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MobileNet V2 Implementation in Skin Cancer Detection

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Abstract

Skin cancer is one of the most worrying diseases for humans. In Indonesia alone, skin cancer occupies the third position after cervical cancer and breast cancer. Currently, doctors still use the biopsy method to diagnose skin cancer. It is less effective because this method requires the performance of an experienced doctor, takes a long time, and is a painful process. Because of that, we need a way in which skin cancer can be classified using dermoscopic images to help doctors diagnose skin cancer earlier. Researchers proposed to classify skin cancer into seven classes, namely actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevus, and vascular lesions. The method used in this study is a convolutional neural network (CNN) with the MobileNet V2 architecture. The dataset used is the HAM10000 dataset, with a total of 10015 images. In this study, a comparison was made between data augmentation, learning rate, epochs, and different amounts of data. Based on the test results, the highest accuracy results were obtained, namely 79%. The best model is implemented into a mobile application.

Keywords: Classification; Convolutional Neural Network; Deep Learning; Skin Cancer

Introduction

Skin cancer is one of the most common cancers affecting people worldwide. In 2020, more than 15 million cases of skin cancer were diagnosed worldwide, more than 120.000 skin cancer-related deaths were reported, and more than 94 million Europeans complain of uncomfortable skin sensations like itch, burning, or dryness [1]. Skin cancer is increasing in terms of morbidity and mortality [2]. Factors for increased ultraviolet light exposure [3], genetic factors [4], unhealthy lifestyles [5], and inflammation of the human papillomavirus [6] can be a cause for the appearance of skin cancer.

Skin cancer results from the development of abnormal skin cells, which often grow on bodies exposed to sunlight, but can occur anywhere. The cells in the constituent parts of the skin are basal cells, melanocyte cells, and squamous cells. Melanoma skin cancer occurs due to the abnormal growth of melanocyte cells [7]. Skin cancer can cause death in sufferers, depending on the type of skin cancer and the level of malignancy of the cancer.

Doctors usually use the biopsy method to diagnose skin cancer. This biopsy method is done by taking or cutting a small portion of tissue to be used as a sample using a syringe. Then the sample is tested by more than one trained and experienced doctor to diagnose. An infiltrative biopsy is a standard for pathological diagnosis of skin cancer. The procedure is difficult and time-consuming, often resulting in unnecessary biopsies and scarring [8]. Although dermoscopy is considered standard of care, the availability of objective tests by dermatologists has limited diagnosis due to the complexity of the visual inputs embedded in dermoscopy images [9].

Deep learning is a branch of machine learning at the forefront of artificial intelligence and aims to bring it closer to its main goal: artificial intelligence. Deep learning technology is used in many fields and research fields, such as speech recognition, image processing, and computer vision. It is one of the fastest growing and most adaptable technologies ever [10].

In the medical world, deep learning techniques have machine learning architectures used to handle large data sets in complex calculations and produce accurate judgments in handling image classification, especially in analyzing diseases. Convolutional Neural Network (CNN) are mainly used for tasks related to computer vision, which is capable of handling image datasets [11]. In this study, we use MobileNet V2 architecture which is a cellphone-based CNN architecture that can overcome the need for excess computing resources and can be implemented on Android [12].

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Based on this background, early detection and classification are one of the solutions to overcome this skin cancer problem. Then the authors research the classification of skin cancer types using the CNN algorithm and investigate the performance of this algorithm in the classification of skin cancer types. A mobile application will implement the model generated from the CNN algorithm.

Several studies classify two types of cancer: non-melanocytic malignant and benign, using CNN [13]–[15]. MobileNet V2 and Faster R-CNN were compared to identify two types of skin cancer: keratosis and melanoma, using 600 images. Faster R-CNN performs better than MobileNet V2 [16]. The effect of learning rate and batch size on the loss function and CNN accuracy values was tested. The best model architecture is produced by the learning rates of 0.0001 and 0.00001, with a batch size of 5 [17]. Comparative analysis of Adam & SGD optimizers was conducted [18]. In addition, an approach by combining several CNN architectures to increase model accuracy has been performed [19], [20].

In this study, we modified the network architecture and adopted the approach of transfer learning to improve the learning capability. A major contribution of this work is optimizing the accuracy by tuning the number of learning rates and epochs. We also compare the usage of data augmentation to get the best model. The best model is implemented into an Android-based mobile application.

