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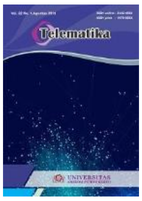

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# CNN-Based for Skin Cancer Classification with Dull Razor Filtering and SMOTE

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**ABSTRACT**

Skin cancer is usually diagnosed by dermatologists through biopsy, which can be a time-consuming process due to limited resources. Early detection of skin cancer can increase the survival rate to over 99%, but if it's detected late, the rate drops to around 14%. This finding highlights the need for a rapid and accurate computing system for early cancer detection, which can prevent severe consequences. The purpose of this study is to classify skin cancer images into benign and malignant classes based on their nature. To facilitate the classification of CNN-based skin cancer, this research employs dull razor filtering. Additionally, the SMOTE method handles the unbalanced dataset. The classification results indicate that the proposed approach has an accuracy of 88.54%, a precision of 88%, and a sensitivity of 88%. These findings suggest that CNN-based methods can aid dermatologists in the diagnosis of skin cancer.

## INTRODUCTION

Cancer is an abnormal growth of cells that can disrupt body function. One of the most frequently diagnosed types in the world is skin cancer, which occurs due to excessive exposure to UV rays (Council, 2016). Cases of death from skin cancer have continued to increase over the last decade. Indonesia ranks third for skin cancer, accounting for 5.9-7.8% of all cancer cases annually after uterine and breast cancers (Wilvestra et al., 2018).

Changes in skin cells in people with skin cancer will become malignant and divide uncontrollably, resulting in DNA damage (Hendaria et al., 2013). There are two types of abnormal cell growth, namely benign and malignant. Benign grows more slowly and is not life-threatening, while malignant can spread to other parts of the body, which can lead to death. Benign can be removed and not grow back, whereas malignant can be removed but will continue to grow. For example, moles are benign, while malignant can cause death with a high mortality rate. Malignant can invade other tissues and spread to other tissues.

Skin cancer diagnosis in the medical field is typically conducted through a biopsy process. During this procedure, a small section of skin tissue is taken and meticulously examined to determine if the tissue contains cancer cells or not. However, due to the limited number of dermatologists, this technique is less effective and requires a significant amount of time and high costs (Gururaj et al., 2023) (Munthe, 2018). On the other hand, the estimated survival rate for people with skin cancer is only around 14% if it is detected too late. However, this survival percentage will increase to 99% if early detection can be done (Esteva et al., 2017). Utilizing images of the patient's cancer tissue allows for early detection and accurate diagnosis with fast computing time. This method helps to distinguish between potentially cancerous skin tissue and benign skin disorders. This method can also help reduce delays in skin cancer treatment for medical professionals.

There have been several studies conducted previously on cancer classification, both using Machine Learning and Deep Learning algorithms, such as Esteva et al. (Esteva et al., 2017), that compared algorithms and dermatologists for classifying malignant melanoma and benign nevus. The pre-trained GoogleNet Inception V3 architecture trained on the ImageNet 2014 dataset can achieve an accuracy value of 93.9%. Hasan et al. (Mehra et al., 2021) reported an 84.87% accuracy for skin cancer classification using ResNet-50, outperforming MobileNet with only 0.79% accuracy (Mohapatra et al., 2021). Similarly, VGG19 has been used to skin cancer classification, achieving 97.5% accuracy on the test set (Abuared et al., 2020). Furthermore, Sa'idah et al. (Sa'idah et al., 2022) utilized a modified GoogLeNet architecture with the CNN to accurately classify benign and malignant skin cancer with 97.73% accuracy with a loss of 1.7063. These findings highlight the reliability of CNN models in skin cancer classification, with GoogLeNet demonstrating the highest accuracy among the architectures studied.

Based on the previous studies on skin cancer, this study aims to

1. propose a method to classify skin cancer images into two classes: benign and malignant, based on CNN with GoogleNet architecture,
2. improve model performance by enhancing image quality through noise reduction using dull razor filtering, contrast enhancement via contrast stretching and contrast limited adaptive histogram equalization (CLAHE), and addressing data imbalance with SMOTE (synthetic minority over-sampling technique) (Mohammed, 2020).

