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by Artikel 3

Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 6, No. 4, November 2021, Pp. 321-328

Skin lesion image classification using convolutional neural network

Lailis Syafa'ah*[1], Ilham Hanami[2], Inda Rusdia Sofiani[3], Mohammad Chasrun[4]
Universitas Muhammadiyah Malang[1,2,3,4]

Article Info
Keywords:
CNN, Deep learning, Dataset, Skin Cancer

Article history:
Received: October 30, 2021
Accepted: November 27, 2021
Published: November 30, 2021

Cite:
Syafa'ah, L., Hanami, I., Rusdia Sofiani, I., & Chasrun, M. (2021). Skin Lesion Image Classification using Convolutional Neural Network. Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, 6(4). https://doi.org/10.22219/kinetik.v6i4.1353

*Corresponding author.
Lailis Syafa'ah
E-mail address:
lailis@umm.ac.id

Abstract
Classification of skin cancer is an important task to detect skin cancer and help with the treatment of skin cancer according to its type. There are many techniques in imaging used to classify skin cancer, one of the superior deep learning (DL) algorithms for classification is the Convolution Neural Network (CNN). One type of skin cancer is dangerous is melanoma. In this study, CNN is proposed to help classify this type of skin cancer. The dataset consists of 15103 images of skin cancer pigments with 7 different types of skin cancer. These three tests proved malignant skin lesions can be classified with higher accuracy than non-melanocytic skin lesions which is 90% and performance evaluation shows melanocytic and non-melanocytic skin lesions detected with the highest accuracy. The tests conducted in this study grouped several types of skin diseases namely the first tests conducted using a group of melanocytic and non-melanocytic skin disease, second testing using groups of melanoma and melanocytic nevus diseases, and the final testing using malignant and benign. The proposed CNN model achieved significant performance with a best accuracy of 94% on the classification of melanoma and melanocytic nevus.

1. Introduction

Skin cancer is the most common form of cancer in the United States, with its annual care cost exceeding $8 billion [1]. According to the Indian society, in 2015, has been reported that the level of skin cancer in India is higher than in other countries like Canada, the US and the UK. It has been reported that nearly 125,693 new cancer cases were detected and an estimated 45,395 people died of cancer [2]. cancer could be considered as one of the major reasons of human death [3]. Skin cancer is classified as melanocytic lesions and non-melanocytic based on its original type melanocytic lesions including melanoma and melanocytic nevus. Non-melanocytic lesions including basal cell carcinoma, actinic keratosis, dermatofibroma, vascular lesions and benign density. The spread of melanoma is not as large as the spread of non-melanoma, which is quickly to spread from localized levels of origin to skin to other human organs through a lymphatic system [4]. Melanoma generally occurs in the skin and often occurs in the mouth, or in an eye. Melanoma is mostly on the back for men and on the legs for women [5]. Although the high mortality rate, 95% of melanoma cases can be cured if cancer is detected in early stages [6]. To cure skin cancer, photodynamic therapy is an alternative way to cure skin cancer and to be able to reduce the pain. But surgery medicine, basically depends on a skilled medical doctor that is quite limited and usually expensive, so automatic cancer surgery system is necessary to be able to cure the patient as a reliable medical assistant [7].

Recently, skin segmentation is one of the important steps in the computer to assist in diagnosing skin diseases through dermoscopy [8]. automatic segmentation of skin lesions on dermoscopy is particularly challenging because variations in the size of lesion, location, shapes and colors in different patients and hair and vena on skin lesion [9]. The analysis and classification of the skin lesion types play an important role in diagnosis and treatment strategies. The automatic analysis and classification of the dermoscopic picture provides an inaccurate and discarding assessment of the time for a type of skin lesion according to the skin surface structure [10]. To identify skin cancer through the dermoscopy image is used by Machine learning, where the data will be submitted to the system and make the system self-study [11]. Self-learning techniques used to help skin doctors to diagnose skin cancer more efficiently are the deep learning technique [12].

Deep learning (DL) techniques in medical have machine learning architecture, driven by competency to handle large data sets of complex calculations, and returns a fairly accurate assessment to address the problem of picture classification, particularly in analyzing diseases [13]. For image classification, the convolutional neural networks (CNNs) are considered the most common architecture in some applications, especially in the medical image classification process [14]. The CNN model is inspired by the structure of a mammal visual system [15]. CNN has a significant conceptual framework, including the weight sharing, perception and domain sampling space, which ensures relative

movement, distortion and scaling characteristics. Progress against hardware and the availability of an open source dermoscopy dataset makes Neural Networks an efficient method for picture classification [16].

