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ESTIMATION AGE OF BLOODSTAIN USING *SMARTPHONE* APPLICATION ON *COLORIMETRIC* ANALYSIS

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Abstrak

Kemajuan teknologi sudah seharusnya dapat membantu pekerjaan ahli forensik khususnya dalam menyelesaikan kasus kejahatan kriminal. Estimasi usia noda darah merupakan faktor penting dalam analisis forensik. Penelitian ini bertujuan untuk membuat identifikasi usia noda darah dengan metode colorimetric dan mengamati perubahan warna noda darah pada permukaan material berdasarkan hasil foto dengan menggunakan kamera smartphone. Penelitian ini merupakan penelitian eksperimental dengan rancangan control time series, dimana sampel noda darah diamati dalam periode tertentu secara longitudinal. Noda darah diteteskan pada lima permukaan material berbeda yaitu keramik, kaca, kardus, kertas dan koran, kemudian dilakukan pengamatan serta pengambilan foto noda darah selama 72 jam. Estimasi usia noda darah menggunakan jaringan saraf tiruan dengan metode backpropagation. Hasil penelitian menunjukan bahwa jaringan saraf tiruan yang dibangun mampu memprediksi usia noda darah berdasarkan klasifikasi waktu. Selain itu terdapat pengaruh yang signifikan dari warna noda darah pada lima permukaan material keramik, kaca, kardus, kertas dan koran yaitu .63,7%; 84,3%; 84,6%; 68,2% dan 86,6%.

Kata Kunci*: noda darah, estimasi usia, kolorimetri, jaringan saraf tiruan, backpropagation*

Abstract

Advances in technology should be able to help the work of forensic experts, especially in solving criminal crime cases. Estimated age of bloodstains is an important factor in forensic analysis. This study aims to identify the age of bloodstains using the colorimetric method and observe changes in the color of bloodstains on the surface of the material based on the results of photos using a smartphone camera. This study is an experimental study with a control time series design, where bloodstain samples are observed in a certain period longitudinally. Bloodstains were dripped on five different material surfaces, namely ceramics, glass, cardboard, paper and newspapers, then observations and taking photos of bloodstains for 72 hours. Estimation of the age of bloodstains using artificial neural tissue by the backpropagation method. The results showed that the artificial neural network that was built was able to predict the age of bloodstains based on time classification. In addition, there is a significant influence of the color of bloodstains on the five surfaces of ceramic, glass, cardboard, paper and newspaper materials, namely. 63.7%; 84.3%; 84.6%; 68.2% and 86.6%.

Keywords: bloodstains, age estimation, colorimetric, artificial neural tissue, backpropagation

1. INTRODUCTION

Technology in the era of industrial evolution 4.0 is characterized by digitization in various aspects, so that technology cannot be separated from human life. Advances in technology should be able to help the work of forensic experts, especially in solving criminal crime cases.

Blood is one of the physical evidence (*trace evidence*) that is often found at the scene of crime (crime scene), especially in criminal cases. Blood coloring can tell about the position, actions and time of a crime event. Who killed and who injured. (James, et al., 2005) (Yudianto, 2013)

Methods of determining the age of bloodstains have long been developed such as, *oxygen electrodes*, *electron paramagnetic resonance* (EPR). *High-performance liquid chromatography* (HPLC), RNA *analysis* and ART-FTIR *spectroscopy*(Lin, et al., 2017) with a high success rate and accuracy but require sample preparation and are carried out in the laboratory and a longer time.

