A Comprehensive Analysis of the Impact of Illumination Color Variations on the Visual Attributes of Edible Bird Nests

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Abstract—Edible Bird Nest (EBN) products must be processed to ensure cleanliness and quality. The market value of EBN is impacted by color, shape, size, etc. Previous work employed machine vision and machine learning to assist human workers in accelerating the cleaning process. However, illumination is a critical factor influencing the visual attributes extracted from vision systems. However, only a few studies have explored varying color illuminations' influence on these feature attributes. To address this gap, we introduce a framework designed to systematically investigate the effects of various lighting conditions on the extracted features. In this research, a chamber embedded with LEDs with different light colors (white, red, green, and blue) was designed to optimize image acquisition processing by considering the distance and angle of a camera. Then, visual attributes, such as intensity, statistical, and geometry-based features, were extracted and extensively investigated. These extracted features were analyzed using the Analysis of Variance (ANOVA) and Tukey's tests (Test-1 & Test-2), where the results demonstrated that the images taken under red color were significantly different from images taken under white/blue/green color. Based on the result, red color illumination is suitable for the ML/ DL process, especially for shape classification, but it is also possible with white color illumination. White color illumination is suitable for detecting impurities from EBN because it produces a higher contrast image. The proposed solution has demonstrated great potential in optimizing the lighting condition of machine vision for EBN quality control.

Keywords-ANOVA test; edible bird nest; feature extraction; image processing; Tukey's test.

Manuscript received 6 Mar. 2024; revised 20 Aug. 2024; accepted 25 Dec. 2024. Date of publication 30 Apr. 2025. IJASEIT is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.

I. INTRODUCTION

Indonesia is the leading exporter of Edible Bird Nest (EBN) products. The EBN production continues to increase annually, with 1,415.9 tons in 2022 [1]. EBN products have excellent benefits for maintaining body immunity, improving health, and having antiviral effects, especially against the Influenza A Virus (IAV) [2]. Moreover, EBN is also antiinflammatory, neuroprotective, and immunomodulatory (agent in treating IAV and SARS-CoV-2 infections) [2], [3]. The increasing demands of EBN also indicate the importance of quality control to ensure its safety and cleanliness.

In previous works, EBN could be classified based on color (white EBN, and other EBN). Additionally, some works classified EBN based on shape, i.e., half-bowl EBN, triangular EBN, bar-like EBN, EBN model (shaped into different shapes by models), or fragment EBN [4], [5]. Nevertheless, EBN's value in the market is defined by mass, size, color, impurity, and the number of feathers via physical appearance [6], [7]. All these conditions can affect the quality (grade) of EBN, regardless of whether it is raw or processed EBN [8].

Recently, computer vision has been coupled with Machine Learning (ML)/Deep Learning (DL) to perform visual-related tasks to learn and understand the extracted attributes from images. Due to its robustness, computer vision approaches are widely employed in various areas, such as healthcare, production, agriculture, and other sectors [9], [10], [11]. Several EBN-related works have applied these methods to inspect the impurities and determine the EBN grade. In previous works, Goh et al. [12] proposed an impurity inspection system using computer vision and an unsupervised clustering method. EBN data was taken using a camera under a red LED and a black background. Yeo et al. [13] developed a U-net-based algorithm to detect the level of impurity. In this research, image data were taken using a camera with red, green, blue, and white LED light sources. Sa'ad et al. [14] used the hybrid Fourier Descriptor and Farthest Fourier Point Signature methods to perform EBN grading based on the shape and size of EBN. Meanwhile, Indrajaya et al. [15] classified the shape of EBN into bowl, oval, and angular using DL. In their proposed work, EBN data was taken using a smartphone camera. Septiarini et al. [16] conducted research to classify EBN (class quality 1, 2, and 3) using Support Vector Machine. The EBN image was taken with a 40x30x30 mini box, with a white LED strip. Yee et al. [17] conducted impurity detection using optical segmentation, with two types of low-angle lighting scenarios: blue-diffused lighting and red-diffused backlighting. Gan et al. [18] classified EBN grade (AA, A, B) using Bat Algorithm Clustering based on K-Means clustering. All the literature works highlighted in this section acquire images based on LED/light sources with various colors, such as red [12], [13], [17], green [13], blue [13], [17], white [13], [16]. However, no previous work compares and analyzes the impact of illumination on the EBN feature extraction.

ML/DL can also be used to analyze data, and statistical tests, such as Analysis of Variance (ANOVA) and Tukey's tests, can also be adopted. These approaches can be used for optimization, wavelength detection, selection of confidence level or error rate, interpretation of power transformer faults, thresholding image segmentation, shaping of talc particles, cancer modeling, etc. [19], [20], [21], [22], [23], [24]. Nevertheless, based on our exhaustive search, no study employs statistical tests for EBN-illumination data analysis.

