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# Identification of the Estrous Period through Texture Analysis of the Cow Vulva Image

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**Abstract**

The application of artificial insemination is complained by farmers because of frequent failures, which are indicated by failed pregnancies. The failure of pregnant cows due to the incorrect detection of the estrous period by farmers. The purpose of this study was to analyze the texture of the cow vulva image using statistical methods, gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM) methods to identify cattle during estrous periods. So it is hoped that this study will obtain an alternative method of identifying the estrous period of cows more easily, cost effective, quickly and precisely. This study took a sample of 35 images of the vulva of cows, consisting of 20 cows during the estrous period and 15 cows that were not in the estrous period. Furthermore, on the image of the vulva, texture analysis was carried out withusing statistical methods, gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM) methods. The results showed that the classification accuracy with k means cluster texture characteristics statistical method was 77.14%, classification accuracy with k means cluster texture features GLCM method was 54.28% and classification accuracy with k means cluster texture characteristics statistical methods was 71.42 %. So texture analysis of the vulva image can be developed continuously to be a method in identifying the estrous period of cows.

**Keywords:** texture features, vulva image, estrous period, Texture statistics, GLCM, GLRLM

## Introduction

One of the known breeding techniques to increase cow production is artificial insemination. Artificial insemination has long been used in dairy cattle in Indonesia and later in cattle and buffalo. People have benefited, which is marked by the high selling price of livestock by means of artificial insemination, but its implementation in the field has not been optimal (the pregnancy rate is less because the detection of estrous is not right) and the results (birth rate) fluctuate (no significant progress) from year to year.

One of the purposes of Artificial Insemination is to improve the genetic quality of livestock. With the Artificial Insemination method, farmers get benefits, including saving the cost of raising male cattle, being able to regulate the birth spacing of cattle properly, preventing inbreeding in female cows (inbreeding), with good equipment and technology, sperm can be stored for a long time, frozen semen can still be used for several years later even though the male has died, avoiding accidents that often occur during mating due to the male's physical size, preventing livestock from transmitting diseases, especially sexually transmitted diseases (1).

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Artificial Insemination (AI) is one of the technologies in beef cattle cultivation to increase the population and genetic quality of livestock. AI is inserting semen/semen into the genitals of a healthy female animal by using an insemination device so that the animal becomes pregnant (2).

In 2007 about 81.77 percent of female cows that were mating using the AI technique were successful in getting pregnant and 42.18 percent of them were successful in getting pregnant with one application of AI. In 2008 the success rate increased to 97.45 percent and 55.84 percent of them succeeded in getting pregnant with one AI application (3). The optimization of AI technology is expected to Shortening of the calving interval, so that it will encourage an increase in beef cattle production.

Artificial Insemination as an effective tool to improve genetic quality and increase livestock populations. Artificial Insemination (AI) is one of the alternative reproductive biotechnology that can be used to improve the productivity of cattle farming in Indonesia. AI is an efficient and effective tool in implementing national livestock breeding policies to improve the genetic quality of offspring quickly (4).

The success of AI is indicated by the number of children born to a number of inseminated mothers. The application of AI technology is believed to have economic and practical added value in genetic improvement and productivity (5). Thus, the optimization of AI will accelerate the increase in the cattle population and can then be used as feeders for the provision of beef. Therefore, knowing the performance of AI and its problems and solutions is very important information in beef/dairy cattle husbandry policies and the provision of beef for consumption.

Detection of estrous is indispensable in artificial insemination. Pregnancy failure is caused by less precise detection of estrous. Therefore, it is very important to continue to develop ways to detect estrous properly.

The vulva of cows in the estrous period has certain characteristics, one of which is its texture. So that by observing the texture of the vulva it is possible to detect the estrous period.Techniques for extracting texture features with good accuracy, including statistical methods and the Gray Level Cooccurence Matrix (GLCM) method to determine the co-occurrence matrix which shows the spatial relationship between the gray level in the texture image (6,7) and the Gray Level Run. Length Matrix (GLRLM) which is able to distinguish between fine and coarse images (8,9). Identification using GLCM and GLRLM has adequate accuracy. Each object has characteristics that distinguish it from other objects, for example in the identification of wood images with accuracy 77,5% (10), fruit images with accuracy 100% (11), eye images with accuracy 93,3% (12), bamboo leaves with accuracy 81,25% (13) and rice image with accuracy 99,75% (14).