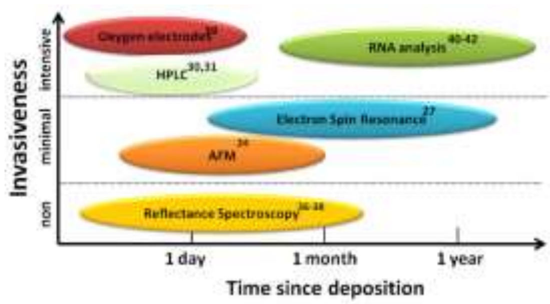

Figure 1 Bloodstain age determination technique. Invasiveness vs time techniques (Bremmer, et al., 2012)

According to Bremmer et al. (2012), The bloodstain age determination technique is categorized as *an intensive*, *minimal*, and *non-intensive* technique. *Non-invasive* there was no sample preparation and was carried out at the scene of the crime. *Invasive at a minimum* there is no sample preparation but the examination is carried out in the laboratory. Meanwhile, *invasive* techniques must be carried out in the laboratory and require sample preparation. (Bremmer, et al., 2012). To preserve the originality of the crime scene and *trace evidence*, non-destructive tests are preferred (Virkler & Lednev, 2009). Non-destructive determination of the age of bloodstains can be done by utilizing *smartphone* technology.

2. MATERIALS AND METHODS

This study is an experimental study with *a color time series* design, that is, the same sample is observed in a certain period longitudinally forward. The population in this study was a change in the color of bloodstains on the image. The study sample is a bloodstain dripped on the surface of the material. The materials used in this study were ceramics, glass, cardboard, paper, and newspapers.

2.1 Sample Preparation

The sample of this study is a bloodstain on the surface of the material. Blood samples were obtained from two volunteers who were willing to fill out *informed consents*. Two female volunteers aged 25 and 30. Venous blood collection from volunteers is assisted by health workers.

The blood from the volunteers was then dripped on the surface of the prepared material. The distance from the blood dropper to the surface $\pm$ is 50 cm and stored at room temperature.

2.2 Sampling

Bloodstains on the surface of the material are observed and photographed for 72 hours from the beginning of the dropper on the surface of the material. The time span of taking photographs every 3 hours or as many as 25 points (0; 3; 6; 9; 12; 15; 18; 21; 24; 27; 30; 33; 36; 39; 42; 45; 48; 51; 54; 57; 60; 63; 66; 69; and 72).

Taking photos of bloodstain samples using the built-in camera of *the smartphone* (VIVO Y20) with *the High-dynamic-range* (HDR) feature on. The distance between the camera and the

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object (bloodstain) ± is 8 cm perpendicular (90°), without the use of *flashlight*, but there is an external lighting of 1500 lux. Replication of bloodstain photos at each point was carried out 10 times, to account for variations in the precision of errors in the experiment, such as inhomogeneous lighting. Temperature and humidity are recorded at each point where bloodstains are taken.

The results of the bloodstain photos are then processed or extracted into primary data using an artificial Neural Network program. The result of the extraction of bloodstain photos is in the form of numbers from the CIELab color space values.

2.3 Program Creation

In this study, a program was built to predict the age of bloodstains. The program is divided into two parts, namely the image feature extraction process and the Artificial Neural Network (JST). Figure 2 shows the flowchart of the extraction process of the image feature from the results of bloodstain photos.

The extraction of image features from bloodstain photos produces primary data that will later be used as a reference by artificial neural networks in predicting the age of bloodstains. Artificial neural networks in this study used the backpropagation method.

Artificial neural networks have the ability to store, recognize and imitate something when given a learning process. While Backpropagation itself is a supervised learning algorithm and is usually used by perceptrons with many layers to change the weights connected to neurons in the hidden layer.