Method

A. Data Collection

This study uses the dataset from Kaggle sites. The dataset is a collection of images consisting of 7 types of skin cancer, namely: actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevus, vascular lesions

B. Data Preprocessing

The data processing stage consists of three parts, namely data labeling, data splitting, and data resizing.

- *Data Labeling*

  At this stage, the image is labelled according to the type of cancer. The type of cancer is obtained from the metadata and the directory name.

- *Data Splitting*

  The data is divided into 3, namely training data, testing data, and validation data. As many as 70 data were used for data testing. The remaining is splitting for training data and testing data with a ratio of 70:30. Details of data splitting can be seen in **Table 1**.

- *Data Resizing*

  Image raw data has various sizes, so it needs to be resized first to fit the architectural requirements of MobileNet v2, namely 224×224 pixels.

Table 1. Partition of Training, Validation, and Testing Data

Class	Data Splitting			
	Training	***Validation***	***Testing***	***Total***
Actinic keratoses (akiec)	222	95	10	327
Basal cell carcinoma (bcc)	353	151	10	514
Benign keratosis like lesions (bkl)	763	326	10	1099
Dermatofibrama (df)	74	31	10	115
Melanoma (mel)	773	330	10	1113
Melanocytic nevus (nv)	4687	2008	10	6705
Vascular lessions (vasc)	93	39	10	142
Total	6965	2980	70	10015

C. Data Augmentation

The accuracy of deep learning models is highly dependent on the amount of training data and the semantics of the context. The alternative approach to deal with the variability in the data can use augmentation techniques [21]. We

manipulate the images by rotation range = 40, zoom range = 0.2, width shift range = 0.2, height shift range = 0.2, shear range = 0.2, horizontal flip = True, fill mode = nearest, rescale = 1/255.

D. CNN Architecture Model Design

MobileNetV2, which improves the top performance of mobile models across a wide range of tasks and benchmarks, as well as a wide range of different model sizes. MobileNet v2 architecture, as shown in **Table 2**.

Table 2. MobileNet V2 Architecture

Input	Operator	t	c	n	s
2242 × 3	Conv2d	-	32	1	2
1122 × 32	Bottleneck	1	16	1	1
1122 × 16	Bottleneck	6	24	2	2
562 × 24	Bottleneck	6	32	3	2
282 × 32	Bottleneck	6	64	4	2
142 × 64	Bottleneck	6	96	3	1
142 × 96	Bottleneck	6	160	3	2
72 × 160	Bottleneck	6	320	1	1
72 × 320	Conv2d 1x1	-	1280	1	1
72 × 1280	Avgpool 7x7	-	-	1	-
1 × 1 × 1280	Conv2d 1x1	-	k	-	

The pre-trained model in this study uses an input shape with a size of 224×224 pixels with 3 RGB color channels. In this model, there are several types of convolutions with different numbers of filters. The first convolution process is carried out with conv2d filter 32, and then seven times the bottleneck with filters respectively 16, 24, 32, 64, 96, 160, 320, then the subsequent convolution is conv2d 1×1 with filter 1280, then average pooling 7×7 and finally conv2d convolution 1×1.

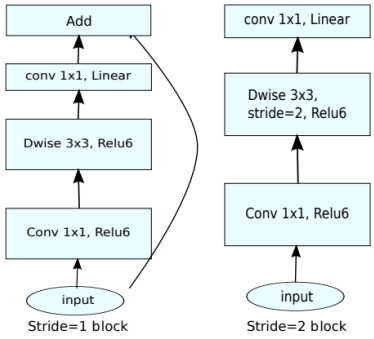

Figure 1. Process at the bottleneck

The structure of the Mobilnet v2 architecture is shown in **Table 2**, where each row describes a sequence of 1 or more identical layers (modulo stride), repeated ***n*** times. All layers in the same order have the same number of ***c*** output channels. The first layer of each sequence has steps of ***s*,** and the others use steps of 1. All spatial convolutions use 3×3 kernels; ***t*** stands for channel expansion rate, and the expansion factor ***t*** is always applied to the input size, as described in **Figure 3**. The process that occurs in the bottleneck is described in **Figure 1**. Some use one stride and two stride. Do conv2d 1×1 with relu6 activation, then deptwiseconv2d 3×3 with relu6 activation, finally conv2d 1×1 [22].