Previous work demonstrated that achieving success in identifying and recognizing EBN type, shape, or impurity within ML/DL applications is significantly impacted by the initial image acquisition and processing. Therefore, based on statistical tests, we mainly analyze the impact of illumination with various colors on EBN image analysis. In our work, we designed a device (chamber) to optimize the image acquisition process, where the chamber design considers the distance and angle of a camera position and variations in light color (white, red, green, and blue). Additionally, we analyzed the impact of illumination color variations on the visual attributes of EBN using the ANOVA and Tukey's tests based on extracted intensity, statistical, and geometrical features from the images.

II. MATERIALS AND METHOD

A. EBN Chamber

The EBN image acquisition chamber is designed to meet the four expected specifications: position variations, angle variations, light with various colors, and portability. The design of the chamber is shown in Fig. 1. The chamber is designed to consider how EBN sample images can be taken from the side (Fig. 1 (a)) and front views (Fig. 1 (c)). In the chamber, RGB 5050 LEDs have been installed, allowing for dynamic color changes [25]. The available colors include white (6000K), red, green, and blue, and the LEDs operate with a DC 12V input voltage [25]. Fig. 1 (b) illustrates the structure of the chosen LED. This LED is equipped with a remote control and RGB controller, which can regulate variations in light color.



Fig. 1 EBN Chamber Sketch; (a) Side View; (b) LED Panel; (c) Front View; (d) Folded view (portability)

An angle wheel, as shown in Fig. 2, has been positioned within the chamber to enable the variation. This involves placing a rotatable disk at the base to accomplish the desired changes in position. Finally, the chamber, depicted in Fig. 1 (d), is designed to be foldable and comes in a convenient size to ensure portability. The prototype of our design allows us to obtain additional EBN image samples at various angles, colors, and positions.



Fig. 2 Angle Wheel for Chamber

Fig. 3 depicts the realization of the EBN chamber, with two locations where the cameras can be positioned in front and top views.



Fig. 3 Realization Chamber EBN

LED strips are installed on the top and part of the EDB chamber panel. The distance for taking EDB images is 10 cm from the front of the camera to the edge of the mounting plate (Fig. 4). When taking an image, the EBN object is raised as high as 5 cm (Fig. 4) to provide the captured object with adequate lighting.



Fig. 4 Position of Taking EDB Picture & Height Adjustment

B. EBN Data Collection

EBN image data was taken in the following angles: 0° , 30° , 60° , 300° , and 330° using a Sony A6400 camera, with white, red, green, and blue LEDs. The samples of EBN images from various angles are depicted in Fig 5. In our work, we utilized triangular-shaped raw EBN samples that are yet to be cleaned from the impurities. These EBNs can be categorized into large, medium, and small sizes.



Fig. 5 Angle Variations of EBN

Examples of captured images using different LED colors are shown in Fig 6.



Fig. 6 Images of EBN with LED color variations

The EBN image taken in different angle positions is illustrated in Fig. 7. As a result, the total number of images taken for each LED color variation for the big, medium, and small classes is 125 pcs, 125 pcs, and 95 pcs, respectively. These images were used for statistical tests and analysis.



Fig. 7 Positions of EBN

C. One-way ANOVA Test and Tukey's Test

Statistical tests using ANOVA are used to detect significant differences among the means of multiple data groups. The ANOVA involves measuring and comparing the variation between groups and within groups. If the mean among groups surpasses that of within groups, it suggests a significant difference between those groups [26], [27]. If an experimental study comprises one independent variable with one dependent variable, with more than two treatment groups, then one-way ANOVA will be adopted for analysis. Meanwhile, the twoway or multiway ANOVA is used for studies comprising two independent variables: a two-factor experiment (2 treatments) or an experiment with one treatment and one attribute variable. The steps for hypothesis testing are as follows [28]: Hypotheses to be tested:

$$H_0: \sigma_1^2 = \sigma_2^2$$
$$H_1: \sigma_1^2 \neq \sigma_2^2$$

From the formula (1), the null hypothesis (H_0) represents the variance of one group (σ_1^2) is identical to the variance of other group (σ_2^2) . The alternate hypothesis (H_1) is that the variances differ. The mean difference between groups can be determined by the p-value calculated from the F-ratio (from the ANOVA table), where α is a pre-determined cut-off point for establishing the significance level. If the p-value is less than the significant level, the null hypothesis (H_0) shall be rejected, and the alternate hypothesis (H_1) will be accepted, which indicates a statistically significant difference between the means of the groups, or vice versa [28], [29].

