JOURNAL MEDICAL INFORMATICS TECHNOLOGY
medinftech.org
ISSN 2988-7003 (online)

Optimization of Melanoma Skin Cancer Detection with the Convolutional Neural Network

Harming Puja Kekal[1] and Daniati Uki Eka Saputri[2]*

[1,2] *Universitas Nusa Mandiri Jakarta, Indonesia*

ARTICLE HISTORY

Received: 08 June 23

Final Revision: 10 June 23

Accepted: 20 June 23

Online Publication: 30 June 23

KEYWORDS

Neural Network, Deep Learning, Convolutional Neural Network (CNN), Skin Cancer, MobileNet

CORRESPONDING AUTHOR

14002622@nusamandiri.ac.id

DOI

10.37034/medinftech.v1i2.10

A B S T R A C T

Currently, skin cancer is a very dangerous disease for humans. Skin cancer is classified into many types such as Melanoma, Basal and Squamous cell carcinoma. In all types of cancer, melanoma is the most dangerous and unpredictable disease. Detection of melanoma cancer at an early stage is useful for effective treatment and can be used to classify types of melanoma cancer. New innovations in the classification and detection of skin cancer using artificial neural networks continue to develop to assist the medical and medical world in analyzing images precisely and accurately. The method used in this research is Convolutional Neural Network (CNN) with MobileNet model architecture. Skin cancer detection consists of five important stages, namely image database collection, preprocessing methods, augmentation data, model training and model evaluation. This evaluation was carried out using the MobileNet method with an accuracy of 88%.

1. Introduction

Melanoma is the most dangerous form of skin cancer, accounting for only 4% of all skin cancers but responsible for 75% of skin cancer deaths [1], [2], [3]. Early detection and treatment are crucial for successful recovery. If not diagnosed in its early stages, melanoma can grow deeper into the skin and metastasize to other parts of the body [4]. Melanoma is also known as malignant melanoma, and it can appear in a variety of colors such as pink, red, black or white, blue, etc. Most melanomas, whether black or brown, can occur anywhere on the body, but are most commonly found on the head, neck, soles of the feet, and near the nails. Melanoma grows faster than other types of cancer and is mainly caused by genetic instability and the accumulation of various alternative molecules [3], [5].

Current diagnostic classifications are unable to reduce tumor heterogeneity and are insufficient to predict treatment success [6]. To classify lesions as malignant, features are extracted from the lesion, which is achieved using segmentation. Most people worldwide suffer from cancer, and cancer treatment can be very painful. Every cancer has several stages, and the disease changes at each stage.

Recent advances in skin cancer detection and classification using artificial neural networks are continuously developing to help the medical and healthcare industry accurately analyze images. Skin segmentation is a computer step in diagnosing various skin diseases through dermoscopic images [5]. The analysis and classification of skin lesion images play an important role in diagnosis and treatment strategies. Although images provide the best results for skin cancer diagnosis, they must still be evaluated to provide accurate results during skin cancer classification [7].

Deep learning approaches are used to classify dermoscopic images of skin cancer, extracting important features contained within the images. In this technique, data is fed into the system, which learns independently [8]. Medical deep learning techniques have machine learning architecture, driven by the ability to handle large data sets of complex calculations and produce reasonably accurate assessments for image classification, especially in analyzing diseases [9]. Convolutional neural networks (CNN) are commonly used in classifying large numbers of images [10], and their model structure is inspired by the mammalian visual system [11]. CNN has a significant conceptual framework, including weight sharing, perception, and domain sampling, which guarantees relative transfer, distortion, and scaling characteristics. Advances in computational hardware and open-source dermoscopic dataset availability make neural networks an efficient method for image classification [12].

In this study, the researchers propose classifying skin cancer pigment using a convolutional neural network algorithm [13], [14], [15], [16]. The dataset is obtained from the International Skin Imaging Collaboration (ISIC) 2018, consisting of 2,750 images focused on three categories: Melanoma, Nevus, and Seborrheic Keratosis.