## RESEARCH METHODS

This study used skin cancer dataset taken from Kaggle (Fanconi, 2019) that consisted of 1800 RGB images, in *.JPG format with the resolution of 224x244 pixels. The dataset consists of 1440 images of benign and 1197 images of malignant, as shown in Figure 1. There are four main stages conducted, i.e. pre-processing, data preparation, modelling, and evaluation as described in Figure 2.

(a) (b)

Figure 1. The characteristic of skin cancer: (a) benign; (b) malignant (Fanconi, 2019).

**1. Pre-Processing**

This research applied three methods to process images: dull razor filtering, contrast stretching, and contrast limited adaptive histogram equalization (CLAHE). A study on the effect of image quality on melanoma classification (Kamas & Akkoca, 2021) highlights the impact of image contrast, noise, and additional object on classification performance. To address the presence of additional objects, dull razor filtering has shown promising result in hair removal, leading to high accuracy (Sa'idah et al., 2022), leading to high accuracy. Meanwhile, contrast and noise issue can be mitigated using contrast stretching and CLAHE, as demonstrated by Erwin (Erwin, 2020) who successfully enhanced image quality, resulting in improved classification performance.

Dull Razor Filtering replaces a pixel's value with the average value of the surrounding pixels when deleting it. In this way, noise or interference in the pixels will be removed, and the image will look clearer. In images of the skin epidermis, dull razor filtering will remove noise from hair objects so that the skin cancer area can be seen more clearly (Sa'idah et al., 2022). First, this method will identify hair pixels that tend to be dark/black. Nearby non-hair pixels replace hair pixels and thin lines near hair boundaries are removed (Lee et al., 1997).

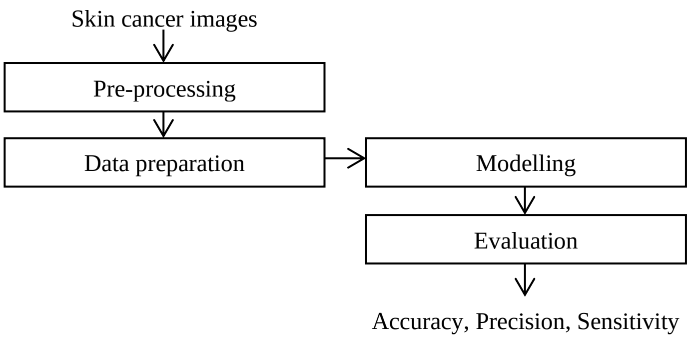



Figure 2. The main stages of proposed approach

Contrast Stretching is a quality improvement technique often used in medical images (Radha & Tech, 2012). The method enhances image contrast by dynamically stretching intensity values (Erwin, 2020). Contrast stretching widens the range of pixel values in an image, resulting in higher contrast. To perform contrast stretching, we must first determine the minimum and maximum pixel values to be adjusted. Then, pixel values outside the lower and upper limits will be limited according to these limits. At the same time, pixel values within the lower and upper limits will be returned to a wider scale. By using this method, improvements can be made to images of skin epidermis that experience noise or that has too bright/dark contrast (Faradilla et al., 2022).

The CLAHE method is a development of the HE and AHE methods, which functions to increase contrast in images that have an uneven distribution of pixel values (Erwin, 2020). This method increases image detail by dividing it into tiles and applying histogram equalization. After that, the pixel value on each tile will be returned to a wider scale so that the image contrast becomes higher. However, to prevent over-saturation or over-exposure in the image, CLAHE uses a clipping limit to limit the number of pixels that will be returned to a wider scale.

## 2. Data Preparation

The dataset must be prepared before training the CNN model. In the train data, the benign class consists of 1440 images, while the malignant class consists of 1197 images. This unbalanced amount of data can affect the performance of machine learning models, ranging from biased predictions over fitting to poor evaluation metrics (Brownlee, 2020). A biased model will perform poorly for minority classes, and the model may not be able to classify or predict outcomes for those groups accurately. An over fit model can perform well on training data but poorly on new data. This is because the model may have learned patterns specific to the training data and not representative of the population. In this study, to address the problem of unbalanced datasets, the SMOTE method was employed. SMOTE is a widely used and highly effective method for oversampling in various domains of applications. This method creates synthetic samples by analysing existing minor class data. SMOTE creates synthetic samples, a linear combination of two samples from the minor class (Mohammed, 2020).