In the past few years a lot of research has been done on medical issues that have brought advances mainly in the fields of skin cancer classification [15]. In 2017, Enakshi Jana et al. [17] proposed a classification of skin lesion to 3 types of skin cancer and used the support vector machine (SVM) algorithm. Unlike Kiran Pai et al. [18] proposed seven different classes of cancer and used the VGG algorithm. Budhiman et al. [19] proposed the ResNet method for melanoma cancer classification yielding 83% accuracy. Muhammed et al. [20] proposed the use of a trained MobileNet and DenseNet-121 model to improve the accuracy of classification by 82.6% and 71.9%. In 2018, Harangi et al. [21] proposed a method to classify skin cancers by using CNNs AlexNet, VGGNet and GoogLeNet models by accuracy 79% of nevus, 85% melanoma and 86% baroic cratosis. That same year, Vatsala et al. [22] proposed the CNN method to classify benign and malignant results 80.3% accuracy. in 2019 Ech-cherif et al. [23] proposed the deep convolutional neural network method of the MobileNetV2 model for detecting skin cancer yields 88% accuracy. In 2018 Shahin et al. [24] proposed the classification of skin lesion to seven classes with 10,015 pictures using the ResNet-50 model and Inception V3 obtained an accurate 89.9% result. In the same year, Kaymak et al. [25] proposed Alexnet's method of dividing skin lesions into three experiments, the first attempt to classify melanocytic and non-melanocytic, the second experiment in classifying melanoma and melanocytic and the last to classify malignant and the accuracy of each trial to obtain 78%.84% and 58% of each.

In this study, researchers proposed to investigate the classification of the skin cancer's pigment by using CNN algorithms. In this study, the datasets were obtained by international skin imaging collaboration (ISIC) 2018 with 10015 skin-filled images of seven skin-type lesions namely melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, dermatofibroma and vascular lesions.

1. Method

The research method used in this research is shown in Figure 1. Which is the process flow from preparing the dataset and then continued with data sharing training and test data for the training process followed by model building and the result evaluation to know the performance of the model that has been constructed.

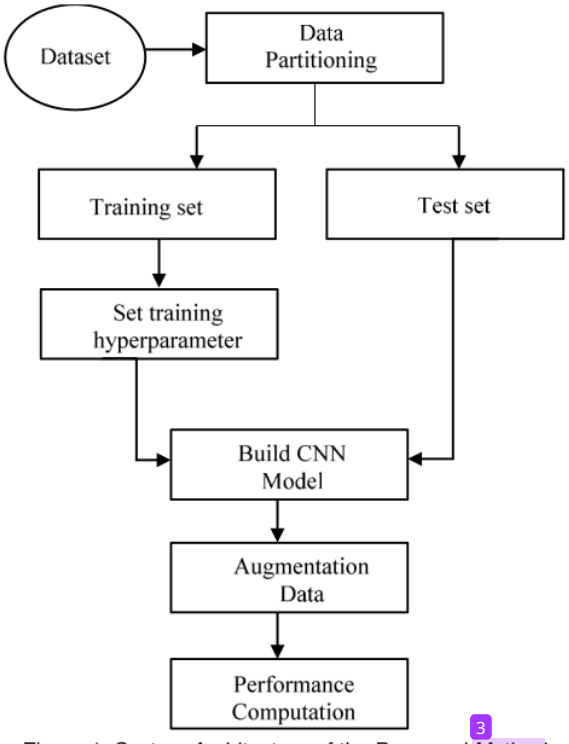
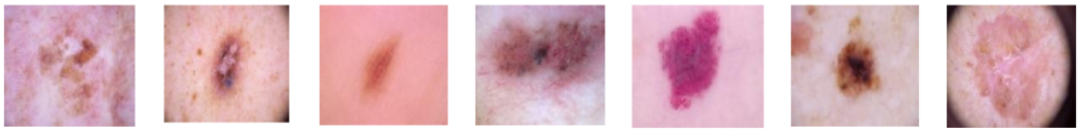


Figure 1. System Architecture of the Proposed Method

2.1 Dataset

The data for this research was taken from a dataset provided through Kaggle named Skin Cancer MNIST:HAM1000 ("Human Against Machine with 1000 training images") and was previously used for "challenge ISIC 2018: Lesion Analysis Towards Melanoma Detection" Skin. The dataset consists of 10015 dermoscopy of a skin with a 450 x 600 pixels image and a JPG picture format. This dataset is categorized as 7 categories: melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis / bowen's disease (ACIEC), benign keratosis (BKL), dermatofibroma (DF) and vascular lesion (VASC). The category can be seen in Figure 2. Here's (a) BKL (b) DF (c) NV (d) BCC (e) VASC (f)MEL (g)AKIE.