2. Research Method

The research method is a way used to collect data, analyze data, and obtain conclusions from the collected data. In this research, the method used includes dividing the dataset into two folders, namely the train data and test data, model augmentation, and model evaluation or performance. The division of the dataset into two folders, train data and test data, is done to train the dataset so that the built model can learn according to the parameters set in the model. The train data is used to train the model, while the test data is used to test the performance of the built model.

Model augmentation is the process of giving a slight modification to skin cancer images so that the model can learn with more variations of data. Examples of model augmentation include rotating, flipping, or enlarging the image.

Model evaluation or performance is the process of evaluating the extent to which the built model can recognize skin cancer images with high accuracy. The evaluation is done by comparing the model classification results with the actual label on the test data.

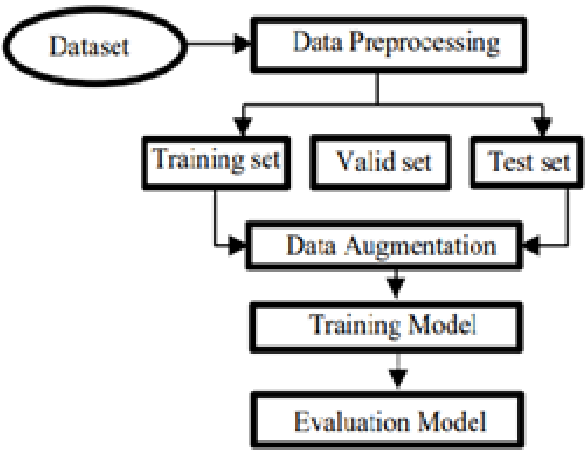

Figure 1. Research method

Figure 1 in this research explains the visual flow of research, starting from dividing the dataset to evaluating the model's performance. By using the right research method, it is expected that this research can produce accurate and accountable.

2.1. Dataset

In this research, the dataset used is skin cancer images obtained from a challenge called "ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection". The dataset consists of 2750 dermoscopic skin images with a size of 224 x 224 pixels and in JPG format. These skin lesion images are categorized into three classes: Seborrheic keratosis, Melanoma, and Melanocytic nevus.

Seborrheic keratosis is a type of non-cancerous skin growth that commonly occurs in middle-aged and older adults. Melanoma is a type of skin cancer that can spread quickly to other parts of the body if not treated early. Melanocytic nevus, also known as a mole, is a benign (non-cancerous) growth on the skin that can occur anywhere on the body.

The images in the dataset are used to train and test the deep learning model to identify and classify skin lesions accurately. The dataset is an essential component of this research, as it provides a large amount of high-quality data to train the model.

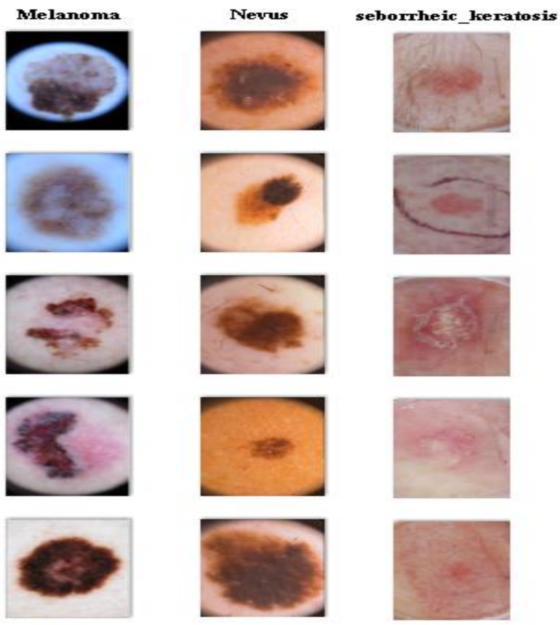

Figure 2. Dataset of 3 classes of skin cancer

This is a visual representation, known as Figure 2, of a dataset that contains information on three different types or classes of skin cancer.

2.2. Architecture Design

In this research project, the architecture design utilized is known as MobileNet, which has 28 layers and employs Average Pooling as its pooling method. The input for this architecture is an RGB image that is resized to 224x224 pixels. This resizing produces a 3-dimensional array where each dimension represents the Red, Green, and Blue colors of the image. MobileNet is initialized with a pre-trained ImageNet model, which is a commonly used dataset for image classification. In essence, the MobileNet architecture is optimized for analyzing images and is configured to take in images of a specific size and color format. By using a pre-trained model such as ImageNet, the architecture can leverage the existing knowledge learned from a massive dataset to improve its performance on other image-related tasks.

