Detection and Analysis of Batik Waste Using Image Processing Methods in Pekalongan Regency

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Abstract - Research was conducted on the detection of batik wastewater in the batik industry of Pekalongan, which generates liquid waste containing synthetic dyes, heavy metals, and hazardous compounds that can potentially pollute the environment if not properly treated. This study aims to develop a simple detection method based on digital image analysis to identify the color characteristics of batik wastewater. Data were obtained by sampling liquid waste from several affected rivers, which were then analyzed using a digital camera and image processing software to determine the intensity values of the red, green, and blue (RGB) channels. The results show that variations in waste concentration significantly influence the distribution of RGB values, enabling faster, cheaper, and more practical identification of pollution patterns compared to conventional laboratory methods. These findings are expected to serve as the foundation for developing a digital technology-based batik wastewater quality monitoring system as part of efforts to mitigate environmental pollution in Pekalongan.

Keywords - Batik wastewater, Digital image analysis, RGB intensity, Environmental pollution, Image processing

1. INTRODUCTION

Water quality in the Pekalongan Regency and City is currently declining due to industrial activities, particularly from the textile and batik sectors, which discharge large amounts of liquid waste directly into rivers without adequate treatment [1]. This waste generally contains synthetic dyes, heavy metals, and other hazardous chemical compounds that are difficult to break down naturally. This condition not only threatens aquatic ecosystems but also has a negative impact on public health and the sustainability of water resources. [2].

The liquid waste contains synthetic dyes, heavy metals, and other chemical compounds that are toxic and difficult to break down, thereby polluting the water and damaging aquatic ecosystems [3]. This pollution not only affects the survival of living creatures in the river but also has the potential to endanger the health of communities that use river water for their daily needs. In addition, high levels of pollution can trigger eutrophication and changes in the physical, chemical, and biological quality of the water [4]. The content of hazardous chemicals in industrial waste, such as chromium, lead, and azo compounds from textile dyes, can cause biological disturbances in aquatic organisms, inhibit photosynthesis in aquatic plants, and disrupt the food chain in waterways [5].

In addition, the presence of heavy metals accumulated at the bottom of rivers can have long-term effects on human health, especially for communities that depend on river water for their daily needs. If not addressed seriously, this pollution can cause wider environmental degradation and complicate efforts to conserve water resources [6]. Conventional methods for detecting industrial waste, particularly liquid waste from the textile and batik sectors, are generally carried out by manually collecting water samples at rivers suspected of being polluted [7]. Testing is conducted in laboratories by analyzing physical, chemical, and biological parameters to determine

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the level of pollution. One of the most common approaches is to measure BOD (Biological Oxygen Demand) and COD (Chemical Oxygen Demand) levels, which indicate the amount of oxygen needed to break down organic matter in water. The higher the BOD and COD values, the higher the level of pollution [8].

Conventional methods of detecting industrial waste, such as manually collecting water samples from rivers suspected of being polluted, have several advantages and disadvantages [9]. The advantages lie in their simplicity and relatively low operational costs, as well as the fact that they do not require sophisticated equipment, making them easy to implement in various locations [10]. In addition, this method allows for detailed laboratory analysis of samples, such as chemical and microbiological testing [11].

However, this method also has a number of weaknesses, including limitations in data coverage because it only represents conditions at a specific time and point, so it does not describe pollution dynamics in real time [12]. With a digital approach, water quality parameters such as pH, temperature, conductivity, organic matter content, and color can be monitored continuously and automatically without the need for manual sampling [13]. Data collected in real time can be accessed immediately through a digital platform, enabling a rapid response to potential pollution. [14]. The advantage of digitization lies in its ability to efficiently monitor large areas, reduce human error, and provide historical data that is useful for trend analysis and evidence-based decision making [15]. However, challenges such as initial investment costs, network infrastructure requirements, and technical skills remain considerations in its implementation [16]. A study has been conducted on the effect of liquid waste on river water quality in the city of Pekalongan [17].

The batik industry in Pekalongan is an important economic sector, but it often has a negative impact on the environment, particularly in terms of wastewater management [18]. Waste is one of the substances that can pollute rivers. Most waste is dumped into rivers, causing pollution [19]. The disposal of liquid waste containing high organic parameters can trigger bacterial growth, which can result in a decrease in dissolved oxygen in the water [20]. Research on batik waste using the tools in this study included beakers, Erlenmeyer flasks, magnetic stirrers, laboratory filters, ovens, analytical scales, as well as COD, TSS, pH meter, and AAS (Atomic Absorption Spectrophotometer) analysis instruments to measure Cr metal levels [21]. The research was conducted using a prototype development approach. Image data of infectious and non-infectious medical waste was collected using an ESP32-Cam camera [22].

The system consists of pH, temperature, turbidity, and water level sensors connected to a microcontroller to read and transmit data in real time to the monitoring dashboard [23]. Palm oil mill effluent (POME) has the potential to pollute the environment because it contains dissolved solids, high acidity levels, and relatively high temperatures [24]. This study uses a digital camera to capture images of tilapia, a computer for data processing, and Convolutional Neural Networks (CNN)-based software implemented using a machine learning library [25].