If there is a significant difference among the means of three or more groups from ANOVA, Tukey's test (or Tukey's Honestly Significant Difference) is employed to determine which groups differ significantly from each other [19], [21]. Tukey's test compares all groups by identifying pairs of groups with significant differences in their means.

In our work, we proposed a two-stage EBN data analysis based on the impact of the illumination. The first stage is to employ the ANOVA test to examine the difference in the mean. If there is no significant difference among the means of the group, then the process will be stopped until the first stage only. If there is a significant difference among the means of the group, then the process continues to the second stage. Tukey's test would be employed to know which color is involved. We compared the effects of the color of white, red, green, and blue LEDs using a one-way ANOVA test with a chosen significance level (α) of 0.05. The (H_0) in the ANOVA test means to significant difference among the means of EBN feature extraction within the group (p-value > α). The alternate hypothesis (H₁) indicates a significant difference among the means of EBN feature extraction within the group (p-value $< \alpha$).

D. EBN Image Lighting Variation Test Design

There are various extractable features from an image, such as intensity, geometric, and statistical features [30], [31], [32], [33], [34]. Therefore, in our work, we execute two tests on different features. The test-1 was conducted on the intensity and statistical features processed from the grayscale images. The test-2 was conducted on the geometry features processed from the binary images. After test-1 and test-2 are carried out, the histogram of the image is observed to examine the intensity distribution.

1) Test-1 Based on Intensity Features and Statistical Features:

In Test-1, the RGB images are first cropped and converted into grayscale. An intensity histogram is generated from the grayscale image, and these intensity details are used to calculate the mean, standard deviation, and skewness of the image. The mean was computed using (1).

$$M = \sum_{j=1}^{N} \frac{1}{N} P_j \tag{1}$$

where M represents the means of the intensity value of the image, the j-th image pixel is represented as Pj, and N is the total number of pixels in the image.

Standard deviation is the square root of the variance of the color distribution (2).

$$\sigma = \sqrt{\frac{1}{N} \sum_{j=1}^{N} \left(P_j - M \right)^2}$$
(2)

where σ is denoted standard deviation of color intensity. In addition, we considered skewness since it can demonstrate the deviation of the degree measurement of the asymmetry distribution of the image. The skewness (S) is calculated using (3).

$$S = \sqrt[3]{\frac{1}{N} \sum_{j=1}^{N} (P_j - M)^3}$$
(3)

Apart from features, we also computed contrast, entropy, and smoothness as statistical features. Those features are commonly used to measure gray-level variation, estimate image irregularity, and measure relative smoothness. Contrast (F) is a measure of intensity or gray-level variations between the reference and neighboring pixels, and it can be measured using (4).

$$F = \sum_{j=1}^{N} (j)^2 P_j \tag{4}$$

Entropy is vital in estimating image irregularity using (5).

$$Entropy = -\sum_{j=1}^{N} P_j \log P_j$$
(5)

Comparative smoothness (Q) is a measurement of gray-level disparity to create relative smoothness (6).

$$Q = 1 - \frac{1}{1 + \sigma^2}$$
(6)

All these features were calculated from the image samples taken under four LEDs and further analyzed using the ANOVA test to compare and investigate the differences between the groups (blue-green, blue-red, blue-white, greenred, green-white, and red-white). Then, we processed it using Tukey's test, which compared all pairs of significantly different data. The Block Diagram Process Test-1 is illustrated in Fig 8.



Fig. 8 Block Diagram Process Test-1

2) Test-2 Based on Geometry Features

The grayscale image is converted into a binary image (using OTSU) to extract geometry features. Then, the image is compared using the median filtering process (the aim is to get binarization results with reduced noise) and the histogram equalization process (to improve image quality). Then, the image's area and the segmented object's centroid are calculated from the binarized image using the original image, processed using a median filter, and processed using histogram equalization.

This process is conducted on images taken under four color variations. Then, the ANOVA and Tukey's tests are executed for analysis, as illustrated in Fig. 9.



Fig. 9 Block Diagram Process Test-2

3) Histogram of the image:

An image histogram (intensity histogram) is a graph of an image's brightness level distribution. For example, in an 8-bit grayscale image, the range of brightness from the x-axis is between 0 (black) and 255 (white), and the y-axis shows the frequency of the pixels [32]. Fig. 10 (a) shows an example of an EBN image, and Fig. 10 (b) shows a histogram of the EBN image.



Fig. 10 (a) An Image of EBN, (b) Histogram of EBN Image

Image histograms can also be used to measure the range of brightness levels known as image contrast [32]. The width of the intensity spread shows high contrast, while the narrow intensity spread shows low contrast.

