Skin Cancer Detection Approach Using Convolutional Neural Network Artificial Intelligence

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Abstract

Skin cancer is a type of cancer that can cause death, where skin cancer is included in the 15 common cancers that occur in Indonesia. The number of skin cancer sufferers was around 6,170 cases of non-melanoma skin cancer and 1,392 cases of melanoma skin cancer in 2018 in Indonesia. Therefore, research related to skin cancer classification is increasing. This is done as an initial step in detecting whether a lesion can be said to be cancerous or not. The deep learning approach has certainly shown promising results in carrying out classification, so this research proposes a deep learning-based method used for skin cancer classification. The proposed approach involves Convolutional Neural Networks with the ISIC 2017 dataset. The models used for skin cancer classification are InceptionV3, EfficientNetB0, ResNet50, MobileNetV2, and NASNetMobile. The highest accuracy of the single model produced reached 69.3% using the MobileNetV2 model. An ensemble model combining the five models was also tested and produced the highest accuracy compared to other single models with an accuracy result of 80.6%.

Keywords: Skin Cancer, CNN, InceptionV3, EfficientNetB0, ResNet50, MobileNetV2 dan NASNetMobile

1. Introduction

The skin is an organ that covers the entire human body where abnormalities that attack the skin are called skin diseases [1]. Skin diseases caused by viruses, bacteria, fungal infections, or allergies [2]. Genetic factors are also one of the causes of skin disorders [3]. One of the diseases that attacks the skin is skin cancer. Skin cancer is a type of cancer that originates from skin cells [4]. According to WHO, in Bangladesh around 2794 died from skin cancer in 2018, WHO also stated that globally in 2018 more than 14 million cases were diagnosed, and deaths reached 9.6 million [5]. In Indonesia alone, skin cancer is included in the 15 common cancers that occur in Indonesia, where some people have a higher risk of contracting skin cancer than others, with the number of skin cancer sufferers around 6,170 cases of non-melanoma skin cancer and 1,392 cases of melanoma skin cancer in 2018 [6].

The highest incidence rates of skin cancer are usually found in countries with high levels of sun exposure and white populations [1]. The two most common types of skin cancer are basal cell carcinoma and squamous cell carcinoma, while the skin cancer that is most dangerous and causes death is melanoma [4][7]. Most types of skin cancer caused by exposure to UV rays[7]. UV rays are a type of invisible radiation that comes from the sun, tanning beds, and sunlamps. UV rays can penetrate and change cells in the skin [6]. It is very important to remember that skin cancer is a disease that can be prevented, where preventive measures can reduce the risk of developing skin cancer, but if the severity is not paid attention to, skin cancer can be fatal and even cause death. [1] [8].

In determining the presence of skin cancer, it is determined from the skin lesions, where the growth of abnormal skin lesions is an indication of skin cancer. Skin lesions indicative of cancer is classified into malignant and benign, malignant lesions indicate skin cancer which can cause death and vice versa [7]. In the conventional method, the doctor analyzes the skin lesion with the help of a dermatoscope and classifies it based on his expertise and then if it is identified

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that the lesion is malignant, he will be advised to carry out a biopsy [4]. Lesions that are difficult to diagnose are prone to misdiagnosis [8]. Conventional diagnosis often takes a long time, so fast early detection is needed to identify skin cancer. Computer-assisted automated systems that rely on sophisticated algorithms can provide benefits in classifying skin diseases more quickly and accurately [5]. Deep Learning Algorithm can provide satisfactory results in computer aided cancer diagnosis (CAD) in various types of cancer, one of which is skin cancer so that the application of Deep Learning Algorithm can provide accurate and efficient results for detecting skin cancer at an early stage [1].