In this research, the dataset is split into three folders: train, validation, and test. In the dataset used, there are separate train and test data. Additionally, validation data was included to optimize the performance and reliability of the resulting model. The training dataset is a subset of the complete dataset that was used to train the model. To evaluate the model being trained, a validation dataset is used, not a test dataset. This is so that the test dataset will only evaluate the model after training. In this way, the model that has been trained will be tested using data that the model has never seen before, thus providing a more accurate picture of the model's performance on new data. The validation dataset is obtained by dividing the contents of the training dataset into 2, 80% for train and 20% for validation (Yohannes & Al Rivan, 2022).

In developing machine learning models, data augmentation needs to be carried out to increase the diversity of training data, prevent over fitting, and increase model generalization to perform well on new, unseen data. Augmentation will apply random transformations to existing data (Mahmud et al., 2019). For example, an image can be transformed by rotating it, flipping it horizontally or vertically, or adding noise to the image. This transformation generates a slightly different version of the original image, enabling the model to recognize the fundamental characteristics of the image, despite variations in the data. Augmentation is significant when the training dataset is small or when it is difficult or expensive to collect more data. By adding existing data, it is possible to train models on larger and more diverse datasets without collecting additional data. In this research, the augmentations used are shear, zoom, rotation, and horizontal flip. In addition, normalization is carried out on the image so that the processed pixels range between 0 and 1 (Mahmud et al., 2019)(Wijaya et al., 2021).

In this study, no segmentation process was carried out, judging from various references to CNN model development, which did not carry out a segmentation process but still produced good evaluation values, as in research (Sa'idah et al., 2022), which only underwent the stages of data acquisition, pre-processing and model training. Other research (Luqman Hakim et al., 2021) did not undergo segmentation stages but rather data pre-processing, data augmentation, model training, and model evaluation.

## 3. Modeling

A Convolutional Neural Network (CNN) is a type of neural network composed of convolutional layers, pooling layers, and fully connected layers (logic layers) [18]. CNN uses convolution operations in matrix multiplication in each layer. The CNN architecture is composed of convolutional, pooling, and fully-connected layers.

The model used to classify skin cancer in this study was developed using the CNN method with the GoogleNet architecture. The CNN architecture is designed to carry out both feature extraction and classification processes CNN uses feature maps extracted from 2D images for classification. Most CNN architectures share common design principles: applying convolution layers to input data, performing down-sampling on the spatial dimension through Max pooling, and regularly increasing the number of feature maps. There is an additional layer in the neural network called the fully connected layer, which is also referred to as the logic layer. This layer is followed by an activation function and a loss function. At the core of CNN are the convolution, pooling, and logic layers (Mustafa et al., 2022). The implemented architecture can be seen on Figure 3.

