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A Novel Approach of Animal Skin Classification Using CNN Model with CLAHE and SUCK Method Support

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Abstract*—This study describes the process of classifying animal skin images which are rather difficult to obtain optimal image characteristics. For this reason, in the pre-processing stage, we propose two methods to support feature extraction: sharpening using a convolutional kernel (SUCK-Sharpening) and adaptive histogram equalization with limited contrast (CLAHE-Equalized). SUCK works by operating on these pixel values using direct math to build a new image; this final value is the new value of the current pixel. CLAHE overcomes the limitations of the global approach by performing local contrast enhancement. Because of the advantages of the two methods, it becomes a solution to get features processed at the feature extraction and classification stage. The process of animal skin imagery has characteristics in terms of shape and texture, including the characteristics of animal skin color. In this study, some experiments have been carried out on several CNN models, with an average classification accuracy of more than 70% using the sharpened and equalized methods on six animal skins. More detail, the average classification accuracy using 3 CNN models supported by two methods, namely Sharpening and Equalize on the CNN Resnet 50V2 model is 67.73% and 73.78%, InceptionV3 model at 82.13%, and 74.76% and Densenet121 models were 87.64% and 87.46 %. This research can be continued to improve the accuracy of other animal skin images, including determining fake or genuine skin images.

***Keywords*— Animal skin; CLAHE; SUCK; CNN; Resnet50 V2; Inception V3; Densenet121.**

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I. INTRODUCTION

In Indonesia, animal skin is one of the raw materials used as the main ingredient in leather and art [1]. During the processing of animal skins into real leather, these animal skins have changed both texture and color. This makes it difficult to identify the type of animal skin from one species to another [2]. To overcome the problem, we need a system to identify the type of animal skin material. The increasing industrial demand for leather is also less capable of a buyer identifying leather materials on the market [3]. Animal skins could be processed into real leather to produce ready-to-use products. In addition, with some information for knowledge about leather will be able to describe the type of leather material and its quality [4].

Some users have not yet understood what animal the animal skin comes from, which is clearly illustrated. So we need the right way or a good method to find out or distinguish the skin of one animal from another. This research contributes to understanding the origin of this animal skin by using several methods ranging from pre-processing to animal skin recognition using deep learning algorithms through several Convolutional Neural Network (CNN) models. Thus, research for the introduction of animal skins is beginning to be continued in further research.

In research on the animal skins classification that has smooth and unstructured texture characteristics, for the initial process, animal skin images are used by two methods to sharpen and bring out image characteristics, namely Convolution Kernel and CLAHE (Contrast Limited Adaptive Histogram Equalization). The Kernel concept utilization - also known as convolution matrix or mask - is very precise and valuable for image processing. Some image management techniques, such as blurring, edge detection, and sharpening, rely on the kernel - a matrix of small numbers - to be applied across the image to process the image as a whole. The kernel can be used to perform mathematical operations on each pixel of the image to achieve the desired effect (like blurring or sharpening an image [5], [6].

The research aims to make it easier for users to distinguish between animal skins such as cow and pig skins, tiger skins, and other animal skins. However, in this study, it is also hoped that it will be able to distinguish between genuine and fake skin, but for this paper, we are carefully looking for the methods and algorithms to solve this problem. This research has also developed an appropriate approach (algorithm and method) to distinguish animal skins that have fine texture patterns between animals. So that in the pre-processing stage, a method is used that increases the sharpness and brightness of animal skin images so that feature extraction and classification or retrieval processes can be carried out.

II. MATERIAL AND METHOD

A study to evaluate the process of classifying animal skin images with very fine and complex texture and shape characteristics requires an appropriate method to support classification accuracy performance. Some studies have been conducted for image classification using feature extraction and different classification methods. Batik image classification carried out k-NN and Neural Network, while image Feature extraction using the MUECS-LBP algorithm [7]. Future research on the classification of traditional fabric patterns is with various types of texture using the CNN model with Inception V3 and ResnetV50 [8]. Other CNN models, namely VGG16, VGG 19, and MobilenetV2, continued this classification study [9]. Research has provided a strong foundation for the image classification process with diverse and complex texture and shape characteristics patterns. In addition, each image pattern studied has also changed scale and rotation. In addition, the reliability of this research has been proven, and although the test images are more than the training images, the average classification accuracy can be more than 80%. Even patterns with fewer complex characteristics can have an average classification accuracy of more than 90 % [10].

In research on animal skin classification that has smooth and unstructured texture characteristics, for the initial process, animal skin images are used by two methods to sharpen and bring out image characteristics, namely Convolution Kernel and CLAHE. The Kernel concept utilization–also known as convolution matrix or mask - is very precise and valuable for image processing. Some image management techniques, such as blurring, edge detection, and sharpening, all rely on the kernel - a matrix of small numbers - to be applied across the image to process the image as a whole. The kernel can be used to perform mathematical operations on each pixel of the image to achieve the desired effect (like blurring or sharpening an image) [11], [12]. In animal skin recognition research, a new detection model was used to recognize the skin texture patterns of leopards, cheetahs, and jaguars. This model combines Histogram of Gradient (HOG) and super-pixel segmentation to extract the features and segmentation of the target animals for classification using the SVM method. The validation classifier achieves an accuracy of 96.67 % [13].

In this study, to analyze the differences between the morphological features of *Locusta migratoria*, *manilensis and Oedaleus decorus asiaticus*, we propose a semi-automatic grasshopper species and an instar information detection model based on grasshopper image segmentation, variable extraction of grasshopper features and classification support vector machine (SVM) [14].