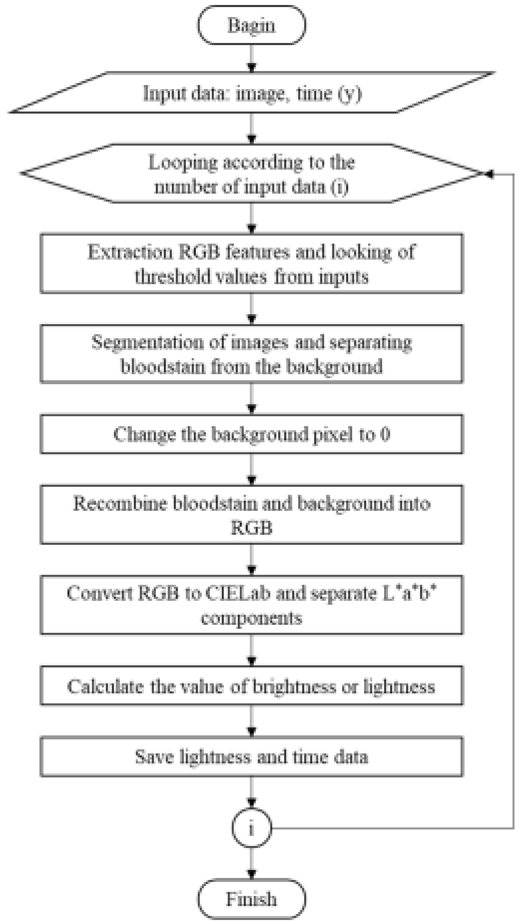

Figure 2 *Flowchart* Extraction Image feature

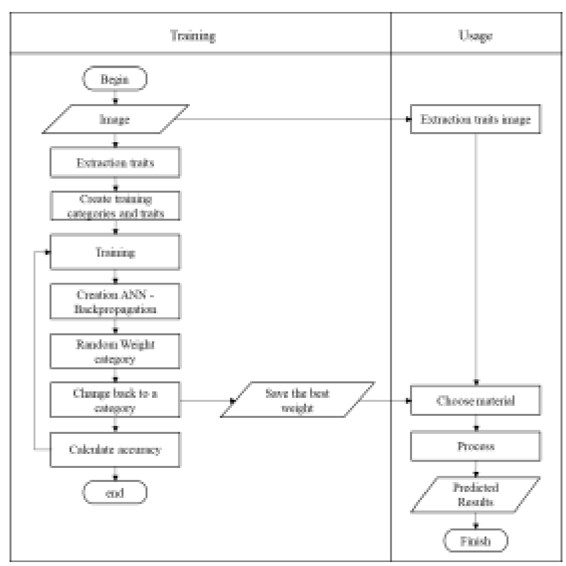

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Figure 3 Artificial Neural Network flowchart for estimation age of bloodstains

3. RESULT

Determination of the age of bloodstains can be done by analyzing the image image from the *smartphone* camera. The results of the study as shown in figure 4 show that the color of bloodstains changes over time and this change can be measured using digital image analysis. Many factors affect color values include temperature, humidity, light, substrate color, environmental factors and cameras.

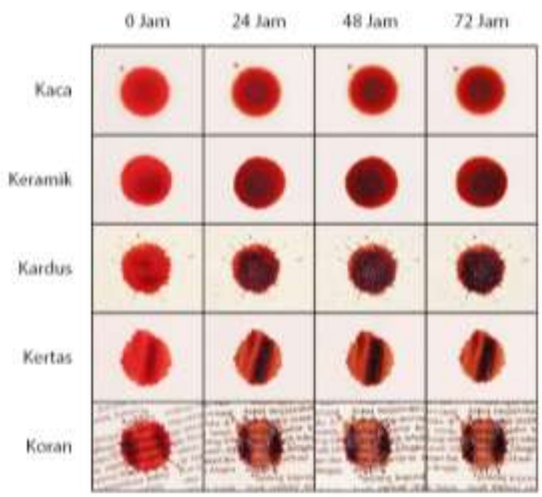

Figure 4 Discoloration of bloodstains on the surface of the material.

The bloodstain photo data in this study totaled 1550 bloodstains photo data consisting of 1250 training data (250 data for material seriap) artificial neural networks and 300 test data (50 data for material seriap) tissue weights.

3.1 Color Change of Bloodstains on the Surface of the Material

Based on figure 5, the change in the color of the bloodstains on each material showed a significant decrease in the 3 hours after the dropper, then slowly experienced a decrease in the rate of change from the next 6 hours to 48 hours. After 48 hours, there was no significant change in the color of the bloodstain, indicated by almost the same brightness value at some endpoints.

3.1.1 Ceramic material

Based on the results of the test analysis of the coefficient of determination of the brightness of bloodstains on ceramic materials, it shows a significant influence of the color of bloodstains on the age of bloodstains, which is 63.7 %.