So in this study, we used the extraction of vulvar texture features with the statistical method, the GLCM method, the GLRLM method to detect the estrous period of cows.

**Materials and Methods**

The first step is to take a photo shoot to get an image of the vulva of the cow during the estous period and the image of the vulva of a normal cow (tidal period of estrous). Then pre-

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processing the image and determining the image object. The second step is to determine the texture value of the vulva image using statistical methods. With this statistical method, the characteristics (mean, variance, skewness, kurtosis and entropy) were obtained. Then proceed with identifying images of the vulva that were included in the estrous period and images of the vulva that were not in the estrous period using the k means cluster classification method. (Fig 1)

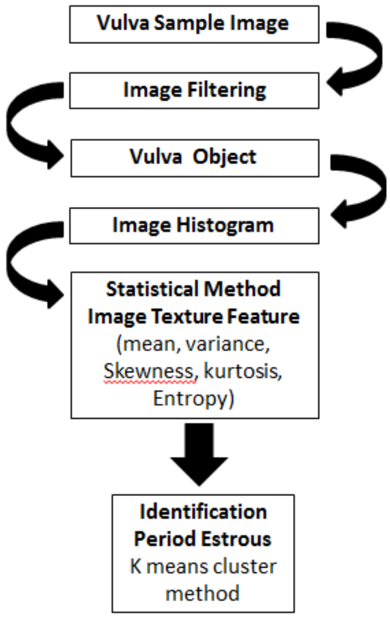


**Fig.1** Statistical method of texture feature extraction research flow

The third step is to determine the texture value of the vulva image using the gray level co-occurrence matrix (GLCM) method. With this GLCM method, characteristics will be obtained, among others (angular second moment/ASM, contrast/Con, correlation/Cor, variance/Var, inverse different moment/Idm, and entropy/Ent). Then proceed with identifying images of the vulva that are included in the estrous period and images of the vulva that are not in the estrous period using the k means cluster classification method. (Fig 2)

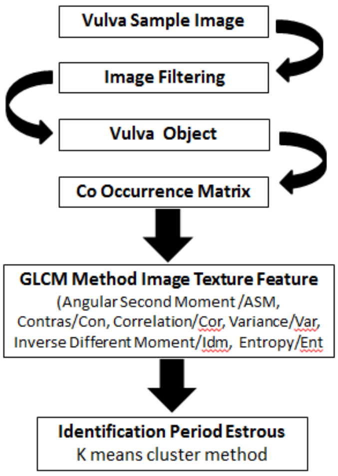


**Fig.2** GLCM method of texture feature extraction research flow

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The third step is to determine the texture value of the vulva image using the gray level run length matrix (GLRLM) method. With the GLRLM method, the following characteristics will be obtained (Short Run Emphasis / SRE, Long Run Emphasis / LRE, Gray Level Uniformity / GLU, Run Length Uniformity / RLU, and Run Pencentage / RPC). Then proceed with identifying images of the vulva that are included in the estrous period and images of the vulva that are not in the estrous period using the k means cluster classification method. (Fig 3)

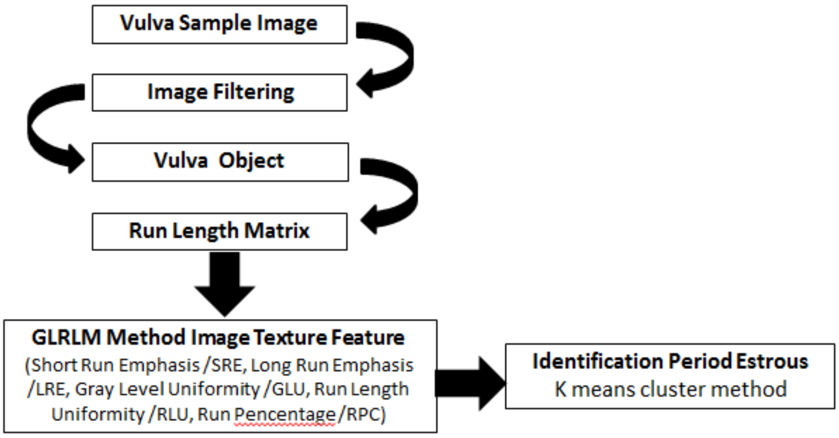


**Fig.3** GLRLM method of texture feature extraction research flow

**Result**

Determination of cow estrous using rectal palpation method carried out by expert oficers at artificial insemination institutions. From 35 samples of cow vulva images, 15 cows were found in normal condition (not in the estrous period) and 20 cows in the estrous period. Figure 4 is an example of an image of a cow's vulva in the estrous period.