(a) (b) (c) (d) (e) (f) (g)

Figure 2. Sample 7 Different Types of Skin Pigment

2.2 Model

The model design, built using this CNN model involves 2 million parameters comprised of 6 convolutional layers with the number of kernels 32 (Conv-1 and Conv-2), 64 (Conv-3 and Conv-4), 128 (Conv-5 and Conv-6) and kernel size 3 x 3, with each volume -max using activation relu, 6 batch, normalization, 3 pooling layers of size 2 x 2 followed by the layers fully fully-connected 1 FC-1 = the last 128 layer of output activation in softmax. The proposed model illustrated in Figure 3.

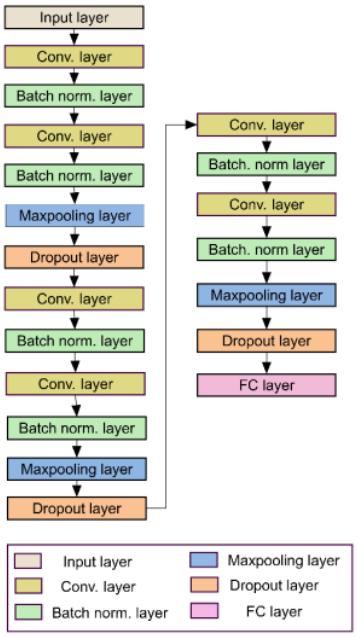


Figure 3. Proposed CNN Model Architecture

2.3 Augmentation

Augmentation is a technique used to extend the size of training data artificial by creating a modified version of the images in the dataset. In this research, modifies images such as rotation_range = 10, zoom_range= 0.1, width_shift_range = 0.1 and height_shift_range = 0.1.

2.4 Test Scenario

The classification of the skin lesion was divided into three scenarios where each of the scenario had its own share. In the test scenario 1, test is conducted on different test and training data. the data used is a model of melanoma and melanocytic nevus. the following table of test scenarios is visible in Table 1. Melanocytic and Non-Melanocytic classes.

Table 1. Melanocytic and Non-Melanocytic Class

Skin Lesion	Training Images	Testing Images	Total Images
Melanoma	7421	397	7818
Non-Melanocytic	5265	2020	7285
Total	12686	2417	15103

In the test 2 scenario, the test was done using melanoma data and melanocytic nevus which each of the data details can be seen in Table 2. Melanoma and melanocytic nevus class. because data between the unbalanced number of image training, augmentation is done in an image rotation, Table 3 advanced augmentation melanocytic and non-melanocytic displayed the details of a balance dataset between classes. After the augmentation was done on scenario 2, and then we tested the 3rd scenario in the malignant class and benign, which are direct descendants of melanoma. Scenario Table 3 Test can be seen in Table 4. Malignant and benign.

Table 2. Melanoma and Melanocytic Nevus Class

Skin Lesion	Training Images	Testing Images	Total Images
Melanoma	800	313	1113
Melanocytic Nevus	5454	1251	6705
Total	6254	1564	7818

Table 2. Augmentation Melanocytic and Non-Melanocytic Class

Skin Lesion	Training Images	Testing Images	Total Images
Melanoma	5623	1090	6713
Melanocytic Nevus	5648	1057	6705
Total	11271	2147	13418

Table 3. Malignant and Benign Class

Skin Lesion	Training Images	Testing Images	Total Images
Malignant	588	253	841
Benign	1257	99	1356
Total	1845	352	2197

2. Results & Discussion

3.1 Classification Melanocytic dan Non-Melanocytic

On scenario 1 testing this, the data used came from melanoma and non-melanocytic at the skin cancer classification which totaled 15103 of 7 different classes, the details of test scenario 1 can be seen in Table 1. Accuracy acquired from scenario testing is 83%, Specificity 96% and Sensitivity 75%. the scenario test details can be seen in Table 5. model accuracy and loss graphs of data train and validation are shown in Figure 4.