Thus, the novelty of this study lies in the development of a laboratory monitoring system using digital imaging methods in the batik industry in Pekalongan. Unlike previous studies, which mostly only used simple physical sensors (such as pH, TDS, or turbidity) and laboratory chemical analysis that required time and money, this study presents a digital image-based approach to analyze the characteristics of batik waste. The use of digital imaging allows the monitoring process to be carried out more quickly, objectively, and non-destructively without having to go through complex chemical procedures. Furthermore, the application of this method in the context of the batik industry in Pekalongan is relevant because this region is known as a batik production center that produces a high volume of liquid waste with distinctive colors and compositions. Thus, this study offers a new contribution in the form of a more efficient and adaptive monitoring system that can be directly applied to support sustainable batik waste management.

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2. RESEARCH METHOD

The methods used in this research include surveys, field analysis, counseling, and mentoring. These approaches are expected to enhance the understanding of camera utilization in batik waste detection. The activities will be carried out at the Electronics and Instrumentation Laboratory of the ITSNU Pekalongan campus from June 2025 to July 2025.

The tools used in this study included a laptop as the primary device for data processing and result analysis, a mirrorless camera for visual documentation and image capture of the samples, and measuring cups to assist in collecting and measuring the volume of waste samples. The research materials consisted of batik liquid waste in red, green, and blue colors, as well as several mixtures of these colors, namely red–blue, red–green, and green–blue batik waste combinations.

The procedure for this study is described in Figure 1.

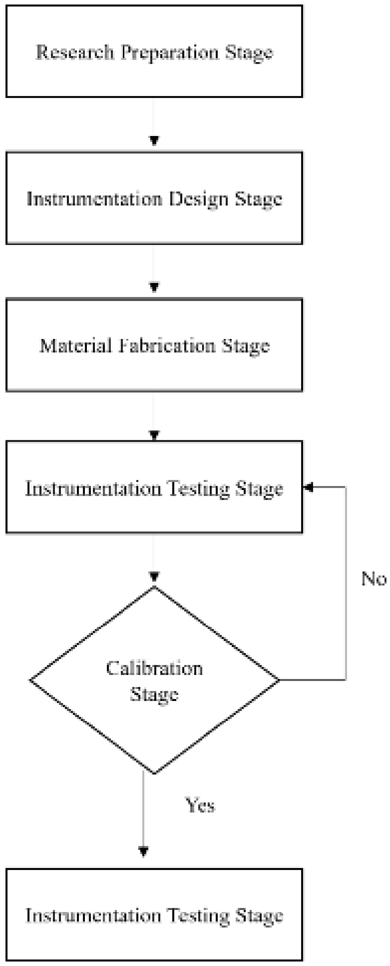

Figure 1. Research flowchart

Based on Figure 1, which illustrates the research procedure for this study, the research was divided into six stages. The first stage was the preparation stage, followed by the tool design stage. The third stage involved material production, the fourth stage was tool testing, the fifth stage was calibration, and the sixth stage was data analysis.

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The setup of this research tool is described in Figure 2.

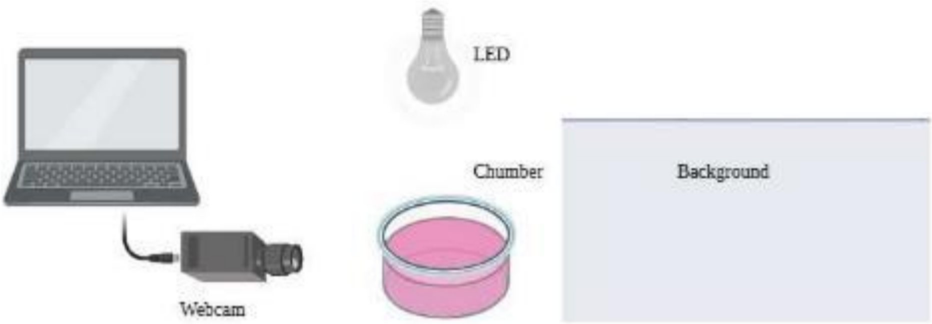

Figure 2. Set up research equipment

Figure 2 illustrates the experimental setup of this research tool, which uses a camera as a detector to measure waste concentration levels with absorption intensities of 5%, 10%, 15%, 20%, and 25%. This image processing method represents a new innovation by integrating a program into the camera system. The analysis conducted involves comparing basic color image analysis, 2D color images, and 3D color images, followed by determining the color intensity values of the images in specific measurement units.

3. RESULTS AND DISCUSSION

3.1 Sample Preparation

The batik waste samples in this study were prepared in a controlled laboratory environment to simulate the characteristics of liquid waste produced from the batik dyeing process. The sample preparation process was carried out by weighing 50 grams of synthetic textile dye using an analytical balance to ensure mass accuracy. The dye was then added to a measuring cup containing 50 ml of clean water. The mixture was stirred thoroughly using a glass stirrer or magnetic stirrer until a homogeneous solution was obtained. This composition was selected so that the color and turbidity levels of the solution resembled the actual conditions of batik wastewater, allowing it to be used as a consistent test material for image-based measurement and analysis. The experiments were conducted with sample mixture variations of 0%, 20%, 40%, 60%, and 80%.