Pattern's research on the classification of traditional cloth patterns that experience changes in rotation and scale using several Convolutional neural network models. For the average resulting classification accuracy of up to more than 75% with 44 types of traditional cloth patterns.[15] Another research on the classification of traditional cloth patterns that experience changes in rotation and scale using several Convolutional neural network models [16]. The average resulting classification accuracy of up to more than 75% with a total of 44 types of traditional cloth patterns [17]. Other research related to patterns resembling animal skin patterns is on Batik cloth patterns, where mulwin-LBP and Deep neural networks are used for feature extraction. For performance, classification accuracy reaches more than 81.6% [18]. In addition, research on batik cloth uses a Convolutional neural network that can study data representation by combining local receptive input, weight sharing, and convolutions to overcome invariance dilemmas in image classification. Using a dataset of 2,092 Batik patches, experiments show that the proposed model, which uses deep ConvNet VGG16 as a feature extractor (transfer learning), achieves an average accuracy of 89 ± 7%, slightly better than SIFT- and SURF-based, which respectively reached 88 ± 10% and 88 ± 8%. Nonetheless, SIFT achieves about 5% better accuracy in rotated and scaled datasets [19]. Another study found out which animal skins are suitable for user needs, especially IoT technology support in dealing with industry 4.0, to make it easier to know the type of animal skin that is fake and genuine [20].

During problem about Image denoising is a crucial topic in image processing. Noisy images are generated due to technical and environmental errors. Therefore, it is reasonable to consider image denoising an important topic for study, as it also helps to resolve other image processing issues [21]. To find out that the process of recognizing animal skin images is optimal, tools are needed to be useful for optimally processing it. This tool is so versatile that it can be used in various situations as it is designed for comparison, variable filtering, transfer function identification, optimization, and sturdy design [22]. This research aims to provide a relationship between customer-oriented business-to-consumer (B2C) where goods or services are sold immediately to customers in the market, especially in the purchase of animal skins that are useful to customers [23] because Quality and innovation have shown a relationship between them as competing rather than supplementary purposes [24].

In this study, an evaluation was carried out for classification accuracy on animal skin images with very fine and complex patterns. Besides that, getting an image of animal skins is rather difficult and has almost the same pattern between the skins. For this reason, in the early stages, after the animal skin image data is collected, a process would be carried out to increase the contrast and sharpness of the skin image pattern so that the structural pattern of the shape and texture of the animal skin is clearly depicted. To know the skin pattern, the Convolutional kernel and CLAHE methods are used for this purpose. The stages in the animal skin image classification research scheme from the start to the classification process can be shown in Figure 1.

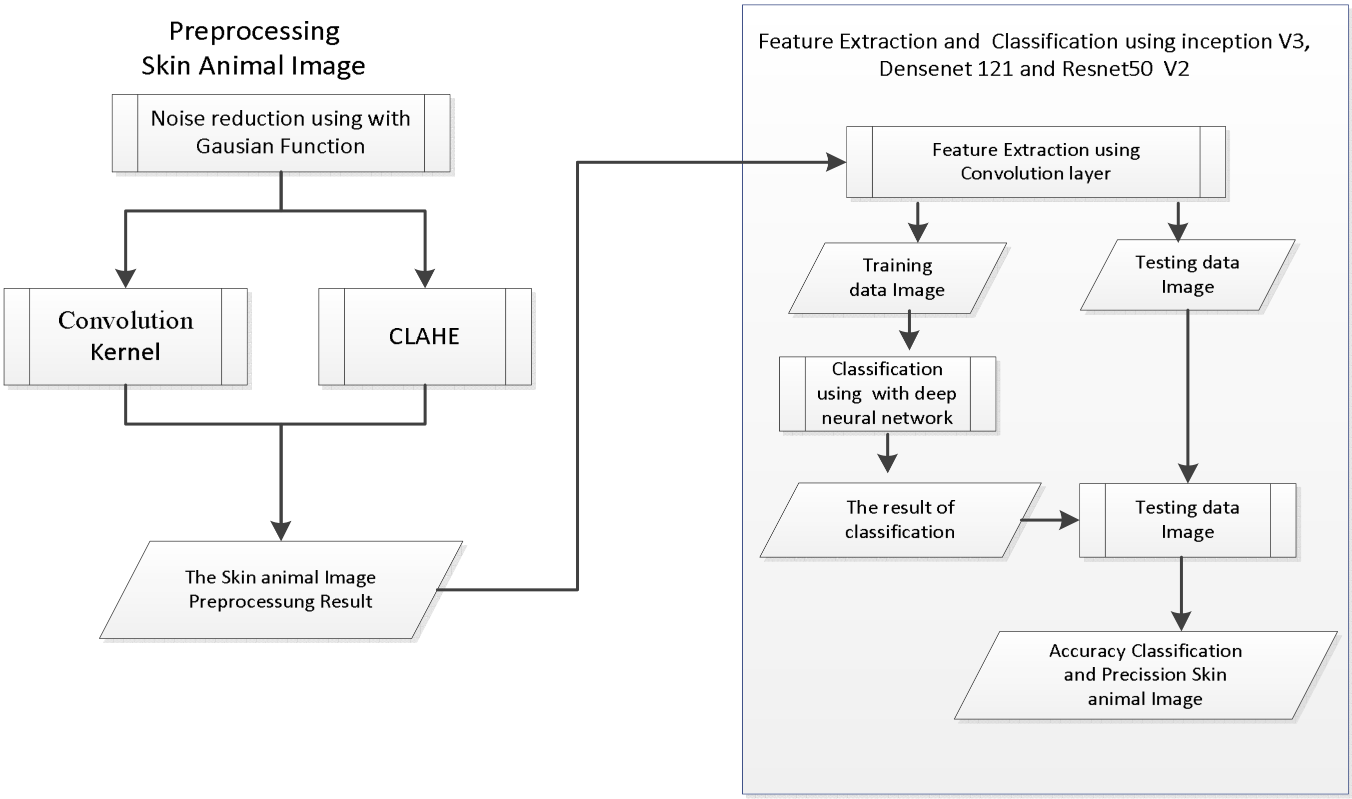

Fig. 1 Classification stages of animal skin images using the CNN Model

Fig. 1 illustrates the stages of the image classification process of animal skins with very fine and complex fur patterns owned by each animal that is the object of research. In general, the texture patterns and shapes of each animal are different. However, for animals, there are two types of skin patterns, inner and outer animal skin patterns. The pattern of animal skins on the outside is delicate and difficult to distinguish. However, a magnifying glass can be used to find the differences, and it seems like the patterns on the skin of a cow and a pig. By knowing the differences in animal skin patterns, both the outer skin and the inner skin, there must be a special way so that animal skin motifs can be clearly distinguished. This problem, the skin image's sharpness, and contrast are fixed using the CLAHE method and the convolutional kernel.