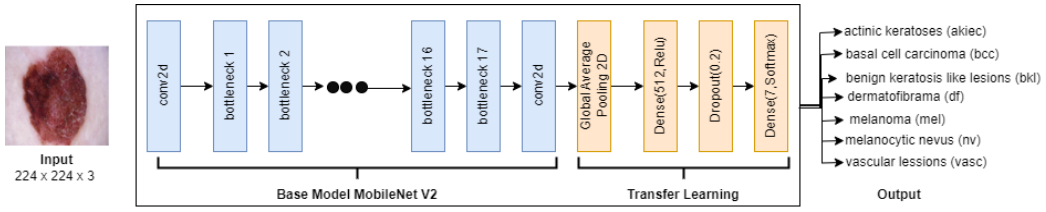

Figure 2. Proposed Model

Our proposed model is carried out using transfer learning on MobileNet V2. We train the model using the MobileNet v2 pre-trained model. We removed the last 2 layers from the MobileNet V2 architecture and then added 4 layers, namely 3 hidden layers and 1 output layer. The hidden layer consists of 2D global average pooling as a flattened layer, a dense layer, and a dropout layer. The dense layer is built with 512 neurons. The Relu function is executed on this layer. At the dropout layer, we remove 20% of the neurons to reduce. Dropout neuron approaches to tackle overfitting and long-time training [23]. In the output layer, we use the softmax activation function and 7 neurons to classify 7 types of skin cancer. The softmax activation function can classify many classes [24]. To improve the deep learning model's performance, we use Adam optimizer. This optimizer is computationally efficient [25].

E. Model Training & Validation

The validation process is carried out simultaneously with the training process. A validation dataset is a sample of data held back from a training model used to estimate model skill while tuning the model hyperparameters. The validation dataset is different from the test dataset that is also held back from the model training. However, it is instead used to obtain an unbiased estimate of the skill of the final tuned model when comparing or selecting between the final models.

F. Model Evaluation

The model evaluation aims to estimate the generalization accuracy of the model to future (unseen/out-of-sample) data. To do this, we measure the performance of a newly trained model on a new and independent dataset. This model compares labeled data with its predictions. We test the models to determine the model's performance. The evaluation method focuses on the accuracy in predicting the end outcomes.

Results and Discussion

To get the model with the best accuracy, we train the model with hyperparameter tuning. Hyperparameter-tuning is essential to find the best sets of hyperparameters to build the model from a specific dataset. The number of learning rates and epochs are the hyperparameters to tune. In addition, we also compare the use of augmentation in the training process to get the best performance results.

The first hyperparameter to tune is the learning rate controlling the step size for a model to reach the minimum loss function. The model learns more quickly with a greater learning rate, but it may miss the minimum loss function and only reach the surrounding of it. A lower learning rate increases the likelihood of discovering a minimum loss function. We train the network using three different learning rates, namely: 0.001, 0.0001, 0.00001.

Secondly, we tune the number of epochs to gain the optimal result. We train the network using 50 and 75 epochs. We use 64 batch size to make the model learn faster. **Table 3** shows the result when trained using augmentation and without augmentation.

A. Comparison of Test Result

Based on the test results shown in **Table 3**, models trained with the augmentation process have higher accuracy than those without augmentation. However, a trained model using the augmentation process takes a long time during the training process. The best deep learning model is obtained by using 50 epochs and 0.0001 learning rate.

Table 3. Comparison of Test Result Using Augmentation and Without Augmentation

Testing	Data	Learning Rate	Epoch	Augmentation	Training Time	Accuracy
A	9945	0.001	50	T	3h 31min 31s	77.95%
				F	2h 55min	71.11%
B	9945	0.001	75	T	4h 46min	78.26%
				F	3h 20min 50s	70.10%
C	9945	0.0001	50	T	3h 27min 38s	78.49%
				F	2h 28min 11s	71.61%
D	9945	0.0001	75	T	5h 48min 49s	78.42%
				F	4h 42min 31s	72.01%
E	9945	0.00001	50	T	3h 33min 3s	75.54%
				F	2h 21min 57s	68.76%
F	9945	0.00001	75	T	6h 29min 39s	76.48%
				F	3h 9min 32s	69.53%
G	4973	0.001	50	T	2h 39min 59s	76.68%