2.3. System Design

Convolutional Neural Networks (CNNs) are a type of deep learning model commonly used in image recognition and classification tasks [17], [18]. The CNN system design method is designed to automatically learn features from raw data without requiring manual feature extraction.

Unlike traditional machine learning models that require preprocessing steps such as feature extraction and feature scaling, CNNs directly take raw image data as input [19], [20]. However, before training a CNN model, the data needs to be prepared by converting it into a format that can be processed by the model [21].

The data preparation process involves reshaping the image data into a 3-dimensional array of 224x224x3. The first two dimensions represent the height and width of the image in pixels, and the third dimension represents the color channels (Red, Green, and Blue) of the image. Each color channel value ranges from 0 to 255, representing the intensity of the color in the image.

To facilitate the learning process of the CNN model, the color values are then rescaled to a range of 0-1 [22]. This is done by dividing the pixel values by 255.0, resulting in values between 0 and 1. Overall, the CNN system design method eliminates the need for manual feature extraction and preprocessing steps, allowing the model to learn directly from the raw image data in Table 1.

Table 1. The total number of datasets for three classes (image).

Skin Lesion	Testing	Training	Validating	Total
Melanoma	117	374	30	600
Nevus	393	1,372	78	2,000
seborrheic_keratosis	90	254	42	150

Augmentation is a common technique used in machine learning for increasing the size and diversity of the training data set. In the context of image classification, augmentation involves generating new images from the existing ones by applying various transformations to them.

In this particular study, augmentation is used to manipulate skin cancer images to improve the accuracy of the classification model. The augmentation parameters used include Rotation_range = 10, zoom_range = 0.1, width_shift_range = 0.1, height_shift_range = 0.1, horizontal_flip = False, and vertical_flip = False. These parameters determine the types of transformations that will be applied to the images during augmentation.

Rotation_range = 10 means that the images will be rotated by a maximum of 10 degrees, zoom_range = 0.1 means that the images will be randomly zoomed in or out by up to 10%, and width_shift_range and height_shift_range mean that the images will be randomly shifted horizontally and vertically by up to 10% of their dimensions. Horizontal_flip and vertical_flip determine whether the images will be flipped horizontally or vertically.

The study aims to classify three types of skin lesions: melanoma, nevus, and seborrheic_keratosis. A total of 2750 images are used for the classification task. The augmentation technique helps to create new images with variations in size, orientation, and lighting conditions, which can improve the accuracy of the classification model by reducing overfitting and increasing the model's ability to generalize to new data.

3. Result and Discussion

The Results and Discussion section of the study describes the process of evaluating the performance of the skin cancer classification model. The model is trained on a dataset of 2750 images of skin lesions, which are classified into three categories: melanoma, nevus, and seborrheic keratosis.

Before training the model, data augmentation is performed to increase the size of the dataset and improve the model's ability to generalize to new data. The augmentation parameters used include Rotation_range = 10, zoom_range = 0.1, width_shift_range = 0.1, height_shift_range = 0.1, horizontal_flip = False, and vertical_flip = False. These parameters determine the types of transformations that will be applied to the images during augmentation.

After data augmentation, the model is created and trained using the Keras deep learning framework. The model consists of several convolutional layers and pooling layers, followed by a series of fully connected layers. The model is trained with a batch size of 32 and 20 epochs.

The performance of the model is evaluated using various metrics, including accuracy, precision, recall, and F1-score. The results show that the model achieves an accuracy of 80.7%, which is higher than the baseline accuracy of 69.4% obtained without data augmentation.

Overall, the Results and Discussion section provides a detailed account of the process of building and evaluating the skin cancer classification model, including the use of data augmentation to increase the size and diversity of the dataset.