All images have been pre-processed and then followed by a feature extraction process using a deep neural network originating from several CNN models. The images that have been pre-processed and feature extracted would be divided into training images and test images. To perform the classification process using several Convolutional Neural Network models to obtain optimal classification accuracy in animal skin image processing. In addition, with this experiment, it is hoped that it would be known which animal skin images would get an accuracy performance of up to more than 90%, including getting the highest average accuracy performance in the CNN model, which can reach more than 87%.

Figure 2 illustrates the initial process of knowing the texture or shape characteristics of animal skin both inside and outside with very diverse and smooth conditions (especially the inner skin) so that it looks brighter and contrasts, making it easy to get these characteristics from animal skins. In this experiment, after collecting all good animal skin images from the data collection results, a resizing process would be carried out so that the image size becomes standard, namely 200x200 pixels. Furthermore, the skin image would undergo a sharpening process and have more contrast to facilitate the feature extraction process using the CLAHE method with a clip limit of 0.03.

Furthermore, all skin images that have been processed would be rotated and scaled so that the classification process becomes reliable by using several CNN models. Furthermore, the processed animal skin image data would be stored in the previously processed animal skin database and divided into internal animal skin images (pig and cow skin) and images of animal skins on the outside (tiger, sheep, cow). This difference is expected to reveal the reliability of each CNN model in classifying several animal skins.