Table 4. Classification Performance of Melanocytic and Non-Melanocytic

Method	Accuracy	Specificity	Recall / Sensitivity
CNN	83%	96%	75%

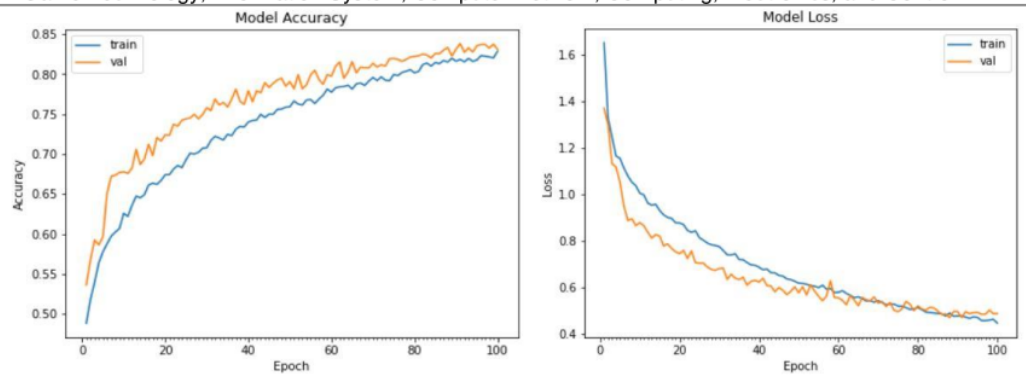


Figure 4. Accuracy & Loss Models from Melanocytic and Non-Melanocytic Classifications

3.2 Classification melanoma dan melanocytic Nevus

In the test scenario 2, the data used came from melanoma and melanocytic nevus. the data used under the 2-scenario totaled 13418 using a CNN model. Melanoma and melanocytic nevus data details can be seen in Table 3. Accuracy generated from scenario 2 testing acquired 94% Accuracy, Specificity 94% and Sensitivity 94%. the test is higher than the 1 scenario test of 90%. Scenario 2 test result details are visible in Table 6. The accuracy and loss model graphs in these 2 scenarios can be seen in Figure 5.

Table 5. Classification Performance of Melanoma and Melanocytic Nevus

Method	Accuracy	Specificity	Recall / Sensitivity
CNN	94%	94%	94%

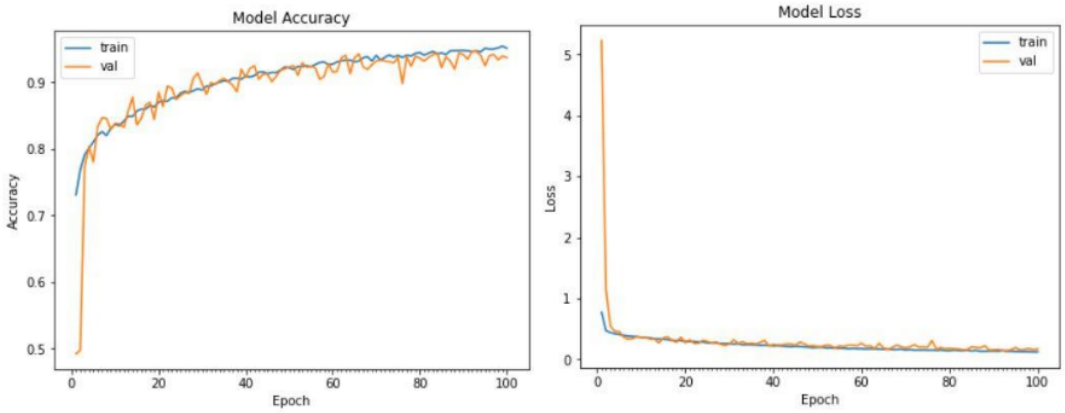


Figure 5. Accuracy and Loss Models from Melanoma and Melanocytic Nevus Classifications

3.3 Classification Malignant dan Benign

In scenario testing 3, the data used comes from malignant and benign. The data used for the testing totaled 2197 using the CNN model. Test 3 scenario data details can be seen in Table 4. Augmentation class melanocytic and non-melanocytic. Accuracy generated by scenario 3 testing obtained Accuracy 70%, Specificity 91% and Sensitivity 55%. scenario test performance 3 can be seen in Table 7. Malignant and Benign performance classification. The accuracy and loss model graphs in this scenario 3 can be seen in Figure 6.