3.2 GUI Development

The Graphical User Interface (GUI) of the Python program was developed using a pixel segmentation method applied to the measured objects. A webcam with a resolution of 1920×1080 pixels and a Complementary Metal–Oxide–Semiconductor (CMOS) sensor was used in this study. The lighting system employed a Light Emitting Diode (LED) light source with an intensity of 90,000 lumens. The GUI display used in this study is shown in Figure 3.

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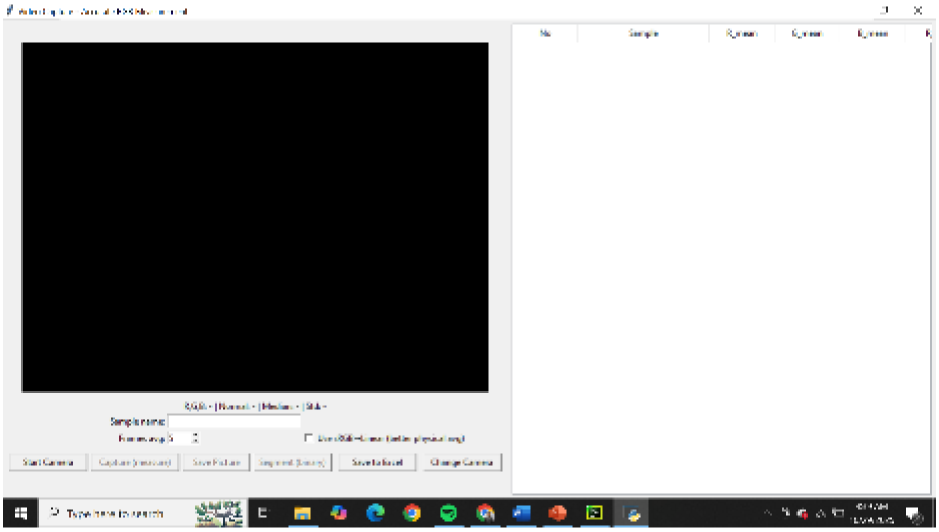

Figure 3. Development GUI

The GUI display of the research shows the measurement results of the color component values (R, G, B) of batik wastewater samples in Pekalongan Regency, showing significant variations in red and blue color intensity compared to clean water. The R value indicates the intensity of red waste, the G value indicates the intensity of green waste, and the G value indicates the intensity of green. Through image segmentation, the liquid area can be separated from the background, making color value collection more accurate. This analysis proves that the image processing method is capable of providing initial identification of the level of batik waste pollution quickly and efficiently, and has the potential to be integrated into a computer-based water quality monitoring system in the batik industry sector.

3.3 Imaging System Calibration Analysis

This stage of the research requires calibration data for characterizing the imaging system on a blank screen using a webcam, as shown in Figure 4 and Figure 5. which shows the image of a white screen.

Figure 4. White Screen

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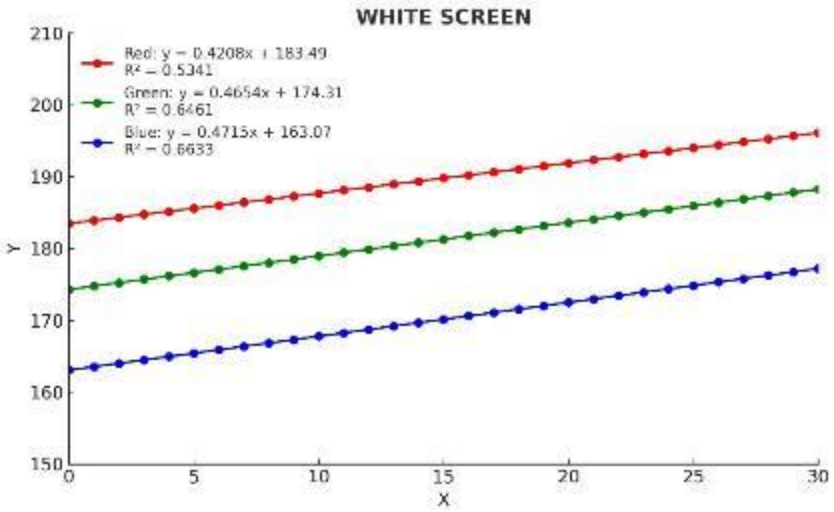

Figure 5. Linearity of White Screen Calibration

Based on the results of calibrating the imaging system on a white screen (Figures 4 and 5), the average intensity values of the red (R) component were in the range of 183–196, green (G) in the range of 172–188, and blue (B) in the range of 160–176 (Table 4.1). The difference in intensity values between channels indicates variations in the camera sensor's response to base colors. Under ideal white screen conditions, the intensity of the three channels should be relatively balanced. The deviation shown in the data, particularly the B value which tends to be lower, indicates greater light absorption in the blue spectrum. This phenomenon can be attributed to the presence of particles or turbidity in the test medium that scatter light more effectively at short wavelengths. Thus, the proportional decrease in B values compared to R and G can be an initial parameter for estimating the level of turbidity. In addition, the relatively stable intensity distribution pattern in most samples indicates homogeneous calibration background conditions, so that any significant deviation can be interpreted as the presence of objects or waste particles in the medium, which modify the spectral distribution of light received by the sensor.