The rate of discoloration of bloodstains occurs at 0-3 hours at the beginning of the dropper with *lightness* values from 19.5903 (0 hours) to 15.0647 (3 hours).

Then at 3-12 hours (15,0647; 13,5037; 12,715; and 11,883) the rate of discoloration of bloodstains decreased but was still observable. At 15-45 hours after the dropper the rate of discoloration begins to slow down, and at 48-72 hours the discoloration of bloodstains on ceramics there is almost no change, or the brightness of the bloodstains is almost equal to the average lightness value (L^*) of 9.7.

One of the factors that affect the rate of discoloration of bloodstains on the surface of ceramics is the calorific properties in ceramics. As an insulator, ceramics absorb the surrounding cold faster so that the temperature on the ceramic surface becomes cooler which

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causes the rate of color change to be faster. So that the HbO_2 reaction occurs faster as well as met-Hb becomes HC.

Glass as an insulator has smaller thermal properties than ceramics, this is due to the irregular structure of glass-

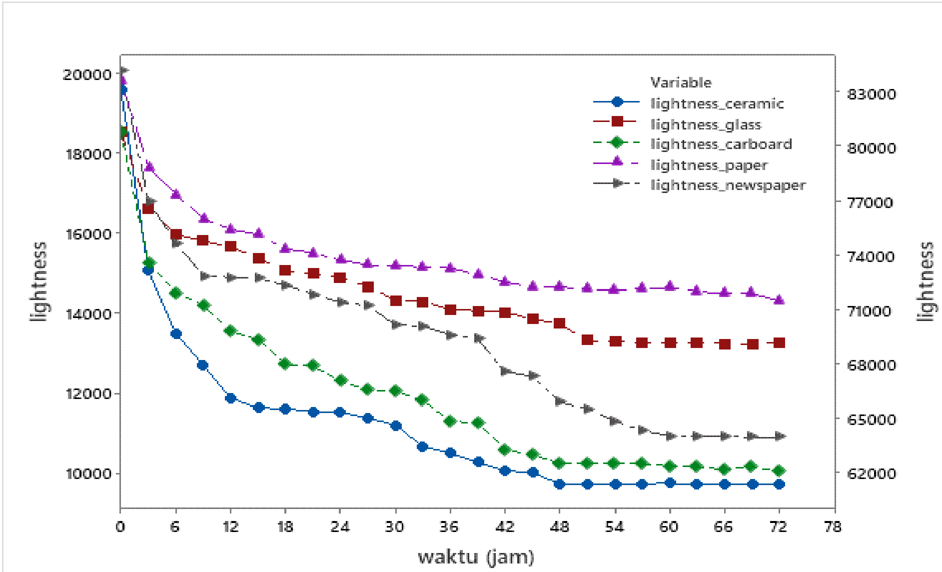

Figure 5 Changes in the brightness level of bloodstains on each material

forming atoms. So that the reaction of HbO_2 to met-Hb and HC occurs a little slower than in glass materials.

3.1.2 Glass Material

Based on the results of the test analysis of the coefficient of determination of the brightness of bloodstains on ceramic materials, it shows a significant influence of the color of bloodstains on the age of bloodstains, which is 84.3%.

Although ceramic and glass materials have a slippery and hard texture, the rate of color change in ceramic materials is slower. Based on *the lightness* value at 0-3 hours changes bloodstains faster. The rate of discoloration of bloodstains occurred at 0-3 hours (18.5423 and 16.6271) at the beginning of the dropper with *lightness* values from 19.5903 (0 hours) to 15.0647 (3 hours). Then it gradually decreased until 48 hours (13,746). the discoloration of bloodstains was almost no change with an average *lightness* value of 13,277 at 51-72 hours.

3.1.3 Cardboard Material

There was a significant effect of 84.6% of the color of the bloodstain on the surface of the cardboard on the age of the bloodstain

The color of the bloodstains at the beginning of the dropper is bright red, over time it turns blackish brown. At 0-3 hours, the rate of discoloration of bloodstains is very fast (18,539 and 15,285). Then at 6-45 hours the color of bloodstains continues to decrease (14,517 – 10,460), and in 48-72 almost no longer experiences a change in the color of bloodstains with an average *lightness* value of 10.2.