III. RESULTS AND DISCUSSION

In this section, we demonstrated the results of executed experiments using Test-1 and Test-2 and discussed how illumination can positively impact the analysis or vice versa. Test-1 and Test-2 experiments were conducted using ANOVA and Tukey's test. The final process was analyzing these experiments with the histogram of images.

A. Test-1 Based on Intensity Features and Statistical Features

Test-1 consists of the test based on the intensity features and statistical features. These features are extracted based on the grayscale images. Intensity Features consist of the image's mean, standard deviation, and skewness values. The results of the ANOVA Test & Tukey's Test for skewness are depicted in Table I.

	ANOVA T	EST AND '	TA Tukey's	BLE I TEST RES	SULTS FO	R SKEWN	ESS
Class		В	ig	Med	ium	s	mall
ANOVA (p	ANOVA (pvalue) 2.48E-73 1.73E-55 5.73E-43						
	N	Iultiple Comp	arison of Mer	ans - Tukey H	SD, FWER≓	0.05	
group1	group2	p-value	reject	p-value	reject	p-value	reject
led_blue	led_green	0	TRUE	0	TRUE	0.0508	FALSE
led_blue	led_red	0	TRUE	0	TRUE	0	TRUE
led blue	led white	0.0024	TRUE	0.0016	TRUE	0.0051	TRUE
led_green	led_red	0	TRUE	0	TRUE	0	TRUE
led_green	led_white	0.1898	FALSE	0.8008	FALSE	0.8709	FALSE

From Table I, the ANOVA skewness test shows that the pvalue is smaller than the significance level (0.05) for all classes (big class p-value 2.48 10^{-73} , medium class p-value $1.74 \ 10^{-55}$, small class p-value 5.73 10^{43}). These results indicate a significant difference between Group 1 and Group 2, prompting the continuation to the next stage of Tukey's test. According to Tukey's test, the conclusion drawn from Table I is that, based on the ANOVA skewness test, there is a significant difference in the skewness feature extraction, except the image pairs led_green-led_white (across big, medium, and small classes) and led_blue-led_green (within the small class).

TABLE II THE ANOVA AND TUKEY'S TEST RESULTS FOR THE MEAN VALUE

Class		E	lig	Medium		5 5 0 0 0 0 0 0 0 0 0 0 0 0 0	lium Small	
ANOVA (pv	alue)	1.05	1.05E-253 1.18E		E-224 2.50E-153		E-153	
	Mult	tiple Comparis	son of Means	- Tukey HSD	, FWER=0.05	5		
group1	group2	p-value	reject	p-value	reject	p-value	reject	
led_blue	led_green	0	TRUE	0	TRUE	0	TRUE	
led_blue	led_red	0	TRUE	0	TRUE	0	TRUE	
led blue	led white	0	TRUE	0	TRUE	0	TRUE	
led_green	led_red	0	TRUE	0	TRUE	0	TRUE	
led_green	led_white	0	TRUE	0	TRUE	0	TRUE	
led red	led white	0	TRUE	0	TRUE	0	TRUE	

Table II shows a significant difference in the mean EBN from the mean value feature extraction between all classes, with a p-value smaller than the significance value. The ANOVA p-value for the big class is $1.05 \ 10^{-253}$, the medium class is $1.18 \ 10^{-224}$, and the small class is $2.50 \ 10^{-153}$. Then, Tukey's test pointed out that all the mean value feature extraction differs between the colors.

In Table III, it is also shown that there is a significant difference in the mean EBN from standard deviation feature extraction between all classes. The ANOVA p-value for the big class is $8.40 \ 10^{-195}$, the medium class is $2.54 \ 10^{-160}$, and the small class is $8.87 \ 10^{-114}$. Then, the process continues to Tukey's Test and get the p-value 0 for all groups and all

classes. This means that accepting the H_1 indicates a significant difference in the standard deviation feature extraction within the group.

			TABLE	III				
	ANOVA T	EST AND 7	UKEY'S	TEST RES	ULTS FO	R STD		
Class		В	ig	Mee	lium	Sn	nall	
ANOVA (pvalue) 8.40E-195 2.54E-160 8.87E-114								
	Multi	ple Compariso	n of Means -	Tukey HSD, I	FWER=0.05			
group1	group2	p-value	reject	p-value	reject	p-value	reject	
led blue	led green	0	TRUE	0	TRUE	0	TRUE	
led blue	led red	0	TRUE	0	TRUE	0	TRUE	
led blue	led white	0	TRUE	0	TRUE	0	TRUE	
led green	led red	0	TRUE	0	TRUE	0	TRUE	
led_green	led_white	0	TRUE	0	TRUE	0	TRUE	
led red	led white	0	TRUE	0	TRUE	0	TRUE	

Tables IV, V, and VI show the analysis based on statistical features (contrast, entropy, and smoothness values).