3.4 Motion Analysis of Empty Glasses

Blank glass analysis in this study was conducted to measure the absorbance intensity recorded by a webcam as a reference in the detection and analysis of batik waste using image processing methods, as shown in Figure 6 and Figure 7.

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Figure 6. Blank Glasses Image

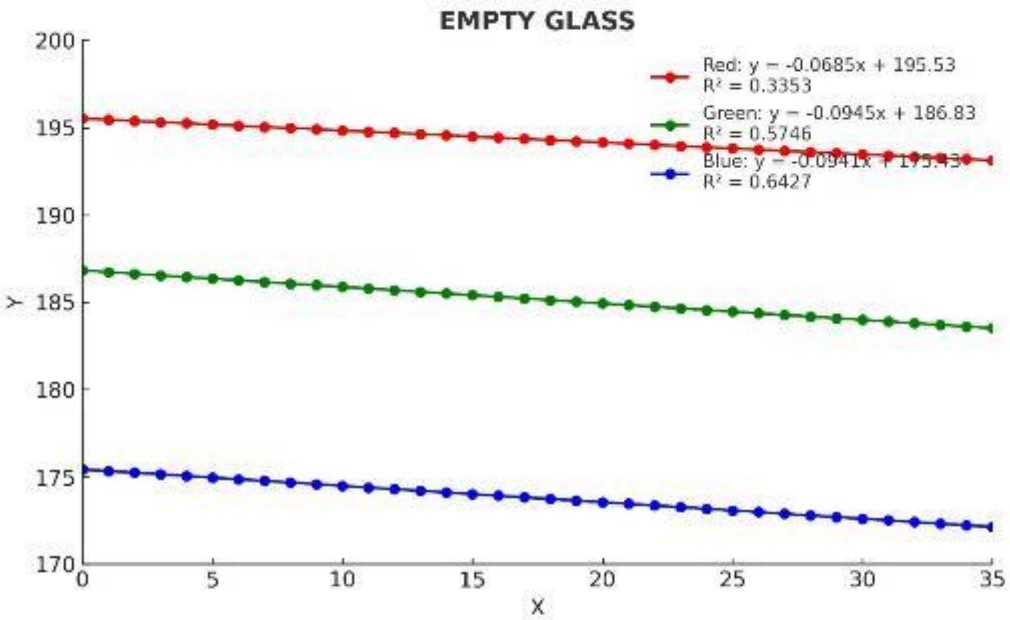

Figure 7. Linearity of Empty Glass

Table 1 Absorbance Table of Blank Glasses

No	Intensity		
	R	G	B

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1	196	186	175
2	196	188	176
3	196	188	176
4	196	187	176
5	196	187	176
6	196	186	175
7	195	186	174
8	195	186	174
9	195	186	175
10	195	186	174
11	194	185	174
12	194	186	174
13	194	185	174
14	194	185	174
15	194	185	174
16	193	185	173
17	193	184	173
18	193	184	173
19	193	185	173
20	193	184	173
21	193	184	173
22	194	184	173
23	195	185	174
24	195	185	173

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25	195	185	174

Based on the results of intensity data collection on empty glass samples (Figures 6 and 7), the average values obtained were approximately 193–196 for the red channel (R), approximately 184–188 for the green channel (G), and approximately 173–176 for the blue channel (B) (Table 4.2). The relatively high and stable intensity values indicate that empty glass media have high light transmittance intensity and low absorbance levels, in accordance with the characteristics of media without interfering particles. The consistent differences between channels, particularly the lower B value compared to R and G, are due to the sensitivity of the webcam sensor and the spectral properties of the glass material to blue wavelengths.

3.5 Analysis of Mixed Red and Blue Batik Waste

This study analyzed batik waste models with red and blue color variations. Analysis of the red, green, and blue histogram intensity of the combination of red and blue batik waste models is shown in Figure 8.