2. Literature Review

Early detection of skin cancer is very important as a means of preventing the severity of the disease. Currently, various imaging techniques have been widely used and developed, especially for skin cancer, one of which is the use of Convolutional Neural Network (CNN) which provides promising results in classification [1]. In this section, several research articles related to the use of CNN in the detection and classification of skin cancer are reviewed. Research by Vipin Venugopal et al. [8] testing the deep neural network DNN network with fine-tuned training and improving learning performance on dermoscopic images to detect skin cancer. This classification uses EfficientNetV2-M and EfficientNet-B4. The dataset used in this research is ISIC data (ISIC 2020, ISIC 2019, and ISIC 2018 databases) refined with 58,032 dermoscopic images. Transfer learning and fine-tuning are applied for faster training of the proposed model on a limited training data set. Transfer learning and data augmentation techniques are applied to improve generalization ability and prevent overfitting of the model. From the research experiments carried out, the DNN network with modified EfficientNetV2-M outperformed deep learning-based multiclass classification models.

Other research has classified skin diseases, namely acne, keratosis, eczema herpeticum and utricaria. The dataset used was obtained from Dermnet with the method used is CNN and uses a maximum pooling layer in the classification system. With a learning rate of 0.01, the accuracy in each class was 85.7%, 92.3%, 93.3% and 92.8% for the skin diseases acne, keratosis, eczema herpeticum and utricaria [9]. Ashutosh Lembhe et al. [6] also carried out skin cancer classification using several different CNN methods from this research, namely feature extraction which applies General Adversarial Networks) to increase image resolution to become images that have high resolution (Image Super Resolution). The models used are VGG16, ResNet and Inception V3. Using Image Super Resolution (ISR) in the feature extraction process can increase initial accuracy by 15.59% for VGG16, 13.85% for ResNet, and 7.78% for InceptionV3. So, the final accuracy results were found to be 70.17%, 86.57% and 91.26% respectively for VGG16, ResNet and Inception V3.

Abdurrahim Yilmaz et al [10] classify skin cancer using the ISIC 2017 dataset. This research compares three CNN methods, namely MobileNet, MobileV2 and NasNetMobile. In general, in its implementation, the general properties used are image shape (224, 224, 3), dropout 0.2, 2D Pooling size 2x2, and the number of epoch numbers is 150. This research conducted experiments with different batch sizes for each model, as for the number of batches. sizes used are 16, 32 and 64. The average accuracy results of the MobileNet, MobileNetV2, and NASNetMobile models are 79.60%, 80.30%, and 79.70% respectively where the NasNetMobile model with a batch size of 16 produces accuracy the highest reached 82% with a precision of 81.77%. This research also concludes that models with small batch sizes have much better performance in class generalization.

CNN development was also carried out by E. Gomathi et al. [11] using the dual optimization based deep learning network (DODL) method to detect skin cancer. DODL is a dual optimization algorithm which is a combination of BFO and PSO used to extract features from segmented images. Model testing using the DODL method was carried out using different datasets, namely MINIST HAM 10000, ISIC 2020, Dermnet dataset and PH2 dataset. Accuracy results respectively reached 98.76%, 98.02%, 96.25% and 97.46. The research that will be carried out is to classify the types of skin cancer, whether the skin cancer images are categorized as malignant or benign skin cancer. The models used are InceptionV3, EfficientNetB0, ResNet50, MobileNetV2, NASNetMobile and ensemble model with the aim of finding out how far each model is accurate in classifying skin cancer.

3. Methodology

This section explains the dataset used and the classification methodology used to classify skin cancer.

3.1. Dataset

A dataset is a collection of data that is used to train, validate, and test the model that will be used. The dataset itself is an important component because it has a significant impact on model performance. A good dataset is a dataset that is diverse, balanced, unbiased, does not contain errors and is also large [12]. The dataset must have labels. The dataset used in this study is a popular dataset sourced from the International Skin Imaging Collaboration (ISIC) where ISIC has more than 25,000 clinical images of skin lesions including lesions related to skin cancer [1]. The ISIC archive itself has a collection of skin cancer data from more than one institution, apart from that, data from ISIC continues to grow by combining different data sets every year[13]. he details of the dataset with a total of 2,750 data that will be used can be seen in Table 1.