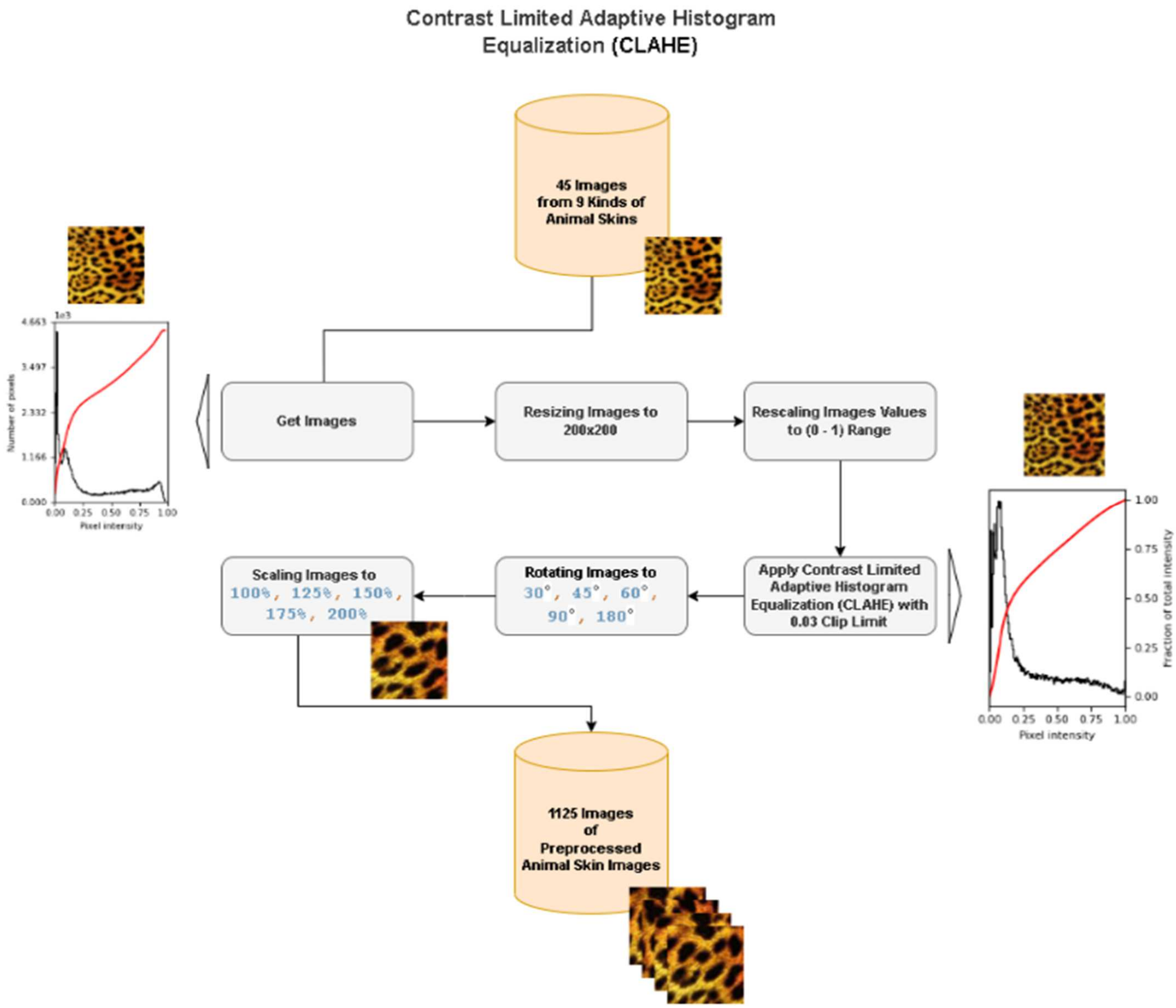

Fig. 2 Skin Animal Pre-processing using CLAHE Method

Fig. 2 and Fig. 3 describes the SUCK and CLAHE method in processing to get the contrast and sharpness of animal skin image features, thus supporting the feature extraction and classification process. The process begins with image retrieval; resizing was carried out by all images to 200 x 200 pixels. Furthermore, the sharpness and contrast enhancement process was carried out on all images using the CLAHE and SUCK methods. The kernel matrix or convolution is a small matrix used for blurring, sharpening, and edge detection of image skin animal processing functions. Wherever this tiny kernel sits on top of the big image and moves from left to right and top to bottom, applying mathematical operations (i.e., convolution) to each (x, y) coordinate of the original image [25]. At each coordinate (x, y) of the original skin animal image, it would stop and check the neighborhood of the pixel located in the center of the skin animal image kernel and then take these pixel neighborhoods and combine them with the kernel to get a single output value.

This output value is then stored in the output skin image at the same (x, y) coordinates as the kernel center to support the feature extraction and classification process [26]. A source animal Skin image was filtered by convolving the kernel with the skin image. The convolution of a skin animal image with a kernel represents a simple mathematical operation between the kernel and its corresponding elements in the skin image. The analysis of the Kernel center was positioned above a certain pixel (p) in the skin image.

- It would be multiplied by the value of each element in the kernel by the pixel element that matches the intensity and contrast and enhances it from the source pixel in the animal skin image.
- Now, add up the products and calculate the average.
- Finally, replace the pixel value (p) with the average value you just calculated

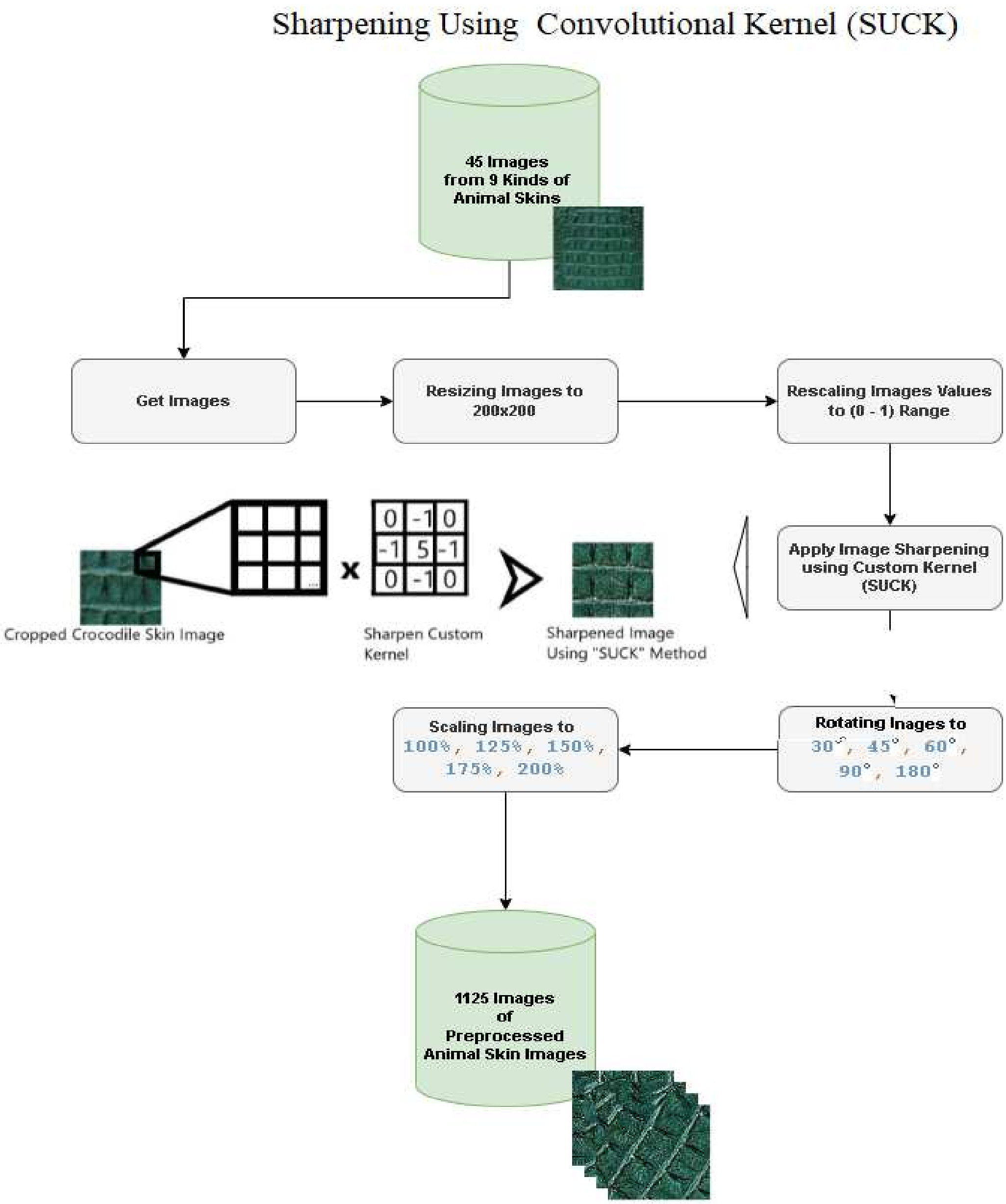

Fig. 3 Skin Animal Pre-processing using Sharpening (SUCK) method

The CLAHE method consists of equalizing histograms of the image sub-areas, so they do not overlap, using interpolation to correct inconsistencies between boundaries. CLAHE has two hyper important parameters: clip limit (CL) and the number of tiles (NT). The first (CL) is a numerical value that controls noise amplification. After the histograms of each sub-area are calculated, several processes would redistribute them so that their height does not exceed the desired "clip limit". Next, the cumulative histogram is calculated to perform the equalization. The second (NT) is an integer value that controls the number of sub-areas to be non-overlapping: based on their value, the image is divided into several (usually squared) non-overlapping areas of the same size [27]. In 200 × 200 images, the number of regions is generally selected to be equal to 64. Fig. 4 shows the image histogram changing process before and after the CLAHE process.