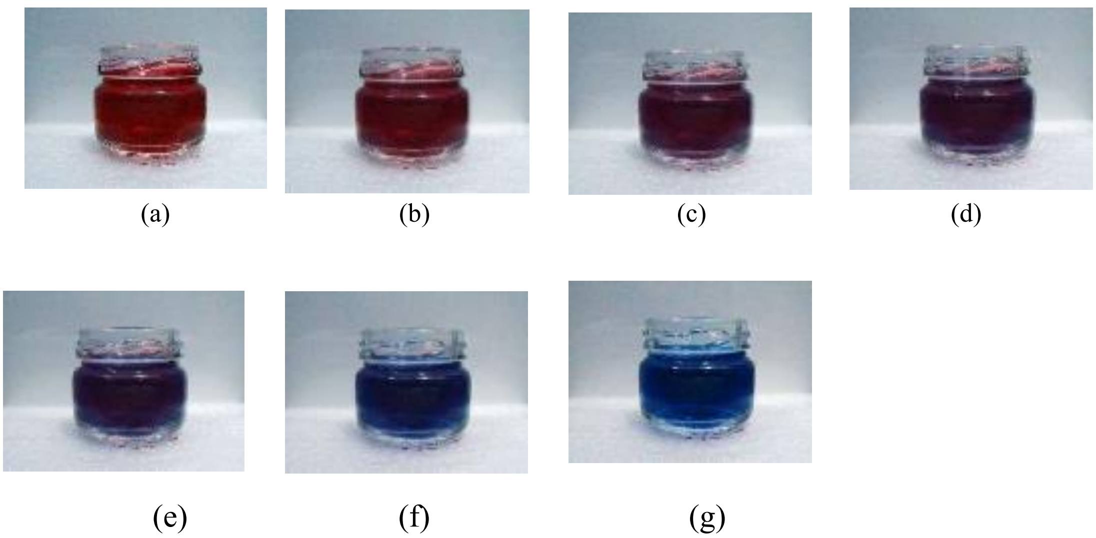

Figure 8. Images of red and blue batik waste with varying concentrations (a)100% red waste image (b)80% red image and 20% blue image (c)60% red image and 40% blue image (d)50% red image and 50% blue image (e)40% red image and 60% blue image (f)20% red image and 80% blue image (g)100% blue waste image

Figure 8. Displaying images of batik waste resulting from a combination of red and blue colors with certain variations in concentration. The image in part (a) shows a complete dominance of red with a composition of 100%, which visually displays the highest intensity of red. In sections (b) to (f), there is a gradual transition from red to blue as the proportion of blue increases from 20% to 80%. This change produces color gradations that increasingly suppress the contribution of the red channel and strengthen the dominance of the blue channel. Finally, in section (g), an image with a 100% blue composition is obtained, showing maximum blue intensity without the influence of the

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red channel. This transition pattern illustrates a linear and systematic relationship between color concentration variations and spectral intensity distribution in batik waste images as shown in Table 2. Based on the research results, the color composition data from Figure 8 is shown in Table 2.

Table 2 Relationship between color concentration variations and spectral intensity distribution in batik waste images

No	Red Waste Concentration (%)	Blue Waste Concentration (%)	Color Composition		
			Red	Green	Blue
1	100	0	80,4	14,6	12,8
2	80	20	65,7	17,7	24
3	60	40	51.09	20.95	35.32
4	50	50	43.77	22.53	50.93
5	40	60	36.46	24.11	46.63
6	20	80	21.83	27.28	57.94
7	0	100	7.2	30.45	69.25

Table 2 shows that changes in red and blue waste concentrations directly affect the resulting RGB color composition. At a concentration of 100% red and 0% blue, the color is dominated by red with a value of 80.4, while green and blue are still low. A gradual decrease in red concentration followed by an increase in blue concentration causes the red value to continue to decline, from 65.7 (80% red) to only 7.2 (0% red), while the blue value increases significantly from 12.8 to 69.3. On the other hand, the green value increases slowly from 14.6 to 30.5 as the proportion of blue increases. This pattern shows an inverse relationship between red and blue intensity, with green tending to increase gradually, so that the resulting mixed color shifts from red dominance to blue dominance. The intensity of the mixed concentration of waste images is shown in Figure 9.

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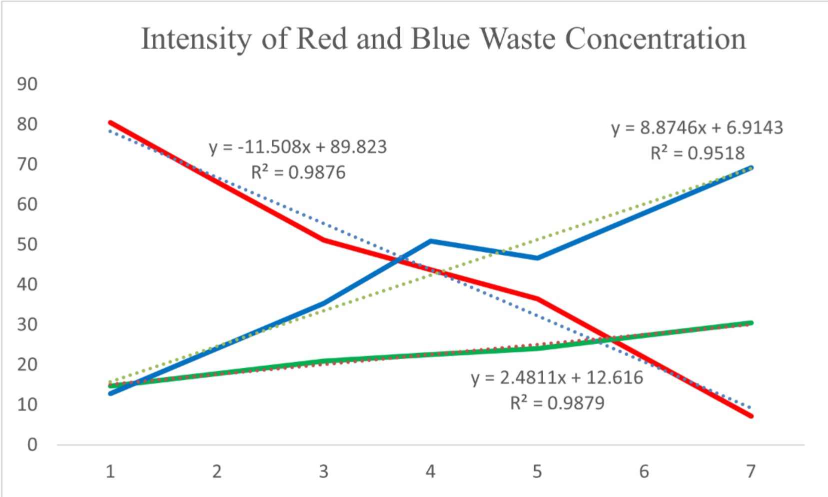

Figure 9. Linearity of Concentration and Intensity

The concentration intensity graph shows changes in RGB color composition as the ratio of red and blue waste varies. The red line shows a downward trend with the regression equation $y = -11.508x + 89.823$ ($R^2 = 0.9876$), which means that as the red concentration decreases, the red color intensity decreases almost linearly. Conversely, the blue line increases sharply with the equation $y = 8.8746x + 6.9143$ ($R^2 = 0.9518$), indicating a strong positive relationship between the increase in blue concentration and its color intensity. Meanwhile, the green line shows a gradual increase with the equation $y = 2.4811x + 12.616$ ($R^2 = 0.9879$), so even though its effect is smaller, the green value still increases as the proportion of blue increases. Overall, this graph shows a consistent linear pattern: red decreases, blue increases significantly, and green rises slowly, so that the color composition shifts from red dominance to blue dominance.