Table 1. Data ISIC 2017

Kondisi Kulit	Total	Type of Cancer
Melanoma	*521*	*Malignant*
Nevus	*1843*	*Benign*
Seborrheic keratosis	*386*	*Benign*

Fig. 1. Type of Skin Cancer

3.2. CNN

The general methodology used for skin cancer classification is by inputting skin images according to the dataset taken as input to the model. Images in the dataset will be processed using a CNN that identifies objects, then the model performs learning on the dataset by differentiating between melanoma (malignant) skin cancer and non-melanoma (benign) skin cancer[14]. CNN itself has a performance like neurons in the human brain. Where CNN can recognize an object with various characters because it processes translation invariance [15]. By utilizing the features in the Convolutional Neural Network (CNN), the stages in this classification are preprocessing the image data then feature extraction for further classification. The data preprocessing carried out before classification is image resizing, image normalization, image augmentation, image filtering, image segmentation which is then continued with feature extraction [1]. The architecture of a Convolutional Neural Network has several layers, namely fully connected layer, pooling layer, convolution layer, rectified linear unit layer [1] [16].

Convolution layer: This layer consists of neurons connected between small areas and the input image and is called a filter. The filter size itself can be specified as 5x5, 7x7, 9x9 or so on. The weights used for the filter use the formula h × w × c, where h: height, w: width and c: the depth of an image. The total parameters in the convolution layer are calculated using equation (1) while the output size can be predicted using equation (2). The description explains the function of two-dimensional convolution in general [9].

$$Total\ Parameters\ =\ (h\ \times w\ \times\ c\ )\ +\ 1 \tag{1}$$

$$Size\ of\ Convolution\ layer = \frac{\{I\ /\ p\ Image\ size - Filter\ size + 2 * Padding\ \}}{Stride} + 1 \tag{2}$$

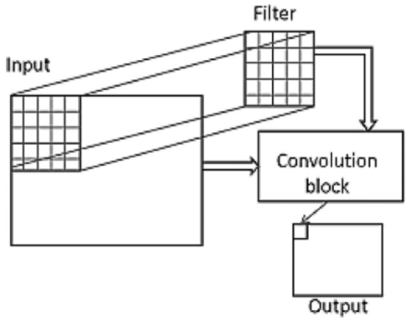

Figure 2. Dimension convolution operation [9]

Rectified linear unit layer (ReLU): is one of the activation functions. This layer performs a threshold operation on the entire image which functions to eliminate negative values in the image[9][17]. The way relu works is by changing negative values to 0 [17].

$$f(x) = \begin{cases} x(x \geq 0) \\ 0(x < 0) \end{cases} \quad (3)$$

Pooling layer: The output from the relu layer is fed into this layer. The image will be divided into several parts according to the specified layer size where the method used in this process is max pooling by selecting the largest value in the matrix, this is shown in Figure 2 [9][17].

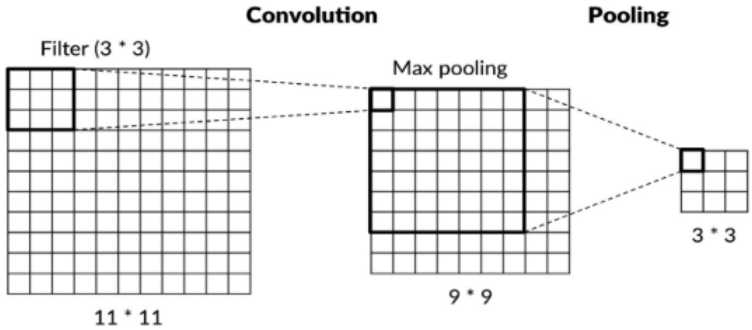

Figure 3. Maximum Pooling Operations [9]

Fully connected layer: is the last layer with full connection by multiplying the output of the previous layer with a matrix and weights and then a bias vector is added to it. This is done to categorize input images into predetermined classes [9].