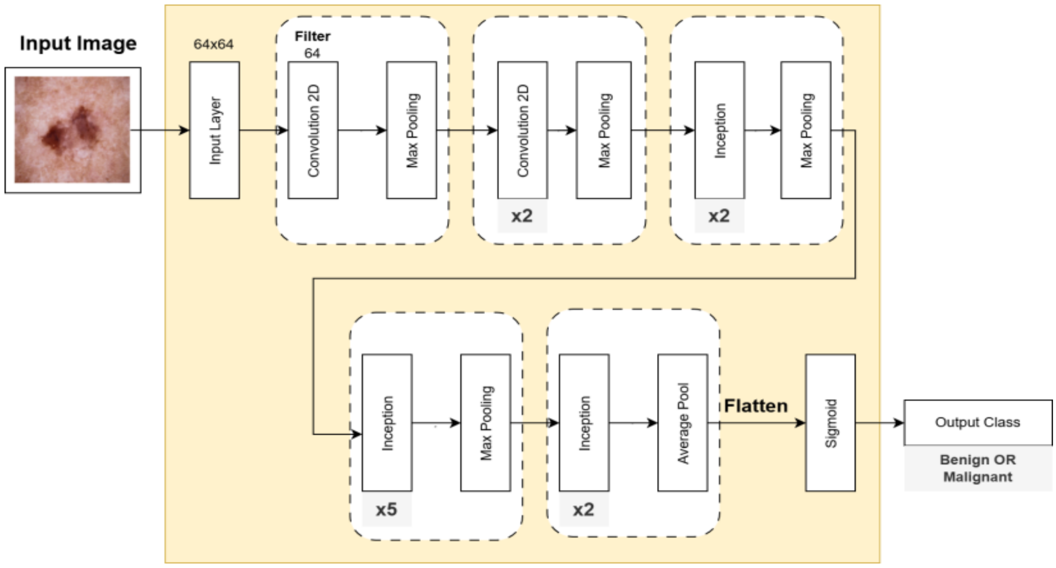



Figure 3. Prominent component of the implemented GoogleNet architecture

The GoogLeNet architecture is a modification of the CNN architecture, which achieved the best model in ILSVRC14. This architecture can accurately detect images with 5 to 22 layers. The deep network relies on activation values, which require unconnected activations due to prior correlation. To meet the necessary conditions, GoogLeNet has inception modules inspired by the human visual cortex model. These modules optimize sparse structures to support computation.

In the GoogLeNet architecture's inception module layer, a 1 x 1 matrix convolution precedes convolution with 3 x 3 and 5 x 5 matrices. This method reduces module dimensions, increasing analysis depth and system performance. In general, in the GoogLeNet architecture, the convolution and pooling layers function to extract data, the inception module functions to reduce the computational load and increase the depth of the data, and the fully connected layer functions to accommodate the results of the pooling layer process at the end of the GoogLeNet architecture. The output will be replaced with global average pooling, which reduces parameter size without sacrificing accuracy (Sa'idah et al., 2022).

This research implements the GoogLeNet architecture in that study (Sa'idah et al., 2022) with modifications to the augmentation stages and parameters. The model is designed to differentiate between benign and malignant skin cancer. In the training process, 125 epochs were completed with a batch size of 32. Table I shows the GoogLeNet architectural model used in this research.

In this research, the convolution and max pooling processes carried out simultaneously are combined into one concatenation. Next, move on to the classification stage which begins with the flatten function that transforms the data arrangement into a single dimension. Restrict incoming neurons with Dropout. Use sigmoid activation to classify skin cancer as benign or malignant.

**4. Evaluation**

In this study, the evaluation process was carried out using a confusion matrix to produce accuracy, precision and sensitivity/recall values, and AUC-ROC curve to measure the model ability to distinguish between classes (Rajput et al., 2022). The accuracy value measures the proximity between the predicted and actual values, and can be expressed as truth or error accuracy. To assess the impact of each image pre-processing step, an ablation study is conducted by applying each pre-processing technique individually.

## RESULTS AND DISCUSSION

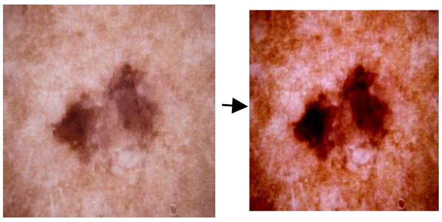
During the pre-processing stage, the skin epidermis image undergoes three filtering methods: dull razor filtering, dull razor filtering with contrast stretching, and dull razor filtering with CLAHE. Image pre-processing is carried out to remove noise and improve image quality, which will later be used in developing the CNN model. The results of the implementation of dull razor filtering can be seen in Figure 4, where the fine hair in the image was successfully removed.

(a) (b)

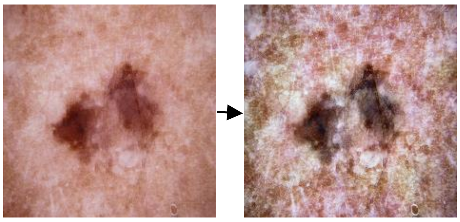
Figure 4. Results of applying dull razor filtering to skin images:
(a) original image; (b) dull razor image

As shown in Figure 3, dull razor filtering succeeded in removing fine hair from the image. This step involves reprocessing the filtered image with contrast stretching and CLAHE methods to enhance its quality and contrast. A comparison between the contrast stretching and CLAHE methods' image processing results is presented in Figure 5.

The contrast stretching method usually yields images with a red and dark appearance, whereas the CLAHE method produces bright and sharp images. In the dataset preparation phase, the first step is to tackle the problem of unbalanced data by applying the SMOTE method to the resulting image.