3.6. Analysis of Mixed Red and Green Batik Waste

This study analyzed batik waste models with variations in red and blue colors. The analysis of the red, green, and blue histogram intensities of the batik waste combinations showed that the red intensity tended to decrease linearly as the red waste concentration decreased and the proportion of blue waste increased. Conversely, the green intensity exhibited a relatively stable and gradual upward trend, although its contribution was not as significant as the changes observed in the red and blue channels. These results indicate that the red channel is highly sensitive to changes in color composition, while the green channel provides a gradual complementary contribution to the transition of color dominance from red to blue, as shown in Figure 10.

(a) (b) (c) (d)

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(e) (f) (g)

Figure 10. Images of red and green batik waste with varying concentrations

(a) 100% red waste image (b) 80% red image and 20% green image (c) 60% red image and 40% green image (d) 50% red image and 50% green image (e) 40% red image and 60% green image (f) 20% red image and 80% green image (g) 100% green waste image

Table 3 presents the results of the color intensity analysis (Red, Green, Blue) of the batik waste model with varying concentrations of red and blue waste. In the initial condition (100% red and 0% blue), the red intensity dominates at 80.4, while the green and blue intensities are relatively low at 14.6 and 12.8, respectively. As the red concentration decreases and the blue concentration increases, the red intensity value decreases significantly—from 65.72 at 80% red to only 12.5 at 0% red and 100% blue. Conversely, the blue intensity increases sharply from 12.8 to 80.7, indicating blue dominance at higher concentrations. The green channel shows a gradual and more stable upward trend, rising from 14.6 under red dominance to 33.2 under blue dominance. Overall, these data reveal a clear transition pattern: the red channel decreases linearly, the blue channel increases exponentially, and the green channel serves as a gradual balancing factor between the two primary colors, as illustrated in Figure 11. Based on the research results from Figure 10, the data is shown in Table 3

Table 3 Comparison of concentration composition

No	Red Waste Concentration (%)	Green Waste Concentration (%)	Color Composition		
			Red	Green	Blue
1	100	0	80,4	14,6	12,8
2	80	20	65.72	17.78	24
3	60	40	51	20.9	35.3
4	50	50	43.7	22.5	40.9
5	40	60	36.4	24.1	46.6
6	20	80	21.8	27.7	57.9
7	0	100	12.5	33.2	80.7

Table 3 presents the results of the color intensity analysis (Red, Green, Blue) of the batik waste model with varying concentrations of red and blue waste. Under the initial condition (100% red and 0% blue), the red intensity dominates at 80.4, while the green

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and blue intensities are relatively low at 14.6 and 12.8, respectively. As the red concentration decreases and the blue concentration increases, the red intensity value declines significantly—from 65.72 at 80% red to only 12.5 at 0% red and 100% blue. Conversely, the blue intensity rises sharply from 12.8 to 80.7, indicating blue dominance at higher concentrations. The green channel exhibits a gradual and more stable upward trend, increasing from 14.6 under red dominance to 33.2 under blue dominance. Overall, these data show a clear transition pattern: the red channel decreases linearly, the blue channel increases exponentially, and the green channel functions as a gradual balancing factor between the two main colors, as illustrated in Figure 11.