The next process will produce an output layer which is the model output layer with the prediction class of the input image, for example the benign or malignant category of skin cancer, which is the result of the model. Apart from that, there is also a CNN architecture that combines dropout, batch normalization, and data augmentation to improve the performance and generalization capabilities of the model [1]. The general CNN architecture can be seen in Figure 3.

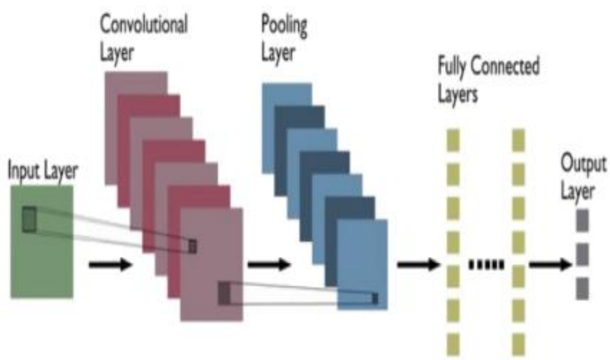

Figure 4. Convolutional neural networks architecture [1]

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Then this subsection will discuss various Convolutional Neural Networks (CNN).

3.2.1. InceptionV3

InceptionV3 is a CNN that focuses on using less computing power [18]. GoogLeNet Inception is more computationally efficient with respect to time and parameters. The InveptionV3 architecture itself is built step by step starting from factored convolution which results in reducing parameters in the network. This serves to streamline computing which is then continued with smaller convolutions to speed up training [15]. In short, inception is a deep learning architecture that combines filters of different sizes in parallel to capture features at different scales, thereby allowing the network to capture features locally and globally to further improve model performance [1].

3.2.2. EfficientNetB0

It is a neural network architecture that aims to improve the work of CNN. EfficientNet itself makes the model more efficient in terms of the number of parameters and computational costs [19]. EfficientNet uses a combination of depth-based scaling and convolution, which allows it to achieve good performance with fewer parameters as depicted in figure 4. This is what makes EfficientNet the choice for applications with limited computing resources [20].

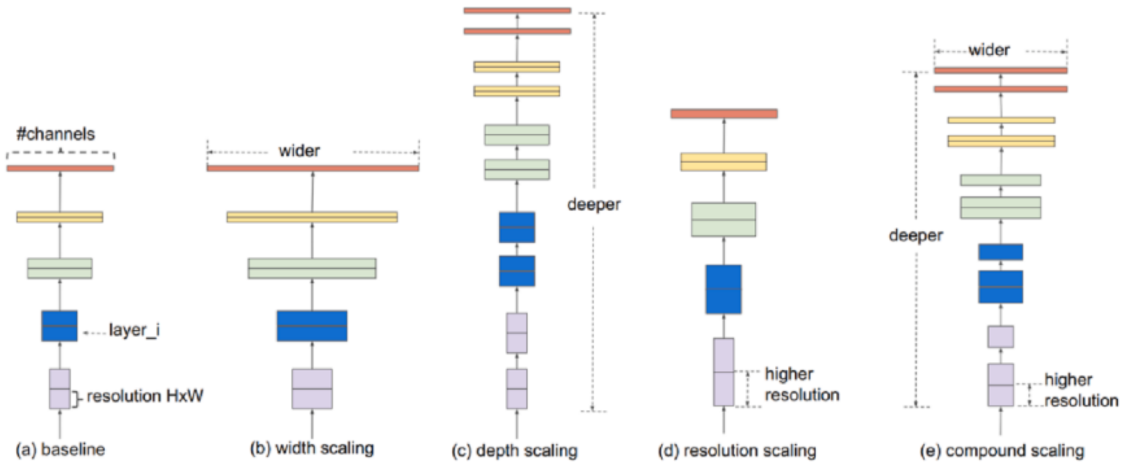

Figure 5. EfficientNet Architecture [20]

3.2.3. ResNet50

Residual Network (ResNet) is a type of neural network that is widely used in computer vision work such as object detection, image recognition, and so on [1]. CNN models, such as ResNet, improve prediction performance significantly [21]. The resnet layer consists of two components, namely the identity shortcut connection and the residual block. The resnet network itself in short is a layer that takes input x then applies a series of convolutional layers by performing batch normalization and activation functions to obtain f(x) then adds an identity shortcut connection to store information from the input and ends with the output of the convolutional layer and an identity shortcut connection to get the output of layer [1].