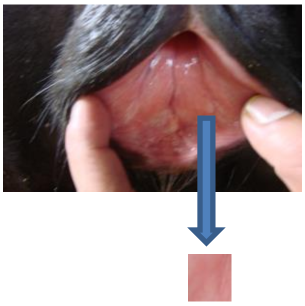

**Fig.4** image of cow vulva

Then from the vulva image object, its texture analysis is carried out using statistical methods, namely using statistical calculations of the gray degree distribution of the image histogram by measuring the contrast, granularity, and roughness of an area from the neighboring relationship between pixels in the image represented by the mans, viarians, skewness values. , kurtosis and entropy (see table 1).

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**Table.1** Texture features of the vulva image statistical method

| Sample | mean | Var | Skew | Kur | Ent |
|---|---|---|---|---|---|
| 1 | 89.95 | 189.8471 | -0.8529 | 0.861 | 5.571 |
| 2 | 99.1808 | 60.8519 | -0.9423 | 1.3243 | 4.8628 |
| 3 | 106.2945 | 686.0216 | -0.0698 | 0.0798 | 6.6622 |
| 4 | 169.7645 | 526.7158 | -0.61 | 0.1281 | 6.4493 |
| 5 | 204.5891 | 44.4335 | -1.7863 | 4.2069 | 4.4377 |
| 6 | 130.1809 | 84.313 | -0.6927 | 0.0854 | 5.1096 |
| 7 | 186.0833 | 316.509 | -0.8335 | 2,148 | 5.9648 |
| etc | | | | | |

Then also carried out texture analysis using the GLCM method which also measures the level of contrast, granularity, and roughness of an area from the adjacency relationship between pixels in the image which is carried out with a co-occurrence matrix, which is an intermediate matrix that represents the neighboring relationship between pixels in the image in various directions. orientation and spatial distance, which is represented by the value of 'angular second moment, contrast, correlation, variance, inverse different moment, and entropy'. (see table 2).

**Table.2** Texture features of the vulva image Gray Level Co occurrence Matrix method

| Sample | Asm | Con | Cor | var2 | idm | Ent2 |
|---|---|---|---|---|---|---|
| 1 | 0.0042 | 5.6331 | 0.9849 | 183.2541 | 0.4633 | 8.5456 |
| 2 | 0.0071 | 2.9473 | 0.9756 | 59.0101 | 0.5029 | 7.6204 |
| 3 | 0.0015 | 17.0394 | 0.9874 | 667.125 | 0.4029 | 10.0179 |
| 4 | 0.0016 | 13.3395 | 0.9871 | 508.5619 | 0.365 | 10.0455 |
| 5 | 0.0143 | 2.3637 | 0.9724 | 41.5662 | 0.5602 | 6.9665 |
| 6 | 0.0061 | 3.1587 | 0.981 | 81.4177 | 0.4915 | 7.9303 |
| 7 | 0.0021 | 18.2737 | 0.97 | 295.3098 | 0.354 | 9.6195 |
| etc | | | | | | |

Then texture analysis was also carried out using the GLRLM method and using the GLRLM method, namely measuring the number of runs on a pixel with the same intensity level in succession in one particular direction. This method is represented by the values of 'Short Run Emphasis, Long Run Emphasis, Gray Level Uniformity, Run Length Uniformity and Run Pencentage (see table 3).