The color of the bloodstains is affected by the surface of the cardboard, where the dripped bloodstains undergo absorption, but changes in bloodstains can still be observed during the study.

3.1.4 Paper Material

In paper material, there is a significant influence of bloodstain color on the age of bloodstains, which is 6 8.2%. The porous texture properties of the paper can affect the color of the bloodstain, this is in accordance with the rate of discoloration of the bloodstain on the paper.

At 0-3 hours (19,833 and 17,656) the rate of change is very fast. At 27-36 hours discolorations are still observed but *lightness* values are not too different (average 15,174). At 39-42 hours a slight change in color is observed. Then from 45-72 hours the color change is not observed or the *lightness value is* the same.

On the surface of the paper, bloodstains dry faster due to absorption due to the porous texture of the paper, but the color of the bloodstains on the paper is easily observed because the white color of the ketas provides good contrast in observations.

3.1.5 Newspaper Materials

In newspaper material, bloodstain discoloration is faster at 0-3 hours (84,236 and 77,012) and 6-9 hours (74,677 and 72,773). Then in 12-54 hours (from 72,711 to 64,872) the rate of discoloration of bloodstains decreased slowly, until finally at 60-72 hours the color change was not observed again with an average *lightness* value of 64,055.

Based on statistical analysis, there was a significant influence of the color of bloodstains on the surface of the newspaper on the age of bloodstains by 8 6.6%.

Bloodstains dripped on the surface of the newspaper experienced greater absorption than on paper. The color of the newspaper material, which is generally gray, also affects the intensity of the color, plus the black print of the newspaper makes observation more difficult.

3.2 Estimated Age of Bloodstains with JST

The estimation of the age of bloodstains was carried out using artificial neural networks based on training results from several training data. The results of the training are the weight of tissue used to predict the age of bloodstains based on time classification according to categories.

3.2.1 Ceramic Material

Artificial neural network training on ceramic materials stops at the maximum *epoch*, meaning that at the 1000th *epoch* the *OBTAINED MSE* value is 0.17287. The *MSE* value obtained has not met the target or has not converged. However, artificial neural networks in ceramic materials were able to recognize 214 of the 250 training data with a network weight accuracy of 85.6%. This result is in accordance with the correlation value obtained, namely R = 0.99834, where in the bloodstain data ceramic material has a strong correlation. The time taken in training during *epoch* 1000 is 3 minutes or 180 seconds with its average time per *epoch* of about 0.18 seconds. By using the same weight, the accuracy of the test data of 82% was obtained, meaning that the network weight was able to recognize 41 data from 50 test data.

3.2.2 Glass Material

The accuracy on the glass material from the artificial neural network training results can be said to be better, which is 100%, meaning that the artificial neural network is able to recognize 250 data or all the training data. But at the time of the maximum *epoch the MSE* value has not reached the desired value. The *MSE* value achieved is 0.0018826, meaning that this value has not reached a convergent point but is better than the weight of the tissue in the ceramic material. The time taken during the training of 1000 *epochs* is 2 minutes 42 seconds or 162 seconds with the average training time per *epoch* being 0.162 seconds. The correlation value obtained in glass material is R = 0.9998, meaning that training data and tissue weights have a strong correlation to estimate the age of bloodstains. The test results using the same weight training results obtained a test accuracy of 98% meaning that the weight of the network was able to recognize 49 data from 50 test data.

3.2.3 Cardboard Material

In cardboard materials, the accuracy and correlation values of artificial neural networks are better than the results of training the weights of other tissues. The accuracy of the cardboard material obtained is 100% with a value of R = 1, meaning that the training data and tissue weights have a strong correlation to estimate the age of bloodstains. Even the *MSE* value on the artificial neural network of cardboard material is smaller than the weight of other material tissues, which is 0.0000059997 which was achieved in the 577th *epoch*. The *MSE* value obtained has met *the error* target or in other words has converged. The time required during training is 141 seconds or 2 minutes 21 seconds with the time per *epoch* being 0.141 seconds. Based on the test results, the accuracy of the network weight is obtained by 100%, meaning that the network weight is able to recognize all test data totaling 50 data.