Table 6. Classification Performance Malignant and Benign

Method	Accuracy	Specificity	Recall / Sensitivity
CNN	70%	91%	55%

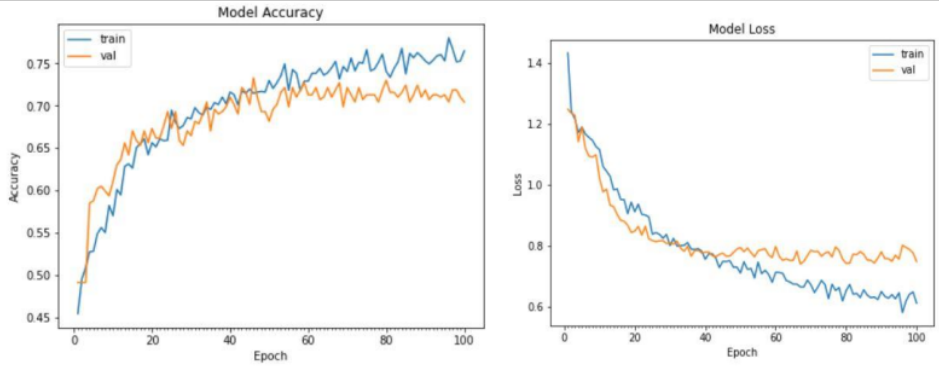


Figure 6. Accuracy & Loss Models from Malignant and Benign Classifications

The result of the testing used confusion matrix indicates a fairly good performance in classifying seven types of cancer lesions. This is shown in Figure 7. TP for BKL class reached 31 of 60 total data, TP for BCC reached 49 of 80 total data, TP for AKIE reached 153 out of 173 overall data, TP for c vas to 1 of 48 overall data, TP for 14 out of 21 overall data.

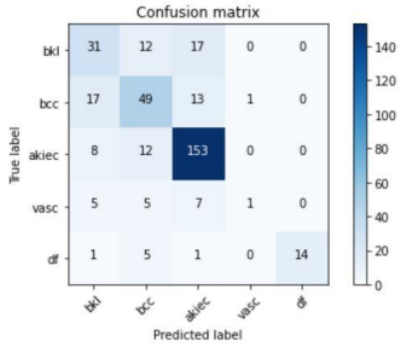


Figure 2.Confusion Matrix of Malignant and Benign

On Table 8 is a hyperparameter detail used in CNN model including the number of convolutional and layers relu, the number of normalization batches, the number of dropout layers, epoch, the fully layers number, kernel on convolutional layer, pooling layer, optimizer, batch size per epoch and dropout rate.

Table 7. Hyperparameter CNN Model

Factor(s)	Values
Convolutional + ReLU layers	1,2,3,4,5,6
Batch Normalization	1,2,3,4,5,6
dropout layers	1,2,3,4
Epoch	100
fully connected layers	1,2,3
Kernel convolutional layer	32,64,128
Pooling layers	Max pooling
Optimizers	Adam
Batch size	48
Step per epoch (Scenario 1,2 dan 3)	201,178,29
Dropout rate	0.25, 0.40, 0.50

In Table 8 is a hyperparameter of the built-in convolutional neural network model architecture. The value taken from the architecture has been through three test scenarios. The architecture has proven to improve the accuracy of the research by Kaymak [25]. On Table 9, it provides a comparison with previous research on CNN's performance using the same data to classify the type of skin cancer disease.

Table 9. Performance Comparison to Previous Research

Performance (%)	Proposed Structure			Kaymak et al.[25]		
	Scenario					
	1	2	3	1	2	3
Accuracy	83%	94%	70%	78%	84%	58%
Specificity	96%	94%	91%	63.5%	83.8%	57.8%
Recall / Sensitivity	75%	94%	55%	83.9%	84.7%	60.6%

On Table 9, it's a comparison between the models of kayak attacks and researchers. In Kaymak [25] models use the AlexNet model of 5 filters screen convolutional screening of 96, 256, 384, 256 and 3 fully recalled, the pooling-in-use is a 3x3-sized maxpooling. The proposed model uses 6 convolutional layer, which is 32,32,64,64,128,128, using maxpooling, filtering size 2x2, and adding the normalization batch after layer convolution. The model differences in previous research with related research were the number of construction layers, the size of pooling and adding batch normalization after the construction layer. Of those differences, a model built can improve the accuracy value of the Kaymak Research [25].

3. Conclusion

Based on the tests conducted, more data is used will result in good accuracy being backed by the use of a CNN model for classifying skin cancer pigment. that is shown in the 1, 2 and 3 scenario tests that results 83%, 94% and 75% accuracy. this accuracy results beyond previous research by Kaymak using the same dataset and test scenario. The difference between the test scenario is that there is a layer addition to the model. The maximum end result was obtained in scenario 2 research using the total dataset of 13418 skin cancer images, with the distribution of 11854 data trains and 1564 test data which was able to generate accuracy 94%.

