When the number of combs exceeded 20, they were all sorted and ranked based on their confidence levels. An additional regional average operation of 15 × 15 pixels was applied to the bounding box center of every comb to obtain a stable comb color. Figure 5 (a) shows an example of automatic comb detection and the selected color region. Figure 5 (b) shows a close-up of the chicken comb prior to detection. Finally, all the data were converted to the CIE L*a*b* color space for analysis.

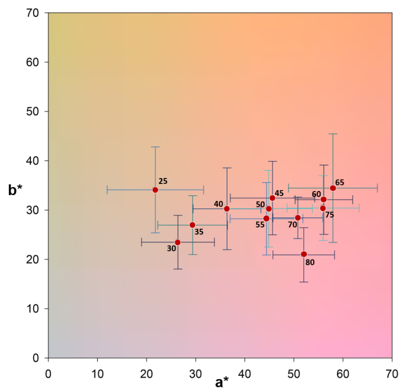


a

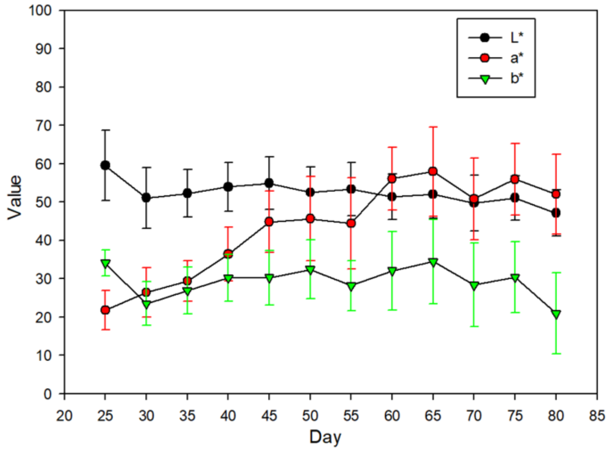
b

Figure 5 – (a) The obtained comb color after detection, and (b) a close-up view of one comb.

It can be observed that the color of chicken combs changes as the chickens grow older. The average colors and data deviations are plotted in Figure 6 (a). Similarly, each channel of CIE $L^*a^*b^*$ was plotted concerning the growth of the chickens, as shown in Figure 6 (b). L^* represents the human perception of brightness. It ranged from 0 (extremely dark) to 100 (white). The L* trend in Figure 6 (b) shows that the comb color became darker each day. Color gamut quantities a^* and b^* ranged from -100 to 100. Reddish and greenish colors are represented by higher and lower a^* values, respectively. Similarly, higher and lower values of b^* indicate more yellowish and blueish colors, respectively. As shown in Figure 6, the chicken comb color turned redder every day.



a



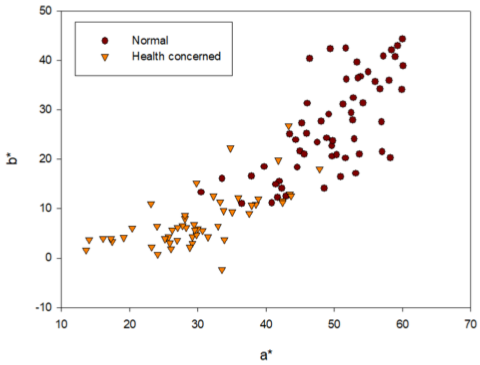
b

Figure 6 – Comb color changes as the chickens grew.

Other chicken color issues in poultry houses

Several chicken color issues may be examined to improve poultry house management. Color is commonly used to identify health conditions because it is an important external aspect. During the experiment, owners reported changes in the comb color of broiler chickens with health concerns. Images were retrieved and compared with those of the typical combs during the same period. In Figure 7 (a), the boxed areas depict chickens suspected of cardiovascular disease. The chickens were nine weeks old when they were sampled for comb colors using a previously published method. The color distributions of the a^*b^* domains are plotted in Figure 7 (b). Significant color differences were observed. The a^* range of the comb color for healthy chickens was scattered between 30 and 60, and the b^* range was scattered between 10 and 50. For chickens with health concerns, the a^* range of the comb color was scattered between 10 and 50, and the b^* range was scattered between 0 and 20. As compared to healthy chickens, the a* and b* values are closer to 0, with an average color difference (ΔE^*) of 28.52, which is easily recognizable.

a



b

Figure 7 – (a) the health concerned chicken, and (b) color comparison with a normal comb.

When chickens have health issues, their comb color can change significantly, culminating in hue shifts in severe situations. The effect of the temperature followed a similar trend. Based on our observations, cold weather may temporarily alter comb colors. Using an automatic monitoring system in conjunction with comb recognition, it was possible to identify chickens with health concerns, enabling owners to take prompt action. The chickens' health status can be determined by their comb color and other external features. The limitation of the proposed method is that it suffers from incorrect color estimation due to the interference of environmental illumination and camera capabilities. It is recommended that color analysis takes into account the same time period of each day and similar weather conditions.

CONCLUSION

This study integrated video camera surveillance and network systems in a poultry house in Yunlin County, Taiwan, to provide intelligent monitoring features. Color analysis was performed by calibrating the colors of the poultry house images to match the actual on-site colors. A color calibration chart was designed and installed in the poultry house to correct the camera for all environmental conditions. Our prior work showed that a 3 × 10 calibration matrix performed better. We effectively performed long-term color monitoring of broiler chickens using this system, particularly for their combs. The unhealthy chickens' comb color deviated from the healthy combs' color range in the same image. In the future, automatic color identification and alert systems can be applied in poultry farming environments by integrating machine learning and image monitoring systems. This system monitors the health status of broiler chickens, reduces the spread of poultry diseases, and improves management.

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DISCLOSURES

The authors declare no conflicts of interest.

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