Fig. 4 describes the classification of animal skin images. Several steps must be taken, such as collecting datasets directly through the internet, magazines, and digital photos. Furthermore, all images are processed and undergo rotation and scale changes simultaneously. After that, all images would perform a feature extraction process, and the results would be stored in the animal skin image database. All extracted skin data would be divided into training and test images. After that, calculate the classification accuracy using several CNN models consisting of Inception V3, Resnet 50 V2, and DenseNet 121.

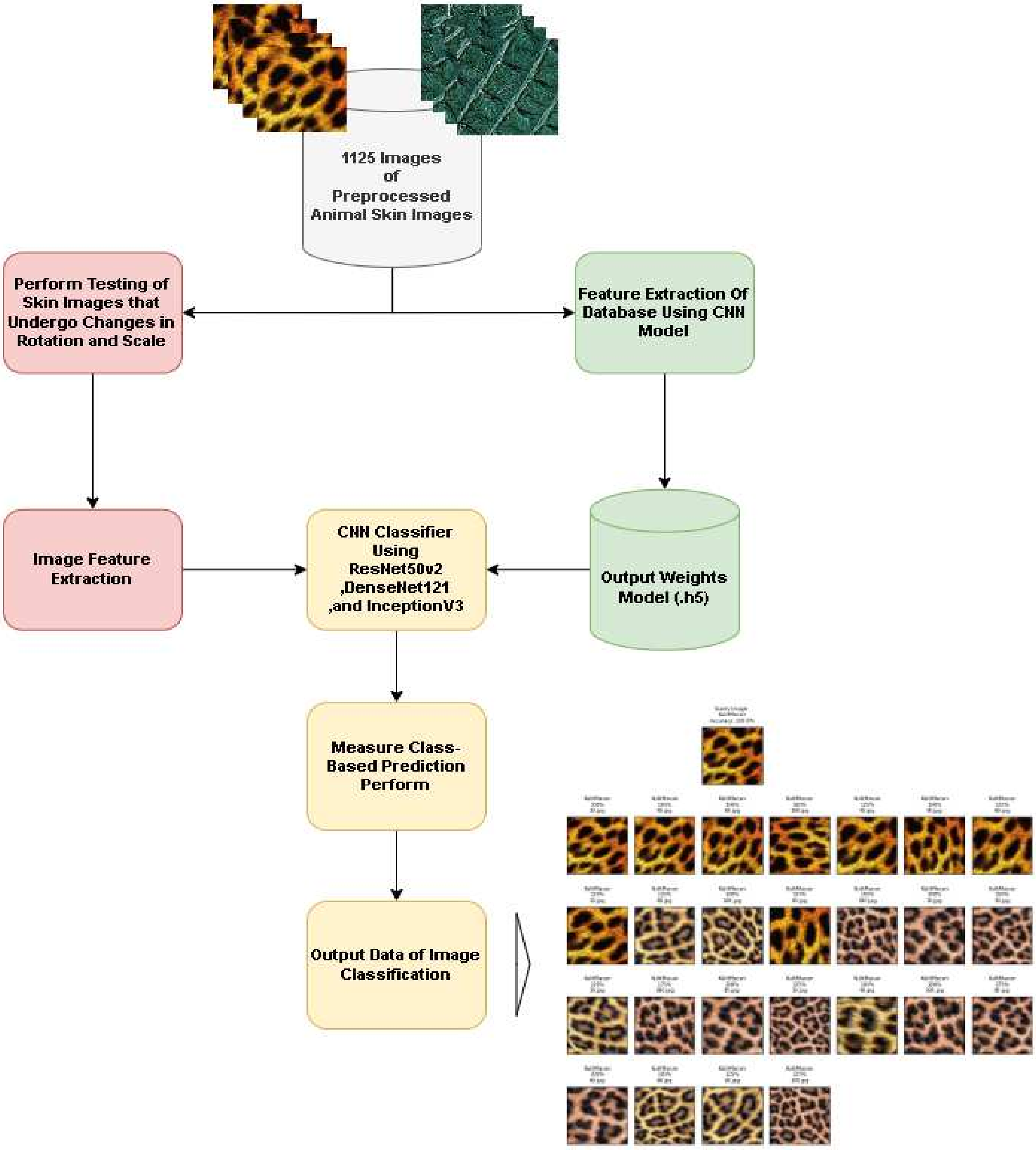

Fig. 4 Animal skin Feature Extraction and classification process

A. Dataset Setup

In the study for the classification of animal skin images, there were 45 images divided into nine classes based on the type of animal. All the images studied have changed scale and rotation simultaneously. Each class of animal skin image has five kinds of animal skins with different patterns. Each animal skin pattern would experience a rotational change of 30, 45, 60, 90, and 180 degrees, then each image that has undergone a rotational change would also experience a scale change of 100, 125, 150, 175, 200% of the original images so that the total animal skin images studied were 1125 images.

B. Preparing Skin Animal Image

Each image would be given a name formatted into two letters followed by a number. In this case, the letters indicate the name, and the numbers indicate the variant of the animal's name. The identification of each image is carried out in this process. For a collection of animal skin images, see Fig. 5.