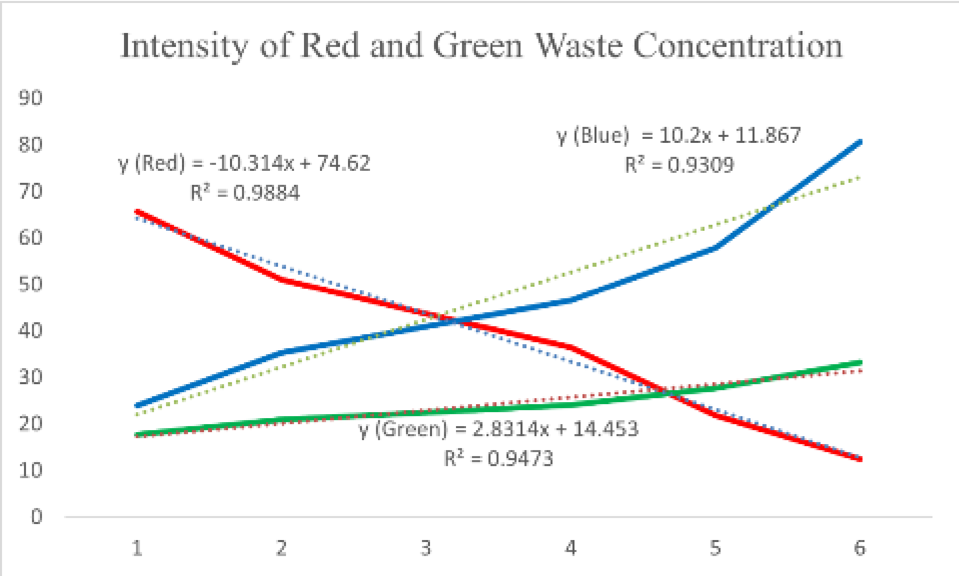

Figure 11. Linearity of Concentration and Intensity

The results of color intensity measurements for variations in red and blue waste concentrations show a clear linear relationship between color composition and the percentage of mixing of the two types of waste. The intensity of the red component decreases significantly as the concentration of blue waste increases, following a linear pattern with the equation $y = -10.314x + 74.62$ and a coefficient of determination (R^2 =0.9884), indicating that this variable is strongly affected by compositional changes. Conversely, the intensity of the blue component increases sharply with increasing blue waste concentration, as described by the equation $y = 10.2x + 11.867$ ($R^2 = 0.9309$), signifying a shift in color dominance from red to blue at higher concentrations. Meanwhile, the green component shows only a relatively small increase, represented by the equation $y = 2.8314x + 14.453$ ($R^2 = 0.9473$), indicating its role as a balancing factor in the color transition. Overall, these results demonstrate that changes in the proportion of red and blue waste cause a shift in the dominant color spectrum from red to blue, with the green component maintaining a relatively stable contribution.

3.7 Analysis of Blue and Green Batik Waste Mixtures.

In this study, an analysis of batik waste models with variations in green and blue colors was conducted. The results of the histogram intensity analysis show that the green

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intensity tends to decrease linearly as the concentration of green waste decreases and the proportion of blue waste increases. Conversely, the blue intensity exhibits a relatively consistent and gradual upward trend, showing more dominant changes compared to the green and red channels. These findings indicate that the green channel is highly sensitive to variations in color composition, while the blue channel contributes significantly to the transition of color dominance from green to blue, as shown in Figure 12.

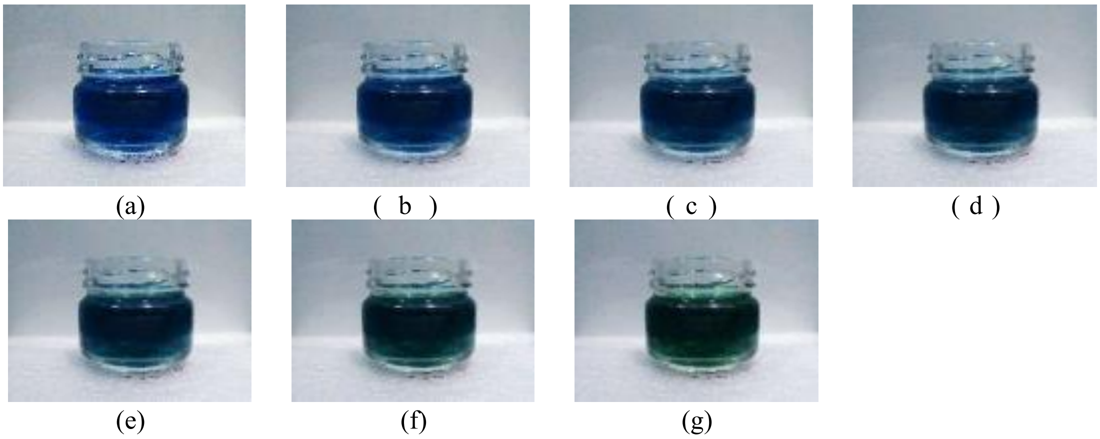

Figure 12. Images of red and green batik waste with varying concentrations

(a) 100% blue waste image (b) 80% blue image and 20% green image (c) 60% blue image and 40% green image (d) 50% blue image and 50% green image. (e) 40% blue image and 60% green image (f) 20% blue image and 80% green image (g) 100% green waste image.

Figure 12 shows images of batik waste with combinations of blue and green colors at various concentration proportions. In image (a), blue appears completely dominant with maximum intensity, while image (g) shows full dominance of green. The variations from images (b) to (f) illustrate a gradual transition, where an increase in the proportion of the green channel is directly proportional to a decrease in the intensity of the blue channel. Image (d), which represents a balanced mixture of 50% blue and 50% green, produces a relatively homogeneous transitional color, serving as the midpoint between the two dominant colors. Overall, this shift in color distribution from blue to green indicates a significant spectral change that can serve as a reference for analyzing visual differences caused by pigment variations in batik waste. Based on Figure 4.7, the corresponding research data are presented in Table 4..