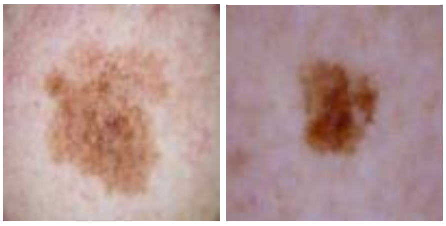
(a)



(b)

Figure 5. The comparison of pre-processing result: (a) dull razor with contrast stretching; (b) dull razor with CLAHE

In the training dataset, there are 1440 images in the benign class and only 1197 in the malignant class. The SMOTE method generates synthetic samples by combining two samples from the minor class to address the disparity in image numbers. As a result, the malignant class will experience up-sampling so that the number becomes 1440, equivalent to the number of benign classes. The Figure 6 displays the synthetic sample generated by using this method.



(a)

(b)

Figure 6. (a) original image; (b) synthetic image resulting from SMOTE

The available training dataset is split into two parts, namely train and validation datasets, in an 80:20 proportion respectively. Based on the results obtained from this division, we can determine the proportion of data that will be processed for training purposes. Specifically, out of the total dataset, 2304 data will be used for training, 576 data for validation, and 550 data points for testing.

An augmentation process is performed to enhance the diversity of the training data, prevent over fitting, and improve the generalizability of the model. This process makes the dataset more diverse, allowing it to perform well on new and unseen data. The augmentation process will apply random transformations to existing data. The transformations used in this research are shear, zoom, rotate, and horizontal flip. These transformations were applied for augmentation. The changes resulting from the augmentation process are visible in Figure 7.

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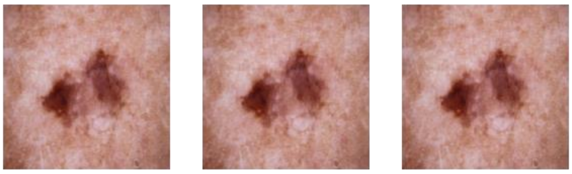
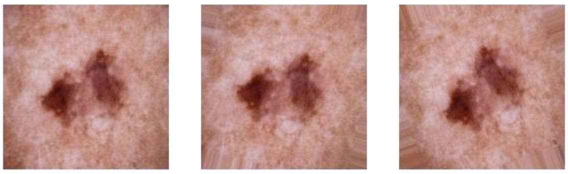
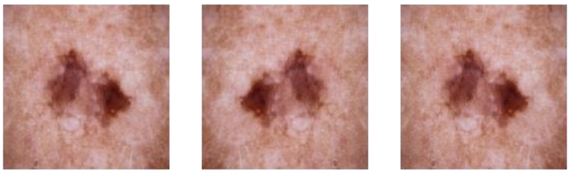


(a)

(a)



(b)



(c)

Figure 7. Image augmentation results with various transformations: (a) shear; (b) zoom; (c) rotate; (d) flip

In Figure 7, the rotation operation has a maximum rotation value of 20 degrees (rotation), a maximum magnification of 20% (zoom), a maximum distortion along the x-y axis of 20% (shear), and the possibility of the image being flipped horizontally. The relatively small parameter values are not visible to the human eye but help the model to learn images with more diverse characteristics. The augmentation process is carried out randomly, so the transformation value is different for each image.

Once the dataset is augmented, it can be used to train a CNN model with the GoogLeNet architecture. The model will classify data into two classes, namely benign and malignant. The model's performance will be assessed using accuracy, precision, and sensitivity metrics. A comparison of the classification results based on differences in treatment during the data pre-processing process is presented in Table 1.

Table 1. Performance evaluation of GoogleNet across different preprocessing techniques.

| Image Characteristics | Accuracy (%) | Precision (%) | Sensitivity %) |
|---|---|---|---|
| No Pre-processing | 85.27 | 88 | 87 |
| ***Dull Razor*** | **88.54** | **88** | **88** |
| *Dull Razor + Contrast Stretching* | 85.63 | 87 | 87 |
| *Dull Razor + CLAHE* | 85.63 | 86 | 86 |

According to Table 1, the Dull Razor Filtering method produces the highest accuracy values when used alone on images. The result suggest that object removal significantly enhance model performance by reducing distractions in lesion images, while excessive contrast and noise modifications may introduce noise or distort lesion features. To further assess the model effectiveness, we evaluate its performance using confusion matrix in Figure 8. In the confusion matrix, the rows depict the actual values, while the columns depict the predicted values. The result displays evaluation of a model that accurately distinguishes between benign and malignant with an 88.54% accuracy rate, with both precision and sensitivity at 88%, indicating a well-balanced performance. This balance is crucial for clinical applications, as high sensitivity minimizes the risk of misclassifying malignant cases, ensuring early detection and reducing the likelihood of undiagnosed skin cancer.