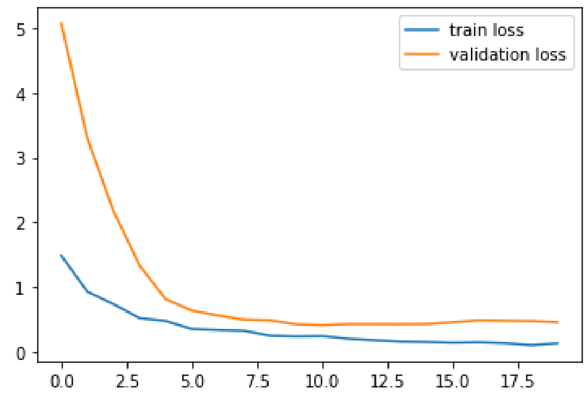

Figure 3. Model loss

The loss graph in Figure 3 is an important visual representation of the performance of the skin cancer classification model. The x-axis shows the number of iterations or epochs, which is a measure of how many times the model has gone through the training data. The y-axis shows the loss value, which is a measure of how well the model is doing in predicting the correct class labels.

A high loss value indicates that the model is not performing well and needs to be adjusted or retrained. On the other hand, a low loss value indicates that the model is performing well and can make accurate predictions on new data.

In this case, the loss graph shows that the loss value is relatively high at 37%, which suggests that the model's performance could be improved by adjusting its parameters or increasing the size of the training data. Further analysis of the loss graph and other metrics can help identify specific areas for improvement in the model's architecture and training process.

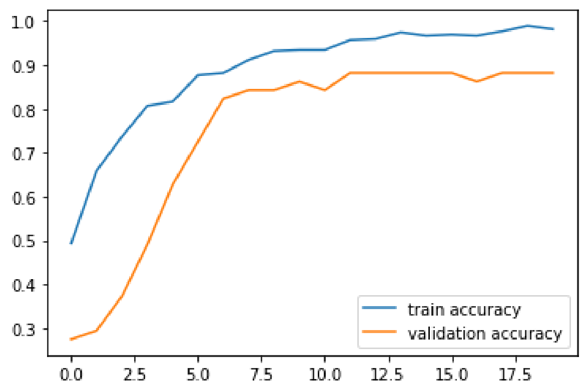

Figure 4. The result of accuracy

The results of the model training were visualized in the form of graphs. Figure 4 shows the accuracy graph of the model. The x-axis represents the epochs (iterations) of the training process, ranging from 0.0 to 17.5, while the y-axis represents the accuracy level, ranging from 0.3 to 1.0. Based on the accuracy graph, the model achieved an accuracy of 88%.

After obtaining the training graph, the model was then evaluated using a confusion matrix and a classification report, as shown in Figures 5 and 6. Figure 5 represents the confusion matrix table, which shows the number of true positive (TP), false positive (FP), false negative (FN), and true negative (TN) predictions made by the model for each class. From the confusion matrix table, it can be seen that the model accurately predicted 33 data points for class 0 (melanoma) and incorrectly predicted some data points for class 0. Similarly, the model accurately predicted 6 data points for class 1 (nevus) and incorrectly predicted 6 data points for class 2 (Seborrheic_keratosis).

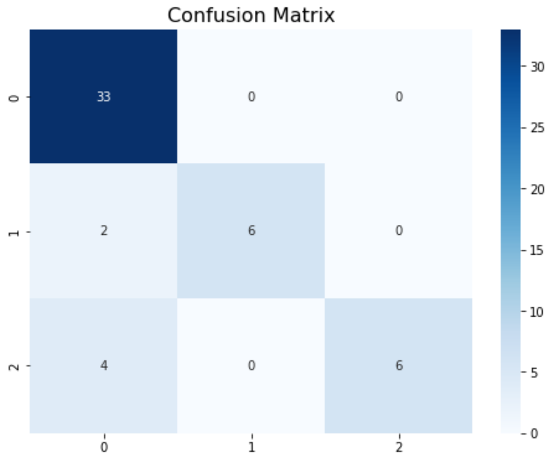

Figure 5. Table of confusion matrix

In Figure 5, the evaluation of the model using classification_report is presented. The results show that the model achieved an accuracy of 88%, with the highest precision and recall values obtained for class 0 (melanoma), which were 0.85 and 1.00, respectively. The f1_score for class 0 was 0.92, which is considered to be high. Additionally, the precision and recall values for class 1 (nevus) were 0.67 and 0.67, respectively, with an f1_score of 0.67. Finally, for class 2 (Seborrheic_keratosis), the precision value was 0.67 and the recall value was 0.50, with an f1_score of 0.57. Overall, the classification_report provides a detailed summary of the model's performance for each class, including precision, recall, and f1_score.