3.2.4. MobileNetV2

MobileNetV2 is a convolutional neural network with a depth of 53 layers [22]. One of the Deep CNN networks that is widely used for image classification, categorization, segmentation, etc. is MobileNet. The creation of MobileNet is based on depth separable filters where the focus of the MobileNet model is to optimize latency with a small network and create a suitable model for implementation. The MobileNet architecture is combined with two steps, namely deep convolution and vertex convolution [23].

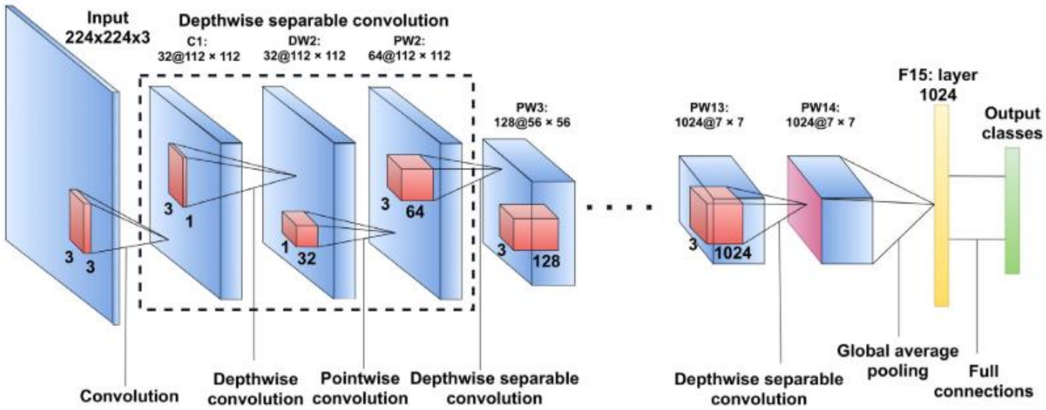

Figure 6. MobileNet Architecture [23]

3.2.5. NASNetMobile

A model that aims to find the best parameters and create the best model by generating NASNet. NAS itself is a Neural Architecture Search which automates search and finds the best algorithm [13]. This method utilizes a parent AI called 'the controller' which is a Recurrent Neural Network (RNN). The NASNetMobile architecture is more reliable than NASNetLarge due to the significant difference in the number of parameters [10].

3.2.6. Ensemble Model

Ensemble models are learning that combines several individual models to get better performance. Ensemble models are broadly categorized into bagging, boosting, stacking, negative correlation based deep ensemble models, explicit/implicit ensembles, homogeneous/heterogeneous ensembles, Decision fusion strategy based deep ensemble models [24].

3.2.7. Bagging

Bagging is a method that can improve the results of machine learning and deep learning classification algorithms by combining classification predictions from several models. This is used to overcome instability in complex models with relatively small amounts of data [25]. Bagging is one of the earliest discovered and simplest ensemble-based algorithms but has been proven to be effective [26] [27].

4. Results and Discussion

In this research, trials were carried out with several conditions as in table 2. The architecture used in this trial used InceptionV3, EfficientNetB0, ResNet50, MobileNetV2 and NASNetMobile. In this trial, the time required is relatively small because the epochs used in each model are few. Based on the universal features of the model, image data is made uniform by changing its size to 299 x 299 x 3 for InceptionV3, EfficientNetB0, ResNet50 and 224 x 224 x 3 for MobileNetV2 and NASNetMobile using the TensorFlow framework in Python. As for each trained model, set trainable to False so that it can adjust the previously trained weights and add a final output layer which is expected to produce a value between 0 and 1 where 0 is closer to benign cancer and vice versa. Due to binary classification, the model continues using binary crossentropy loss accuracy.