Testing	Data	Learning Rate	Epoch	Augmentation	Training Time	Accuracy
				F	2h 10min 6s	69.02%
H	4973	0.001	75	T	3h 12min 30s	76.48%
				F	2h 57min 11s	76.61%
I	4973	0.0001	50	T	2h 41min 15s	76.01%
				F	1h 47min 56s	70.09%
J	4973	0.0001	75	T	2h 58min 12s	76.08%
				F	2h 21min 18s	69.22%
K	4973	0.00001	50	T	2h 19min 33s	73.45%
				F	2h 4min 36s	67.94%
L	4973	0.00001	75	T	2h 54min 33s	74.66%
				F	2h 10min 30s	68.68%

The use of data augmentation will always increase training time; this is because the amount of data used for training increases. These experiments proved augmentation to increase mean accuracy by 8.02%. The model learns faster in large data using a learning rate of 0.001. However, the model converges at a learning rate of 0.0001. The model accuracy decreases again using a learning rate of 0.00001, as shown in **Figure 3**.

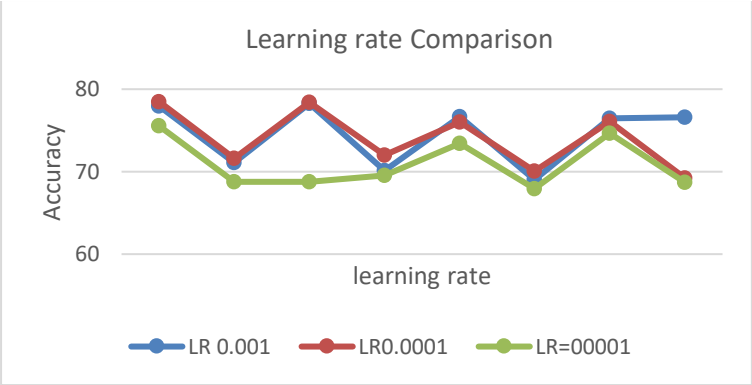

Figure 3. Learning Rate Comparison

When using a learning rate of 0.00001, the model gets stuck. The learning rate interacts with other aspects of the optimization process, and the interactions are nonlinear. Using many epochs from this experiment only sometimes increases the system accuracy value, as shown in **Figure 4**. It happens because the epoch interacts with other aspects of the optimization process.

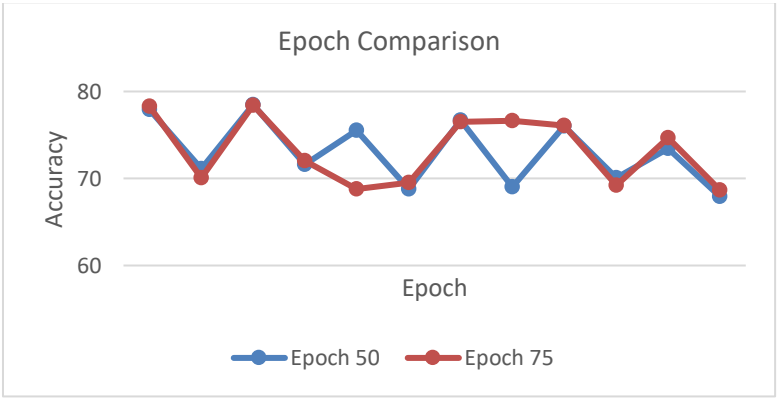

Figure 4. Epoch Comparison

After getting the best parameters from the training process, we build a model with those best parameters. Then, we carry out tests on the test data. From testing the data, the results were obtained in **Table 4**.

Table 4. Testing Result

Metric	*Result*
Precision	0.66

Metric	*Result*
Recall	0.55
F1- Score	0.58
Accuracy	0.79
Time execution	3.25 s

From **Table 4**, we can see that the model is a good fit. Even though the accuracy obtained was only 79%, the model produced in this experiment was quite stable, both for recognizing training data and testing data.

To date, it has been virtually impossible to compare different skin cancer analysis strategies. This is due to the need for standardized assessment measures and datasets as well as difficulties in sharing code and data. Based on **Table 5**, our proposed method has better model performance compared to previous studies, except for the ensemble model proposed in [20].