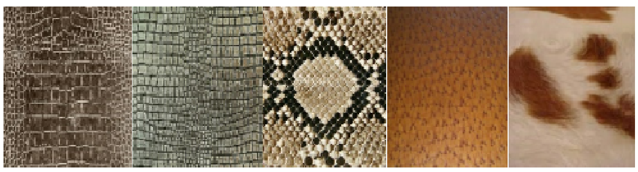

Fig. 5 Resized collected animal skin images 1. Babi 2. Crocodile 3. Lion, 4. Snack 5. Shep

C. Accuracy, Precision, and Recall

To calculate the precision value, there are two necessary variables. The first variable is the number of positive samples the model correctly classified, and the last is the total number of samples classified as positive (whether the model correctly classified them or not). The range value of precision is from 0 to 1, with 0 as its lowest score and 1 as its highest score. This precision value reflects the model's reliability when classifying the positive samples [28]. The result of precision is obtained by dividing only correctly classified positive samples by the total number of positive samples. Compared to precision, a recall is calculated by dividing the number of positive samples that the model correctly classified and the number of total positive samples. Recall completely ignores the negative samples and only focuses on the result of the positive samples [29]. The range is the same as accuracy, precision, and recall measure how many positive samples are correctly classified by the model [30]. Both precision and recall formulas are illustrated below:

$$\text{Precision} = \frac{TRUE_{positive}}{TRUE_{positive} + FALSE_{positive}} \quad (1)$$

$$\text{Recall} = \frac{TRUE_{positive}}{TRUE_{positive} + FALSE_{negative}} \quad (2)$$

$$\text{Accuracy} = \frac{TRUE_{positive} + TRUE_{negatif}}{TRUE_{positive} + TRUE_{negatif} + TRUE_{positive} + FALSE_{negative}} \quad (3)$$

Where:

- TRUE $_{positive}$ = total of positive samples that the model correctly classified
- TRUE $_{negative}$ = total of negative samples that the model correctly classified
- FALSE $_{positive}$ = total of negative samples that the model mistakenly classified as positive samples
- FALSE $_{negative}$ = total of negative samples that the model could not be classified.

III. Result and Discussion

This experiment carried out two methods in pre-processing and three models CNN to get the optimal result in skin animal image classification. The average classification accuracy using 3 CNN models can be seen in the picture Fig. 6.

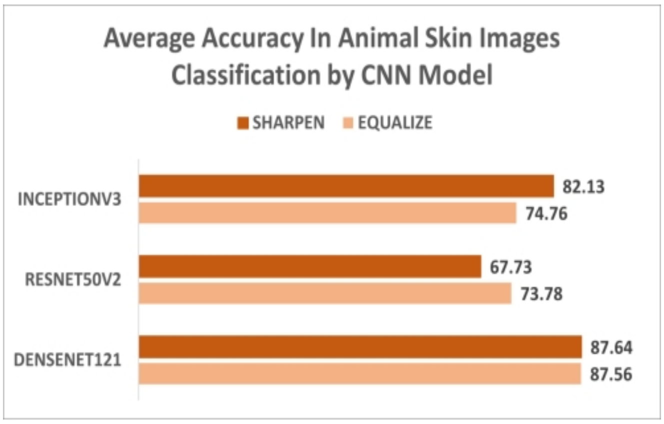

Fig. 6 Average Accuracy of Skin Image Used 3 CNN models and 2 Methods

Fig. 6 describes the results for nine classes of animal skins. For the highest average accuracy on the CNN Densenet 121 model, both were using the image Sharpen and CLAHE methods up to more than 87%. This was followed by the CNN InceptionV3 model, with the Image Sharpen method reaching more than 82%. This result shows that the Convolutional Kernel and CLAHE methods can accurately support animal skin image classification.

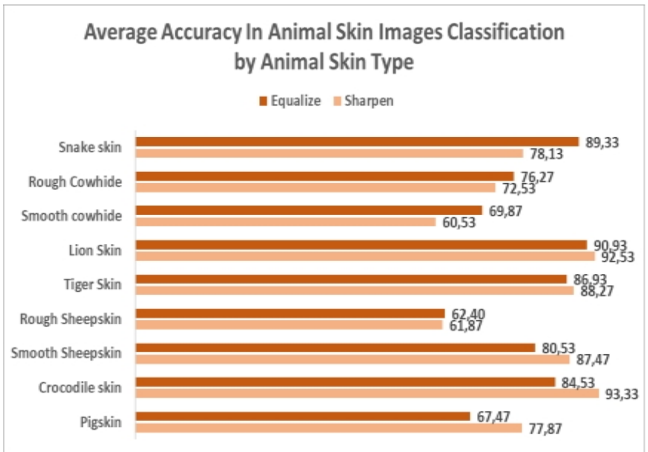

Fig. 7 Average Accuracy of Skin Image Used 3 CNN models and 2 Methods

Fig. 7 describes the results of the average classification accuracy of nine animal skin types that are the object of research. In this experiment, the highest average accuracy on tiger and crocodile skins, including smooth sheep skins, with a range between 86 – 93%. Even crocodile skin can have a classification accuracy of up to 93% using Convolutional Kernel method

Fig. 8 Average Accuracy of Skin Image Used 3 CNN models and 2 Methods

Fig. 8 describes three animal skin images with more than 85% classification accuracy using the Equalized (CLAHE) method. The highest classification accuracy in Lion skin images of up to 90.93% included Tiger skin images of up to 89.33%. However, accuracy performance is not much different from a tiger skin image. It can be concluded that the Sharpen and SUCK Methods are more effective in supporting the accuracy classification, even though the difference between using the two methods is not so high.