3.2.4 Paper Material

The results of tissue weight training on paper material stopped at the maximum *epoch* with an *MSE* value obtained of 0.26395. The *MSE* value in the paper material has not converged because it does not meet the set error target of $1e^{-6}$ or 0.000001. The time taken during the training of 1000 *epochs* is 153 seconds or 2 minutes 33 seconds with the average time per *epoch* being 0.153 seconds. However, the accuracy value obtained is greater than that of ceramic materials, which is 87.2%, meaning that artificial neural networks are able to recognize 218 of the 250 training data. Based on the correlation value (R) from the results of tissue weight training, it has a strong correlation of 0.99746, meaning that tissue weights can be used to test the estimated age of bloodstains on paper materials. The results of the network weight test obtained an accuracy of 82%, where the network weight was able to recognize 41 data from 50 test data.

3.2.5 Newspaper Materials

Artificial neural network training on newspaper material gives the lowest of the weights of other tissues. The *MSE* value achieved at *epoch* 1000 is 0.62452 or less than the weight of the tissue in other materials. Just like other network weights, *the MSE* value in newspaper material has not yet reached a convergent point or target *goal* so that weight improvement can be made by increasing the number of *epochs* which has an impact on longer training times. The time taken

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during training of 1000 *epochs* is 3659 seconds or 1 hour 59 seconds with its average time per *epoch* being 3.659 seconds. The accuracy obtained in this network weight training was 78.8% or it can be said that artificial neural networks were able to recognize 197 of the 250 training data. Based on the correlation value of the training results obtained the value *of R* = 0.99414, meaning that the weight of the tissue can be used to test the estimated age of bloodstains on the paper material The accuracy of the tissue weight test obtained is 76%, meaning that the network is only able to recognize 38 data from 50 test data.

3.3 Limitations of Artificial Neural Networks

The network weight of the training results can be used to perform bloodstain age estimation testing by classifying the training output into time according to the specified category input. The accuracy of the tissue weights largely depends on the *MSE* value. If the *MSE* value is close to the target *goal*, the weight accuracy of the network is higher, on the contrary, the greater the *MSE* value , the lower the network weight accuracy. To overcome the magnitude of the *MSE* value, it can be done to add *an epoch* value to the network weight training, but this requires a longer training time.

Image image quality such as the size or resolution of the photo result and the background color of the image image can affect the output of network weight training. The large image size or resolution of the image has an impact on the length of time of network weight training. Background *colors* with more than one color can make it difficult for programs to segment or separate the red bloodstain (target) color from the *background* color, so that the results of segmentation can be incorrect on the target color. For example, in newspaper materials, the results of network weight training showed a greater *MSE* value than other materials, and the accuracy value was lower than others.

4. CONCLUSION

4.1 Conclusion

Based on the research that has been carried out, it can be concluded as follows:

1. The color of bloodstains based on *the* lightness value (CIELab color space) gives different results to each material. The color of bloodstains on ceramic, glass, cardboard, paper, and newspaper materials affected the age of bloodstains by 63.7%; 84.3%; 84.6%; 68.2% and 86.6%.
2. Identification of bloodstains *by the colorimetric* method can be done digitally with the backpropagation artificial neural network method. The identification stage starts from entering bloodstain image data as *input*, reading the extraction of characteristics from image data, conducting *training* from the extraction of characteristics on artificial neural networks, and *the output* of JST is the weight of the network. The weight of the tissue is then used to recognize or identify the age of the bloodstain.
3. The results of artificial neural network training on ceramic, glass, cardboard, paper and newspaper materials provide high accuracy of 85.6%; 100%; 100%; 87.2%; and 78.8%. While the accuracy of the tissue weight test results on each material is sequentially as follows: 82%; 98%; 100%; 82% and 76%.

4.2 Suggestion

Research is still possible to be developed again into a better system in the future. Subsequent research is expected to develop more accurate segmentation methods with the use of more sensitive color spaces.

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