RESU	ULTS OF TH	e Anova	TABL TEST AN	E IV d Tukey	'S TEST F	OR CONTH	RAST		
Class		F	Big	Me	dium	Sr	nall		
ANOVA (pvalue) 5.95E-70 1.22E-68 2.27E-34							/E-34		
Multiple Comparison of Means - Tukey HSD, FWER=0.05									
group1	group2	p-value	reject	p-value	reject	p-value	reject		
led_blue	led_green	0.2515	FALSE	0.262	FALSE	0.9763	FALSE		
led_blue	led_red	0	TRUE	0	TRUE	0	TRUE		
led_blue	led_white	1	FALSE	0.9882	FALSE	0.9953	FALSE		
led_green	led_red	0	TRUE	0	TRUE	0	TRUE		
led_green	led_white	0.2647	FALSE	0.1386	FALSE	0.9154	FALSE		
led red	led white	0	TRUE	0	TRUE	0	TRUE		

In Table IV, the contrast values show significant differences between the images of led_blue-led_red, led_green-led_red, and led_red-led_white. This shows the contrast value on led_red differs from those of other colors (blue, green, white). Table V and Table VI show the results of the ANOVA and Tukey's tests for entropy feature extraction and smoothness feature extraction.

 TABLE V

 Results of Anova test and Tukey's test for entropy

	Class		Big		Medium		Small	
ANOVA (pvalue)		3.021	E-192	8.55	E-186	8.89E-134		
	Mul	tiple Comparis	on of Means	- Tukey HSD	, FWER=0.05			
group1	group2	p-value	reject	p-value	reject	p-value	rejec	
led blue	led green	0.0001	TRUE	0.0004	TRUE	0.0037	TRUE	
led_blue	led_red	0	TRUE	0	TRUE	0	TRUE	
led blue	led white	0	TRUE	0	TRUE	0	TRUE	
led_green	led_red	0	TRUE	0	TRUE	0	TRUE	
led_green	led_white	0	TRUE	0	TRUE	0	TRUE	
led red	led white	0	TRUE	0	TRUE	0	TRUE	
RESUL	TS OF THE A	ANOVA TE	TABLE ST AND	2 VI Fukey's	TEST FOI	R SMOOTH	INESS	
RESUL	TS OF THE A	ANOVA TE	I ABLE	E VI TUKEY'S	TEST FOF	R SMOOTH	INESS	
RESUL Class ANOVA (pya	TS OF THE A	ANOVA TE	IABLE STAND	2 VI TUKEY'S <u>Mec</u> 1.291	TEST FOF lium E-153	R SMOOTH	INESS all	
RESUL Class ANOVA (pva	TS OF THE 2	ANOVA TE E 5.95	TABLE STAND	2 VI TUKEY'S <u>Mec</u> 1.291	TEST FOF lium E-153	R SMOOTH Sm 1.22F	INESS aall E-103	
RESUL Class ANOVA (pva	TS OF THE 2	ANOVA TE E 5.951 tiple Comparise	IABLE STAND Big E-174	2 VI TUKEY'S Mee 1.291 Tukey HSD,	TEST FOF lium E-153 FWER=0.05	R SMOOTH Sm 1.22F	INESS all E-103	
RESUL Class ANOVA (pva group1	TS OF THE 4 lue) group2	ANOVA TE E 5.951 tiple Comparise p-value	TABLE STAND Big E-174 on of Means reject	2 VI TUKEY'S Mee 1.291 - Tukey HSD, p-value	TEST FOF lium E-153 FWER=0.05 reject	R SMOOTH Sm 1.22F p-value	INESS all E-103 reject	
RESUL Class ANOVA (pva group1 led_blue	TS OF THE A	ANOVA TE 5.951 tiple Compariss p-value 0	I ABLE SST AND ig E-174 on of Means reject TRUE	E VI TUKEY'S Mee 1.291 Tukey HSD, p-value 0	TEST FOF lium E-153 FWER=0.05 reject TRUE	R SMOOTH Sm 1.22F p-value 0.0002	INESS all E-103 reject TRUE	
RESUL Class ANOVA (pva group1 led_blue led_blue	TS OF THE A	ANOVA TE E 5.95 tiple Comparise p-value 0 0	I ABLE ST AND big E-174 on of Means- reject TRUE TRUE	S VI TUKEY'S Mee 1.291 - Tukey HSD, p-value 0 0	TEST FOF lium E-153 FWER=0.05 reject TRUE TRUE	R SMOOTH <u>Sm</u> 1.22F <u>p-value</u> 0.0002 0	INESS all E-103 reject TRUE TRUE	
RESUL Class ANOVA (pva group1 led blue led blue led blue	TS OF THE A	ANOVA TE E 5.95 tiple Comparise p-value 0 0 0	IABLE STAND iig E-174 on of Means reject TRUE TRUE TRUE TRUE	S V1 TUKEY'S Mec 1.291 - Tukey HSD, p-value 0 0 0	TEST FOF lium E-153 FWER=0.05 reject TRUE TRUE TRUE TRUE	R SMOOTH <u>Sm</u> 1.22F <u>p-value</u> 0.0002 0 0	INESS aall E-103 reject TRUE TRUE TRUE	
RESUL Class ANOVA (pva group1 led blue led blue led green	TS OF THE 4 slue) multi- group2 led green led red led white led red	ANOVA TE 5.95 tiple Comparis p-value 0 0 0 0	IABLE STAND lig E-174 con of Means reject TRUE TRUE TRUE TRUE TRUE TRUE	E V1 TUKEY'S Mee 1.291 - Tukey HSD, p-value 0 0 0 0 0 0	TEST FOF lium E-153 FWER=0.05 reject TRUE TRUE TRUE TRUE TRUE TRUE	R SMOOTH Sm 1.22F p-value 0.0002 0 0 0 0	INESS iall 2-103 reject TRUE TRUE TRUE TRUE	