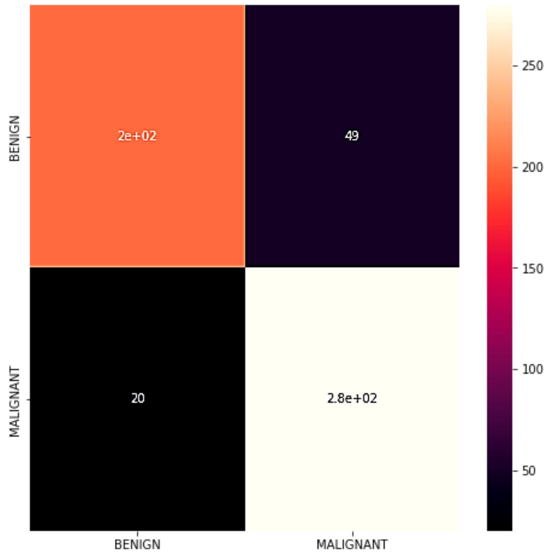
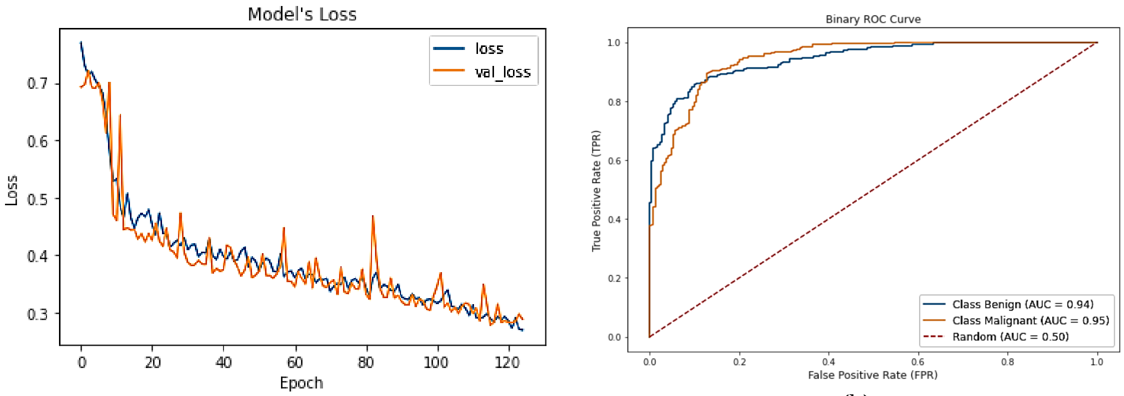



Figure 8. Confusion matrix CNN model

To evaluate the performance of a model, we can check if the loss curve indicates a good fit. A model is considered fit if the loss curves and validation loss curve both decrease to the stability point and have a small distance between them (Brownlee, 2018). The training curve of the GoogLeNet CNN model exhibits these characteristics, as shown in Figure 9, although some fluctuations remain. Additionally, model performance is further assessed using the AUC-ROC curve, which measures the model's ability to distinguish between benign and malignant cases. The area under the curve (AUC) values are 0.94 for the benign class and 0.95 for malignant class, indicating high discriminative ability and enabling the model to effectively differentiate between the two classes. The AUC value is competitive with the current state-of-the-art (SOTA) model for skin cancer classification (Ha et al., 2020), which achieves an AUC of 0.96.




(a) (b)

Figure 9. GoogLeNet CNN model training's (a) loss curve; (b) AUC-ROC curve

## CONCLUSIONS AND RECOMMENDATIONS

This study has presented a novel scheme for completing the research regarding the classification of skin cancer, especially benign and malignant cancers. The performance evaluation result which consists of accuracy, precision, sensitivity, and AUC-ROC reached up to 88.54%, 88%, 88%, and 0.94 respectively. These results were obtained from the skin cancer image classification process by applying the GoogleNet architecture to the CNN model and the dull razor filtering method at the pre-processing stage. This study also applied the SMOTE method to overcome imbalanced datasets. The evaluation results indicate that the proposed scheme can classify skin cancer images well and is expected to help dermatology detect and diagnose skin cancer to preclude worse effects. However, further CNN-based research must continue to be carried out to achieve maximum skin cancer classification performance.

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