Table 5. Proposed Model Result Comparison with Previous Work

Ref	*Experiment*	*Result*			
		Type Of Cancer	*Model*	*Accuracy*	*Dataset*
Li [18]	Conducted a comparative analysis of performance 2 optimizers (Adam and SGD)	8	VGG19 with SGD	0.7143	ISIC 2019
			Resnet50 with SGD	0.7655	
			Vgg19 with Adam	0.7429	
			Resnet 50 with Adam	0.7725	
Singh [19]	Uses a combination of CNN and ANN which leverages the image data and tabular data to predict the type of skin cancer.	6	Hybrid CNN and ANN	0.69	Mendeley
Filali [15]	Conduct a comparative study between different deep learning approaches for skin cancer classification and analysis.	2	AlexNet	0.68	PH2
			VGG16	0.69	
			GoogleNet	0.69	
			ResNet	0.70	
Aldwgeri [20]	Taking the mean output of 6 base models to generate the final prediction.	7	Resnet50	0.74	HAM 10000
			Inception V3	0.76	
			Ensemble	0.8	
Savera [14]	Conduct a comparative study between KNN and CNN approaches for skin cancer classification.	2	KNN	0.75	Not Mentioned
			CNN	0.76	
Hakim [13]	Classify 2 types of Skin cancer using CNN (13 layer).	2	CNN	0.75	ISIC 2018
Proposed Method	Tuning the number of learning rates and epochs in transfer learning using MobileNetV2 architecture.	7	MobileNetV2	0.79	HAM 10000, ISIC 2019

B. Mobile Application Implementation

The interface of the mobile app is shown in **Figure 5**. The best deep learning model is implemented into the mobile app based on the test results. The best models are saved in **.tflite** format. To be able to use this application, users must input images first. Image input can be done directly using the camera. The second option user can use images stored in the cellphone gallery. The image is loaded on the user mobile screen page. The user can press the detect button to find out the type of skin cancer. The system provides the classification results along with their confidence values.

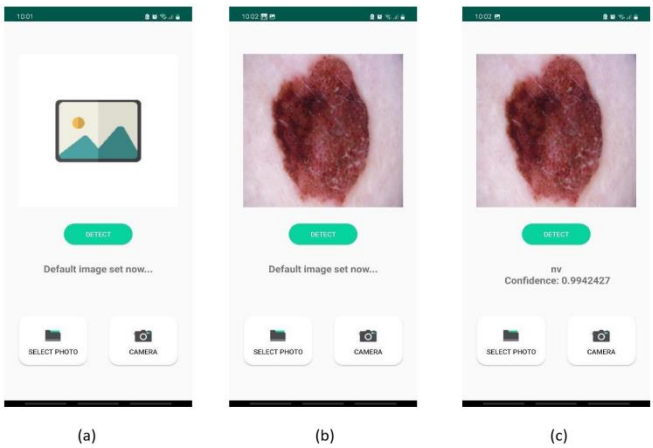

Figure 5. (a) Main Page (b) Image Input Process (c) Classification Result

Testing using the mobile application is shown in **Table 6**. This testing uses 20 data for each class. The melanocytic nevus (nv) class has the highest accuracy, while the dermatofibroma (df) class has the lowest accuracy.

Table 6. Testing Results on the Mobile Application

Class	HAM 10000		ISIC 2019	
	Correct	***Wrong***	***Correct***	***Wrong***
Actinic keratoses (akiec)	2	8	2	8
Basal cell carcinoma (bcc)	6	4	2	8
Benign keratosis like lesions (bkl)	10	0	4	6
Dermatofibrama (df)	1	9	0	10
Melanoma (mel)	5	5	2	8
Melanocytic nevus (nv)	9	1	7	3
Vascular lessions (vasc)	7	3	1	9
Total	40	30	18	52
Percentage	57.14%	42.86%	25.71%	74.92%

Conclusion

Deep neural network training commonly uses augmentation data, the number of epochs, and the learning rate to improve the model performance. These experiments proved augmentation to increase mean accuracy by 8.02%. The learning rate and the number of epochs interact with other aspects of the optimization process, and the interactions are nonlinear. Our proposed model can produce 79% accuracy with 3.25 s for time execution. However, further improvement is needed so that the proposed method can address the imbalanced dataset problem.

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