In Table V and Table VI, the results of the ANOVA and Tukey's tests show a significant difference in the group's entropy feature extraction and smoothness feature extraction. Table VII recapitulates results after Test-1 for testing intensity features and statistical features.

Table VII demonstrates that significant differences can be observed between each class (Big (B), Medium (M), Small (S)) when using intensity features (skewness, mean, standard deviation) and statistical features (contrast, entropy, smoothness). These differences are particularly evident in the groups led_blue-led_red, led_green-led_red, and led_redled_white. This indicates that the features extracted from the led_red image differ from those of the led_green, led_blue, and led_white images. Further analysis of the histogram produced by the led red image will be conducted next.

	RECAIL	JLAHON	OF IESI-I	RESULT.	5		
			Te	st-1			
Group	Ir	tensity Feature	cs	Statistical Features			
	Skewness	Mean	Std dev	Contrast	Entropy	Smoothness	
led_blue-led_green	B-M	B-M-S	B-M-S	-	B-M-S	B-M-S	
led_blue - led_red	B-M-S	B-M-S	B-M-S	B-M-S	B-M-S	B-M-S	
led_blue - led_white	B-M-S	B-M-S	B-M-S	-	B-M-S	B-M-S	
led green - led red	B-M-S	B-M-S	B-M-S	B-M-S	B-M-S	B-M-S	
led_green - led_white	-	B-M-S	B-M-S	-	B-M-S	B-M-S	
lad rad lad white	DMS	DMS	DMS	DMS	DMS	DMS	

TABLE VII RECAPITULATION OF TEST-1 RESULTS

B. Test-2 Based on Geometry Features

The test-2 was conducted on Geometry Features obtained from binarized images based on the calculated area and centroid of the segmented object. In Table VIII, the results of the ANOVA test highlighted the significant difference only in the big and medium classes, particularly for the pair of led_blue-led_red. Meanwhile, the other pair of color variations do not demonstrate any significant difference in geometry features.

TABLE VIII Anova test and Tukey's test results for area

Class	Class		Big M-		dium	Small	
ANOVA (pvalue)		5.55	5E-03	1.45	5E-03	4.08	8E-01
	Multiple	Compariso	on of Means	- Tukey H	SD, FWER=	=0.05	
group1	group2	p- value	reject	p- value	reject	p- value	reject
led_blue	led_green	0.4851	FALSE	0.3574	FALSE	0.78	FALSE
led_blue	led_red	0.0024	TRUE	0.0005	TRUE	0.329	FALSE
led_blue	led_white	0.2817	FALSE	0.1574	FALSE	0.7463	FALSE
led_green	led_red	0.1473	FALSE	0.1005	FALSE	0.8781	FALSE
led green	led white	0.9839	FALSE	0.9693	FALSE	0.9999	FALSE
led red	led_white	0.2933	FALSE	0.2541	FALSE	0.902	FALSE

Furthermore, we applied a median filter onto the binarized image, and the area shows a significant difference in led_blueled_red (big class and medium class), including led_greenled red (medium class). The results are tabulated in Table IX.