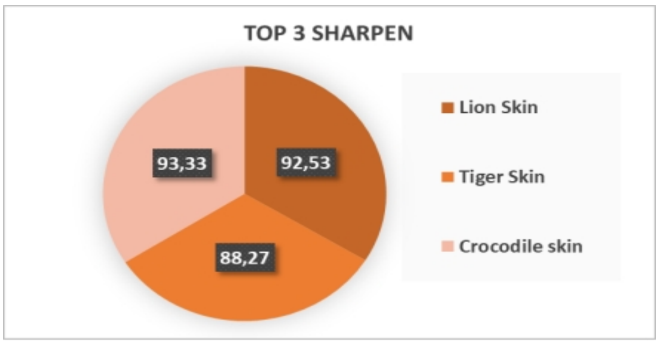

Fig. 9 Average Accuracy of Skin Image Used 3 CNN models

Fig. 9 describes three animal skin images with more than 88% classification accuracy using the Sharpen (Convolutional kernel) method. The highest classification accuracy in Crocodile skin images of up to 93.33%, including Lion Skin images of up to 92.53%. After experimenting to determine three skin animals with the highest accuracy. It can be concluded that the Sharpen / SUCK Method is more effective than CLAHE, even though the difference using the two methods is not so high. The experiment results Used 3 CNN Models, and 2 Pre-processing Methods: Animal Skin Images Classification Used Inception V3 and Sharpen or Equalize Method.

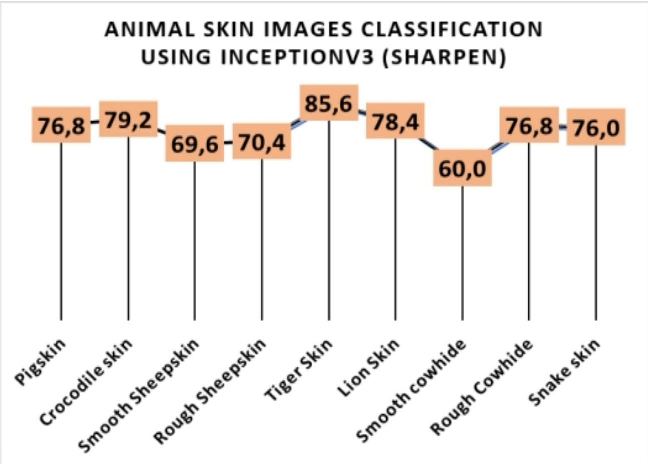

Fig. 10 The Classification accuracy used the Inception V3 model and supported with Sharpen (SUCK).

Fig. 10 describes the experimental results of the classification accuracy of animal skin images using the Inception V3 model and the Sharpen method, where the highest classification accuracy is in tiger skin images up to 85.6%, followed by crocodile skin at 79.2% and other lion skin at 78.4%. In this experiment using the CNN inception V3 model supported by the SuCK method, the average accuracy can be more than 73%. So it can be concluded that the classification process with this model has good results.

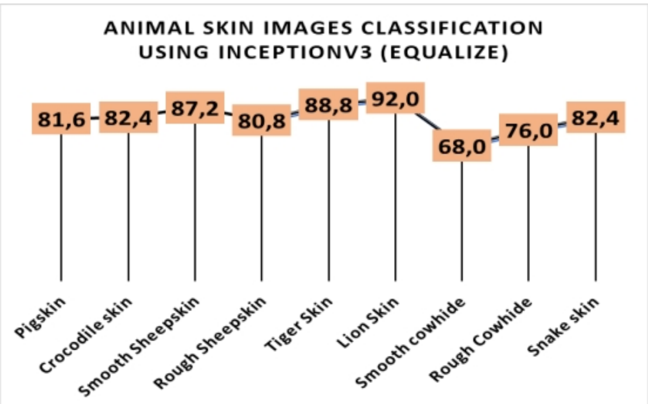

Fig. 11 The Classification accuracy used the Inception V3 model and Supported with Equalized (CLAHE) method

Fig 11 describes the experimental results of the classification accuracy of animal skin images using the Inception V3 model and the Convolutional Kernel (Equalize) method, where the highest classification accuracy is in lion skin images up to 92.0%, followed by Tiger skin images at 88.8% and Snake Skin include Crocodile Skin images at 82.4%. Animal Skin Images Classification Used Resnet50 V2 and supported with Sharpen or Equalize Method.

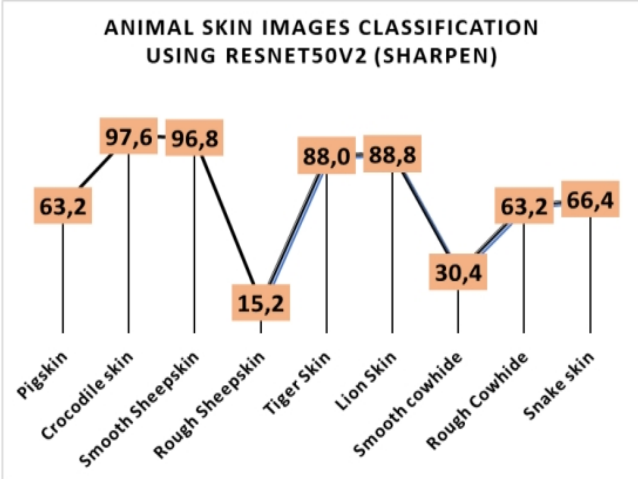

Fig. 12 The Classification accuracy used the Inception V3 model and Supported with Sharpen (SUCK).

Fig. 12 describes the experimental results of the classification accuracy of animal skin images using the Resnet50 V2 model and the Sharpen method, where the highest classification accuracy is crocodile images up to 97.6%, followed by smooths sheepskin at 96.8%, including lion and tiger skin image up to 88%. This experiment shows that some animal skin images have very low classification accuracy, such as rough sheepskin and smooth cowhide. So, this can be input for further research. In this experiment using the CNN Resnet V2 50 model supported by the SuCK method, the average accuracy can be less than 70%. So it can be concluded that the classification process with this model has enough results.