Table 2. General Properties

Property	Value
Data size	2750
Image Shape (InceptionV3, EfficientNetB0, ResNet50)	299 x 299 x 3
Image Shape (MobileNetV2 & NasNetMobile)	224 x 224 x 3
Epoch Number	10
Batch Size	64
Optimizer	rmsprop

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Table 3. Results Accuracy

	Accuracy	
Model	**With Threshold**	**Without Threshold**
InceptionV3	65.5%	**80.6%**
EfficientNetB0	59.0%	80.0%
ResNet50	60.8%	78.3%
MobileNetV2	**69.3%**	78.7%
NASNetMobile	56.0%	75.5%
Aveerage	62.1%	78.6%

It is sensitive in determining whether cancer is malignant or not so that predictions of malignant and benign cancer are determined by a threshold. With a range of 0-1, cancer is said to be benign if it is in the range 0-0.3 and for 0.3-1 it is classified as malignant cancer, which means the threshold value in this study is 0.3. With a total of 10 epochs tested, the results shown in table 3 are given. By using the accuracy model performance, it is known that without using a threshold, the average accuracy value obtained is 12% higher. However, to minimize classification, a threshold is used. By using a threshold, the highest accuracy value reached 69.3% in the MobileNetV2 model, while other models had accuracy values below 66%.

Followed by comparing the specificity, sensitivity of melanoma classification and ROC (Receiver Operating Characteristic) score on the performance of the classification model using threshold. The results of specificity, sensitivity in melanoma classification and ROC for each model can be seen in table 3.

Table 4. Results Sensitivity and Specify

Model	**Sensitivity**	**Specificity**	**ROC Score**
InceptionV3	0.7094	0.6418	0.676
EfficientNetB0	0.7094	0.5610	0.635
ResNet50	0.7350	0.5776	0.656
MobileNetV2	0.6068	0.7142	0.661
NASNetMobile	0.7094	0.523	0.617

From the accuracy results which were still relatively low, a model trial was carried out using the ensemble model. The five models (InceptionV3, EfficientNetB0, ResNet50, MobileNetV2 and NASNetMobile) are combined to classify skin cancer as benign or malignant. In this model, the image shape is uniform, and the epoch used is still 10. From the results of the ensemble model applied, higher accuracy results are obtained, either without a threshold or using a threshold compared to the single model that has been done previously. The results of the ensemble model trials can be seen in tables 4 and 5.

Table 5. Accuracy Ensemble Model

	Accuracy	
Model	**With Threshold (30%)**	**Without Threshold**
Ensemble	*80.60%*	***8**1.53%*

Table 6. Results Sensitivity, Specify & ROC Score Ensemble Model

Model	**Sensitivity**	**Specificity**	**ROC Score**
InceptionV3	*0.120*	*0.975*	*0.547*

5. Conclusion

In research using 5 different deep learning models with predetermined conditions for skin cancer classification using the ISIC 2017 dataset. By comparing the performance of the InceptionV3, EfficientNetB0, ResNet50, MobileNetV2 and NASNetMobile models. Although deep learning models can generally provide good results with certain datasets, they require hyperparameter optimization and even quite complex pre-processing such as segmentation to be able to provide the best results. In this study, we compared the extent of each model in classifying skin cancer. Using the model mentioned above, the average accuracy value without a threshold has a superior value, but to minimize diagnosis errors, a threshold is set so that the highest accuracy value reaches 69.3% using MobileNetV2. Best accuracy was carried out using an ensemble model in classifying skin cancer by combining the five methods to produce an accuracy value of 80.60%. This proves that the ensemble model has the best accuracy compared to other single models.

6. Declarations

6.1. Author Contributions

Conceptualization: SNH, LW, and RI; Methodology: LW; Software: SNH; Validation: SNH, LW, and RI; Formal Analysis: SNH, LW, and RI; Investigation: SNH; Resources: LW; Data Curation: LW; Writing Original Draft Preparation: SNH and RI; Writing Review and Editing: LW and SNH; Visualization: SNH; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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