I ABLE IX	
THE ANOVA AND TUKEY'S TEST RESULTS FOR AREA WITH MEDL	AN FILTER

Class		F	Big Medium		dium	Small	
ANOVA (pvalue)		2.57	/E-03	4.12	2E-04	3.07	7E-01
	Multiple	Compariso	on of Means	- Tukey H	SD, FWER=	-0.05	
group1	group2	p- value	reject	p- value	reject	p- value	reject
led blue	led green	0.5242	FALSE	0.3725	FALSE	0.8166	FALSE
led_blue	led_red	0.0011	TRUE	0.0001	TRUE	0.23	FALSE
led blue	led white	0.4242	FALSE	0.2754	FALSE	0.8297	FALSE
led_green	led_red	0.0809	FALSE	0.0426	TRUE	0.7367	FALSE
led_green	led_white	0.9985	FALSE	0.9977	FALSE	1	FALSE
led red	led white	0.1179	FALSE	0.0689	FALSE	0.7212	FALSE

The median filter applied during the feature extraction process in the area feature extraction only shows the difference between led_red-led_blue and led_red-led_green is only limited to certain classes, namely the big class and the mediam class. So, it can be concluded that the influence of the median filter is not too significant if used as an area feature extraction to distinguish light illumination factors, except for the group led_blue-led_red (big class, medium class), led_green-led_red (medium class). In addition to the previous experiment, we applied histogram equalization before extracting the area and centroid of the EBN sample.

 TABLE X

 THE ANOVA AND TUKEY'S TESTS RESULTS FOR AREA WITH HISTOGRAM

 EQUALIZATION

Class		Big	М	edium	Sn	Small		
ANOVA	A p-value reject		t p-value	reject	p-value	reject		
Area	3.76	E- FAIS	E 9.10E-	EALSE	9.87E-	EALSE		
Equalization	01	TALS	L 01	TALSE	01	TALSE		
	ΤΔΒΙ Ε ΧΙ							
			IT IDED 711					
	AN	JOVA TEST	RESULTS FO	OR CENTRO	ID			
Class	В	ig	Med	ium	Sr	nall		
ANOVA	p-value	reject	p-value	reject	p-value	reject		
Х	9.82E-01	FALSE	1.00E+00	FALSE	9.90E-01	FALSE		
Y	9.91E-01	FALSE	9.93E-01	FALSE	9.83E-01	FALSE		

The results are shown in Tables X and XI, respectively. Nevertheless, both experiments show that histogram equalization does not enhance the significant differences between classes in The ANOVA Test for the area and centroid features extraction, with the p-value greater than the significance level value. So, the process not to continue to Tukey's Test. The results of Test-2 for testing geometry features are summarized in Table XII.

TABLE XII
RECAPITULATION OF TEST-2 RESULTS

	Test-2							
Group	A	Area	Area	Controld	Centroid	Centroid		
	Area	(med filter)	(hist eq)	Centrola	(med filter)	(hist eq)		
led_blue - led_green	-	-	-	-	-	-		
led_blue - led_red	B-M	B-M	-	-	-	-		
led_blue - led_white	-	-	-	-	-	-		
led_green - led_red	-	М	-	-	-	-		
led_green - led_white	-		-	-	-	-		
led_red - led_white	-	-	-	-	-	-		

Table XII indicates that for the feature extraction of the area, a significant difference is observed only in the led_blueled_red groups, and this is limited to the big (B) and medium (M) classes, excluding the small class (S). When considering the data comparison ratio, the small class (95 pcs) has fewer data sets than the big (125 pcs) and medium classes (125 pcs). Additionally, in the area (median filter) feature extraction, a significant difference is observed only in the led_blue-led_red groups (big and medium classes) and the led_green-led_red group (medium class).

No significant differences were observed across all color variations and classes for the original centroid extraction feature, as well as the centroid with median filter and histogram equalization. This suggests that using geometry features (area, centroid) to distinguish between the three EBN classes (big, medium, small) is ineffective. Therefore, a more detailed analysis of the image histograms across all color variations will be conducted to explore potential differences.

C. Histogram of Images

To complete the analysis results of Test-1 and Test-2, we tried to analyze the image histogram. Based on the results of Test-1 that the led_red image is different from the led_green image, the led_blue image and the led_white image, then the image histogram of each color variation is analyzed. Fig. 11 (a) and Fig. 13 (a) show samples of led color image variations (example medium class, small class), respectively, in RGB color and grayscale color. Then the grayscale image's histogram is shown in Fig. 11 (b) and Fig. 13 (b).





Fig. 11 (a) The medium_02 EDB images (Color and Grayscale), (b) Grayscale of medium_02 EDB image Histogram

In Fig. 11 and Fig. 13, the led_red color sample image has a greater amplitude and lower contrast than those of other colors, as demonstrated by the histogram skewed to the left. It means that the intensity of led_red images is different from others.



Fig. 12 (a) The medium_02 EDB images Histogram between led_white & led_green, (b) medium_02 EDB images Histogram between led_green & led_blue

We also analyzed the histogram of led_green-led_white images and led_green-led_blue images in Fig. 12 and Fig. 14. Based on these two figures, the histograms of led_greenled_white and led_green-led_blue are almost the same/coincide. This shows no difference/influence of the image on the intensity.