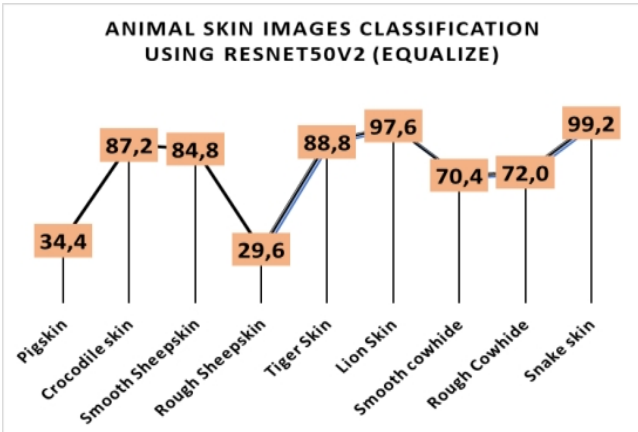

Fig. 13 The Classification accuracy used the Resnet 50 V2 model and supported with Equalized (CLAHE) method

Fig 13 describes the experimental results of the classification accuracy of animal skin images using the Resnet50 V2 model and the Equalize method. The highest classification accuracy is lion skin images at up to 97.6%, followed by tiger skin images at 88.8% and crocodile skin image at 87.2%. In this experiment, it can be seen that some animal skin images have low classification accuracy. So, this can be input for further research. In this experiment using the CNN Resnet V2 50 model supported by the CLAHE method, the average accuracy can be less than 70%. So it can be concluded that the classification process with this model has enough results. Animal Skin Images Classification Used Densenet121 Supported with Sharpen and Equalize Method.

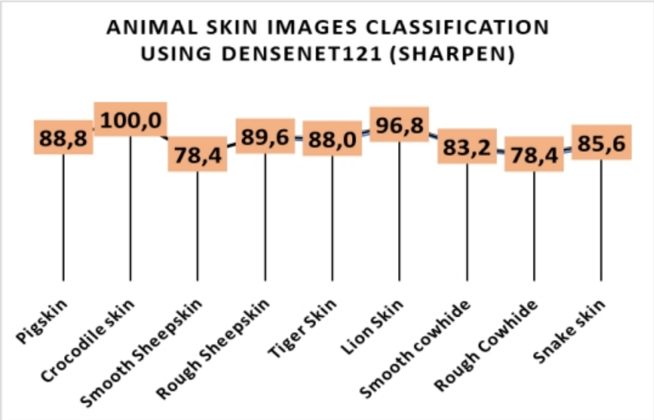

Fig. 14 The Result of classification used the inception V3 model and Sharpen (SUCK) methods

Fig. 14 describes the experimental results of the classification accuracy of animal skin images using the Densenet121 model and the Sharpen method, where the highest classification accuracy is crocodile skin images up to 100%, followed by lion skin images at 96.8% and rough sheep skin at 89.6%. Based on this Experiment Densenet121 combination with Sharpen method has accuracy the highest compared to the other model and method. In this experiment, the resulting classification accuracy is optimal because the average can reach more than 82%. Even though this experiment uses the CNN Densenet121 model supported by the CLAHE method, the average accuracy can be more than 86%. So it can be concluded that the classification process with this model has very good results.

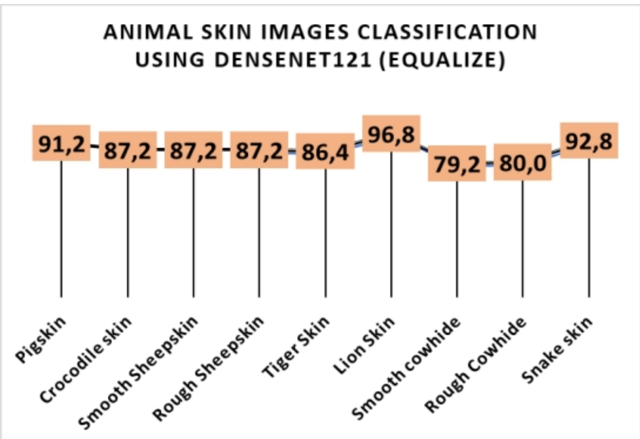

Fig. 15 The Result of classification used the inception V3 model and Equalized (CLAHE)

Fig.15 describes the experimental results of the classification accuracy of animal skin images using the Densenet 121 model and the Equalize method, where the highest classification accuracy is lion skin images at up to 96.8%, followed by Snake skin images at 92.8% and smooth sheep skin at 87.2%. In this experiment, the resulting classification accuracy is optimal because the average can reach more than 85%.

IV. CONCLUSION

In this animal skin research, both inside and outside of the animal skin, in carrying out feature extraction and image classification using 3 Convolutional Neural Network models consisting of Inception V3, Resnet50 V2, and Densenet121. To make the classification process more optimal, it is supported by two pre-processing methods, namely Convolutional Kernel (Sharpen) and CLAHE (Equalize). In experiments, it is hoped to produce optimal classification accuracy of up to above 90%. In these experiments, nine classes of animal skin (inner and outer skin) were carried out with a total of 1125 animal skin images that had undergone changes in rotation and scale.

Based on the experiments, it can be seen that animal images that have the highest accuracy performance start from snake, lion, and tiger skin images, with an average accuracy ranging from 88% - 96%. Even snakes-kin images have an accuracy of between 98% - 100%. However, for several other animal skin images, some have a classification accuracy of less than 50%, some even less than 30%, especially on animal skins that have fine and varied image patterns (inner skin). Thus, this can be a challenge for further research on animal skin images.

This research on animal skin images can be continued later by adding several other animal skins with fine and varied image patterns. Hopefully, this problem of recognizing animal skin patterns can be continued in future studies, including determining whether this is an image of real or fake animal skin.

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