**Table.3** Texture features of the vulva image Gray Level Run Length Matrix method

| Sample | SRE | LRE | GLU | RPC | RLU |
|---|---|---|---|---|---|
| 1 | 0.5823 | 6.0155 | 208.6119 | 0.4996 | 817.107 |
| 2 | 0.3782 | 35.9914 | 126.5411 | 0.2384 | 186.0651 |
| 3 | 0.4754 | 12.0395 | 170.0272 | 0.3827 | 458.5616 |
| 4 | 0.4907 | 17,522 | 207.3183 | 0.3347 | 392,789 |
| 5 | 0.4941 | 13.3846 | 184.1267 | 0.3688 | 447.4549 |

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| | | | | | |
|---|---|---|---|---|---|
| 6 | 0.5314 | 12.2723 | 222.0533 | 0.3867 | 522.4227 |
| 7 | 0.3966 | 26.3574 | 289.4354 | 0.2718 | 234.6967 |
| etc | | | | | |

Please note, this method is only used in healthy cows, this study has not yet reached cows that are sick or inflamed due to infection.

From each method of texture analysis, classification is then carried out using k means clusters. In table 4, from the texture characteristics of the statistical method, the classification accuracy is obtained at 77.14%. There are 27 samples that have the right classification and 8 samples are wrong in the classification.

In table 5, from the texture characteristics of the statistical method, the classification accuracy is obtained by 54.28%. There were 19 samples that were correctly classified and 16 samples were misclassified. In table 6, from the texture characteristics of the statistical method, the classification accuracy is obtained by 71.42%. There were 25 samples that were classified correctly and 10 samples were misclassified.

**Table.4** The accuracy of the classification of k means clusters using the texture characteristics of the statistical method

| classification | Normal | Estrous Period |
|---|---|---|
| Normal | 9 | 6 |
| Estrous Period | 2 | 18 |

Sensitivity = 81.81%
Specificity = 75%
Accuracy = 77.14%

**Table.5** The accuracy of the classification of k means clusters using the texture characteristics of the GLCM method

| classification | Normal | Estrous Period |
|---|---|---|
| Normal | 11 | 4 |
| Estrous Period | 12 | 8 |

Sensitivity = 47.82%
Specificity = 66.66%
Accuracy = 54.28%

**Table.6** The accuracy of the classification of k means clusters using the texture characteristics of the GLRLM method

| classification | Normal | Estrous Period |
|---|---|---|
| Normal | 11 | 4 |
| Estrous Period | 6 | 14 |

Sensitivity = 64.70%
Specificity = 77.77%
Accuracy = 71.42%

**Discussion**

Texture analysis is an image analysis technique based on the assumption that the image is formed by variations in pixel intensity, both gray and color images. Texture analysis can be considered as a grouping of similarities in an image. The properties of these local subpatterns give rise to received light, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, irregularity, smoothness, and so on. Because the computer does not have a sense of sight, the computer only knows the pattern of a digital image from its texture characteristics. Texture characteristics or characteristics are obtained through a feature extraction process with various methods such as statistical methods, GLCM, and GLRLM. So that texture analysis can be applied to analyze the vitra vulva of cows.

The image of a cow's vulva with an estrous period has certain characteristics that are different from the image of a cow's vulva that is not in an estrous period. So by recognizing these characteristics will be able to identify the estrous period. The results of the study on the image of the cow's vulva showed the highest accuracy was the use of the texture characteristics of the statistical method, which was 77.14%.

Texture analysis is commonly used as an intermediate process for classifying and interpreting images. An image classification process based on texture analysis generally requires a feature extraction step, which can be divided into three methods, namely statistical methods, spectral methods and structural methods. The statistical method uses a statistical calculation of the gray degree distribution (histogram) by measuring the contrast, granularity, and roughness of an area from the neighboring relationship between pixels in the image.

This statistical paradigm is not used limited, so it is suitable for unstructured natural textures of sub-patterns and rule sets (microstructures). The use of image texture features with statistical methods is quite good for various purposes (15,16). The texture characteristics of the statistical method are quite good for classicizing lung disorders (17), for facial analysis (18), for classifying brain magnetic resonance images (19).

**Conclusion**

Texture analysis of cow vulva images can be used to identify the estrous period of cows. Accuracy of classification with k means cluster texture characteristics statistical method is 77.14%, classification accuracy with k means cluster texture features GLCM method is 54.28% and classification accuracy with k means cluster texture features statistical method is 71.42%.

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**Ethical Approval**

This study and all of the experimental procedures in volving animals were conducted in accordance with the animal care guidelines of the State Islamic University of Maulana Malik Ibrahim Malang, Indonesia.

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