Table 4. Comparison of concentration composition

No	Blue Waste Concentration (%)	Green Waste Concentration (%)	Color Composition		
			Red	Green	Blue
1	100	0	12.5	33.2	80.7
2	80	20	11.2	24.9	70.2

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3	60	40	10.1	27.6	51.9
4	50	50	6.8	26.9	47.6
5	40	60	6.7	26.3	43.3
6	20	80	6.6	25.9	35.7
7	0	100	6.4	23.5	26

Based on Table 4, it can be observed that the comparison between blue and green waste concentrations has a clear effect on the resulting color composition. When the blue waste concentration is 100% and the green waste concentration is 0%, the blue component value reaches 80.7, while the red and green components are relatively lower at 12.5 and 33.2, respectively. As the percentage of green waste increases, the blue intensity decreases consistently, reaching a value of 26 at a green concentration of 100%. Conversely, the green component remains relatively stable within the range of 23.5–33.2, although it tends to decrease as the blue waste concentration decreases. The red component shows a sharper decline, dropping from 12.5 to 6.4. These results indicate that the dominance of the blue color is directly proportional to the high concentration of blue waste, whereas an increase in green waste concentration enhances the contribution of the green color, albeit with relatively small fluctuations. Thus, variations in the proportion of blue and green waste affect the balance of the overall color composition, particularly in the blue channel, which is the most sensitive to changes in waste composition, as shown in Figure 13.

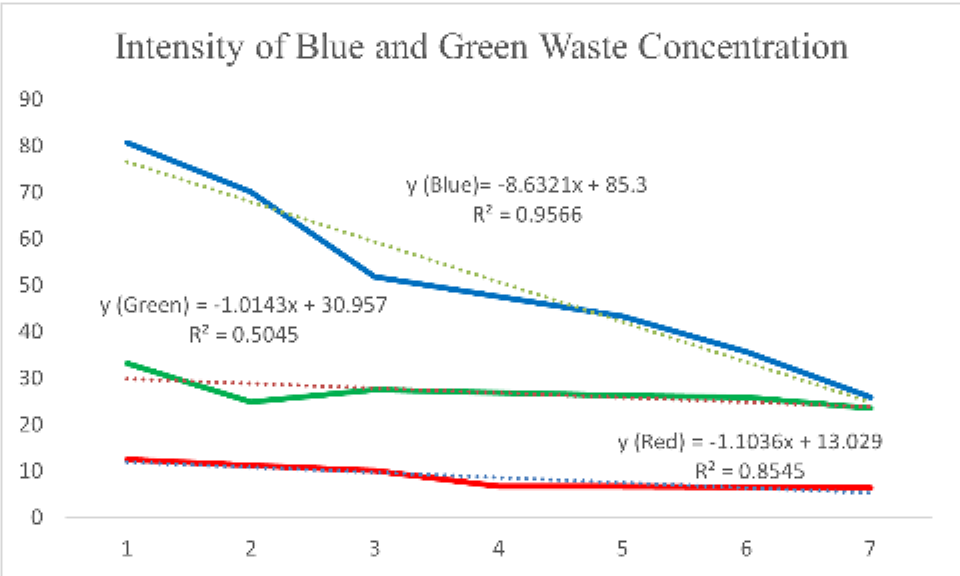

Figure 13. Linearity of Concentration and Intensity

Based on the results of the graph analysis in Figure 13, which illustrates the concentration of batik waste, it can be observed that the blue color component experienced the most significant decrease as the mixing proportion increased. This trend follows a regression equation of $y = -8.6321\ x + 85.3$ y=−8.6321x+85.3 with a coefficient of determination $R^2 = 0.9566$ R^2=0.9566, indicating a very strong linear

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relationship. The green component also showed a downward trend, although more gradual, with the equation $y = -1.0143\,x + 30.957$ y=−1.0143x+30.957 and an R^2 value of 0.5045, suggesting a weaker relationship with concentration variations. Meanwhile, the red component remained relatively stable, showing only a slight decrease, as represented by the equation $y = -1.1036\,x + 13.029$ y=−1.1036x+13.029 and an R^2 value of 0.8545. Overall, these results indicate that within batik waste mixtures, the decrease in blue color concentration is the most dominant compared to the green and red components. Therefore, it can be concluded that blue dye compounds are more sensitive to the mixing or degradation process than the other two components.

4. CONCLUSION

Based on the overall results of the analysis of batik waste mixtures with variations in red, blue, and green colors, it can be concluded that changes in the proportion of waste concentration have a significant effect on the distribution of color intensity in the resulting images. The red channel shows high sensitivity to mixing, exhibiting a sharp downward trend as the concentration of red waste decreases. Meanwhile, the blue channel displays a dominant increase in mixtures with a higher proportion of blue and serves as the strongest indicator of color spectrum shifts. Although its contribution is relatively smaller, the green channel acts as a stabilizer, showing gradual increases or decreases depending on the color combinations being mixed. The consistent linear transition patterns observed in the three RGB channels confirm that the applied image processing method can be used as a quantitative approach to identify the color composition of batik waste. Therefore, this study demonstrates that image-based analysis is not only effective in describing visual changes but also has strong potential as a rapid monitoring method for detecting the characteristics of batik waste associated with synthetic dyes.

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