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Cite: Syafa'ah, L., Hanami, I., Rusdia Sofiani, I., & Chasrun, M. (2021). Skin Lesion Image Classification using Convolutional Neural Network. Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, 6(4). https://doi.org/10.22219/kinetik.v6i4.1353

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Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 6, No. 4, November 2021, Pp. 321-328

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Article Info
Keywords:
CNN, Deep learning, Dataset, Skin Cancer

Article history:
Received: October 30, 2021
Accepted: November 27, 2021
Published: November 30, 2021

Cite:
Syafa'ah, L., Hanami, I., Rusdia Sofiani, I., & Chasrun, M. (2021). Skin Lesion Image Classification using Convolutional Neural Network. Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, 6(4). https://doi.org/10.22219/kinetik.v6i4.1353

*Corresponding author.
Lailis Syafa'ah
E-mail address:
lailis@umm.ac.id

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Classification of skin cancer is an important task to detect skin cancer and help with the treatment of skin cancer according to its type. There are many techniques in imaging used to classify skin cancer, one of the superior deep learning (DL) algorithms for classification is the Convolutional Neural Network (CNN). One type of skin cancer is dangerous is melanoma. In this study, CNN is proposed to help classify this type of skin cancer. The dataset consists of 15103 images of skin cancer pigments with 7 different types of skin cancer. These three tests proved malignant skin lesions can be classified with higher accuracy than non-melanocytic skin lesions which is 90% and performance evaluation shows melanocytic and non-melanocytic skin lesions detected with the highest accuracy. The tests conducted in this study grouped several types of skin diseases namely the first tests conducted using a group of melanocytic and non-melanocytic skin disease, second testing using groups of melanoma and melanocytic nevus diseases, and the final testing using malignant and benign. The proposed CNN model achieved significant performance with a best accuracy of 94% on the classification of melanoma and melanocytic nevus.

1. Introduction

Skin cancer is the most common form of cancer in the United States, with its annual care cost exceeding $8 billion [1]. According to the Indian society, in 2015, has been reported that the level of skin cancer in India is higher than in other countries like Canada, the US and the UK. It has been reported that nearly 125,693 new cancer cases were detected and an estimated 45,395 people died of cancer [2]. cancer could be considered as one of the major reasons of human death [3]. Skin cancer is classified as melanocytic lesions and non-melanocytic based on its original type melanocytic lesions including melanoma and melanocytic nevus. Non-melanocytic lesions including basal cell carcinoma, actinic keratosis, dermatofibroma, vascular lesions and benign density. The spread of melanoma is not as large as the spread of non-melanoma, which is quickly to spread from localized levels of origin to skin to other human organs through a lymphatic system [4]. Melanoma generally occurs in the skin and often occurs in the mouth, or in an eye. Melanoma is mostly on the back for men and on the legs for women [5]. Although the high mortality rate, 95% of melanoma cases can be cured if cancer is detected in early stages [6]. To cure skin cancer, photodynamic therapy is an alternative way to cure skin cancer and to be able to reduce the pain. But surgery medicine, basically depends on a skilled medical doctor that is quite limited and usually expensive, so automatic cancer surgery system is necessary to be able to cure the patient as a reliable medical assistant [7].

Recently, skin segmentation is one of the important steps in the computer to assist in diagnosing skin diseases through dermoscopy [8]. automatic segmentation of skin lesions on dermoscopy is particularly challenging because variations in the size of lesion, location, shapes and colors in different patients and hair and vena on skin lesion [9]. The analysis and classification of the skin lesion types play an important role in diagnosis and treatment strategies. The automatic analysis and classification of the dermoscopic picture provides an inaccurate and discarding assessment of the time for a type of skin lesion according to the skin surface structure [10]. To identify skin cancer through the dermoscopy image is used by Machine learning, where the data will be submitted to the system and make the system self-study [11]. Self-learning techniques used to help skin doctors to diagnose skin cancer more efficiently are the deep learning technique [12].

Deep learning (DL) techniques in medical have machine learning architecture, driven by competency to handle large data sets of complex calculations, and returns a fairly accurate assessment to address the problem of picture classification, particularly in analyzing diseases [13]. For image classification, the convolutional neural networks (CNNs) are considered the most common architecture in some applications, especially in the medical image classification process [14]. The CNN model is inspired by the structure of a mammal visual system [15]. CNN has a significant conceptual framework, including the weight sharing, perception and domain sampling space, which ensures relative