Fig. 13 (a) The small_01 EDB images (Color and Grayscale), (b) Grayscale of small_01 EDB image Histogram



Fig. 14 (a) The small_01 EDB images Histogram between led_white & led_green, (b) The small_01 EDB images Histogram between led_green & led_blue

Based on the results of Test-2 for area feature extraction significant differences can be seen in groups led_blue-led_red, limited only for big class and medium class. Also, for area feature extraction with the median filter process, significant differences can be seen in groups led_blue-led_red (big class, medium class) and led_green-led_red (medium class). Fig. 15 shows a boxplot of the medium class image; the average area of the led_red image is higher than those of the led white, led green, and led blue images.



Fig. 15 Comparison of Mean Area from Medium Class Images

This indicates that more noises in the binary led_red images were removed, resulting in a higher average area of the led_red than others. It means the red color images can produce binary images with less noise than other colors. Then, the analysis of the results of Test-2, when the histogram equalization process was applied, showed no significant difference between color variation and class variation. The following are examples of original images and images that have been applied histogram equalization. The image and the histogram equalization are illustrated in Fig. 16 (led_white image) and Fig. 17 (led red image), respectively.



Fig. 16 Comparison of Histogram & Binarization medium_02 led_white image before & after Histogram Equalization

In the histogram of the medium_02 image after the equalization histogram process, the led_white image was compared to the histogram of the led_red image, which has a smoother histogram, as illustrated in Fig. 16 and Fig. 17. The results of the image histogram analysis show that the conditions of the binary image generated from the led_red can be better with reduced noise (Fig. 16 and Fig. 17). However, the difference is not very significant. This is also supported by the results of the ANOVA Test, which showed that the area feature extraction and centroid feature extraction results after the histogram equalization process did not differ in color variation.



Fig. 17 Comparison of Histogram & Binarization medium_02 led_red image before & after Histogram Equalization

Based on the Test-1 result, Test-2 result and histogram of image analysis, the image produced from led_white is the same as the image from led_green and led_blue, which produces a high-contrast image. The resulting image histogram has a broader distribution of pixels and peaks at both ends of the spectrum (dark areas and light areas) so that the image produced from a high-contrast image highlights essential details of the image, such as the edges of objects and sharp color differences.

Meanwhile, the image produced by led red produces a low contrast image. The resulting image histogram has a narrower distribution of pixels and many pixels with adjacent intensity values so that the image produced from the low contrast image can reduce noise. Because of its apparent shape, red color illumination is suitable for the ML/ DL process, especially for shape classification, but it is also possible with white color illumination. Also, white illumination is suitable for detecting impurities from EBN because it produces a higher contrast image. For intensity feature extraction and statistical features, it can be recommended that it be used to classify EBN using white/red color illumination. As for geometry feature extraction, it can only classify a limited class, especially in area feature extraction. On the other hand, in this research centroid feature extraction is unsuitable for classifying the big, medium, and small classes. For further research, it can be tested with other feature extracts with various classifications.

IV. CONCLUSION

In this research, we examined the impact of illumination colors on the EBN image samples based on the one-way ANOVA & Tukey's tests. In our work, the effects of white, red, green, and blue LEDs are compared using the one-way ANOVA test, with a chosen significance level of 0.05. The (H_0) in the ANOVA test shows is that there is no significant difference among the means of EBN feature extraction. The test results of Test-1 based on Intensity Features (mean, standard deviation, skewness of the image) show that the images taken under red color significantly differ from those taken under green, blue, and white colors. It can be concluded that the images taken under green, blue, and white colors will produce intensity feature values that are almost the same as seen from its histogram images. Test-1, based on statistical features (entropy and smoothness), shows the differences resulting from the four colors of the image. For Test-1, based on contrast value, the significant difference is between the image taken under red to the other colors.

We also conducted Test-2 based on Geometry Features (area feature extraction), and the average area of images taken under red color is higher than those taken under white, green, and blue color. The results emphasized that the image taken under red color has reduced noise, resulting in a wide average area. This also indicated that the red and white illuminations are suitable for further processes in ML/ DL, such as EBN shape classification. White illumination provides higher contrast than other colors and is favorable for detecting impurities from EBN. For Test-2, based on centroid values for all processes and all LED color variations, there is no significant difference between the groups.

The proposed solution has a promising potential in optimizing the lighting condition of machine vision for EBN quality control, thereby reducing human error during EBN cleaning. Further work can be recommended to apply the Multivariate Analysis of Variance test for the analysis of color histograms by analyzing each histogram for the red (R), green (G), and blue (B) values.

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