	precision	recall	f1-score	support
0	0.85	1.00	0.92	33
1	1.00	0.75	0.86	8
2	1.00	0.60	0.75	10
accuracy			0.88	51
macro avg	0.95	0.78	0.84	51
weighted avg	0.90	0.88	0.87	51

Figure 6. Classification report

The conclusion summarizes the findings of the research study, which indicate that the performance of the convolutional neural network model is influenced by several factors, including the number of layers, kernel size in the input layer, accuracy of data augmentation, data quality, and data balance. The authors note that the difficulty the model had in classifying some data was due to the fact that certain classes had several variations within them, as each class consisted of a combination of several previous categories. The researchers highlight the importance of using appropriate augmentation techniques to improve the accuracy of the model, and note that the amount of data used in the training phase has a significant impact on the model's performance, with greater amounts of data leading to higher accuracy rates. Additionally, they suggest that data frequency balance in each class can also affect the model's accuracy, and that a balanced dataset can improve the model's performance.

The proposed model was able to achieve an 88% accuracy in classifying skin cancer pigments, with the highest precision and recall values found in class 0 (melanoma) at 0.85 and 1.00, respectively, and an f1_score of 0.92. The authors suggest that future research should explore other methods related to the CNN architecture for further development.

Based on the study, the authors concluded that the performance of the convolutional neural network model depends on several factors such as the number of layers, the size of the kernel_size in the input layer, the accuracy of data augmentation, data conditions, and data balance. The difficulty of the model in classifying data was due to the data conditions in a class that had several variations, which was caused by each class consisting of a combination of several previous categories. Using appropriate augmentation techniques is necessary to increase the accuracy of the model. The dataset size is also a crucial factor in the performance of the built model. The more data that is processed, the higher the accuracy of the model. Additionally, the frequency balance of data in each class can also affect the accuracy of the model. A balanced dataset can improve the accuracy of the model.

4. Conclusion

The proposed model achieved an accuracy of 88% in classifying skin cancer pigments, with the highest precision and recall values found in class 0 (melanoma), at 0.85 and 1.00, respectively, and an f1_score of 0.92. Finally, the authors suggest that future research should experiment with other methods related to CNN architecture

References

[1] N. Codella et al., “International Skin Imaging Collaboration (ISIC),” pp. 1–12, 2018,2021.

[2] R. L. Siegel, K. D. Miller, and A. Jemal, “Cancer statistics, 2018,” CA. Cancer J. Clin., vol. 68, no. 1, pp. 7–30, 2021.

[3] T. L. D. Munthe, “Klasifikasi Citra Kanker Kulit Berdasarkan Tingkat Keganasan Kanker Pada Melanosit Menggunakan Deep Convolutional Neural Network (DCNN),” Repos. Institusi Univ. Sumatera Utara, pp. 44–48, 2021.

[4] R. Suganya, “An automated computer aided diagnosis of skin lesions detection and classification for dermoscopy images,” 2016 Int. Conf. Recent Trends Inf. Technol. ICRTIT 2016, 2021.

[5] M. U. Rehman, S. H. Khan, S. M. Danish Rizvi, Z. Abbas, and A. Zafar, “Classification of Skin Lesion by Interference of Segmentation and Convolotion Neural Network,” 2018 2nd Int. Conf. Eng. Innov. ICEI 2018, pp. 81–85, 2021.

[6] Y. Ji, X. Li, G. Zhang, D. Lin, and H. Chen, “Automatic Skin Lesion Segmentation by Feature Aggregation Convolutional Neural Network,” 2021.

[7] Y. Guo and A. S. Ashour, “Multiple convolutional neural network for skin dermoscopic image classification,” arXiv, pp. 365–369, 2021.

[8] X. Dai, I. Spasic, B. Meyer, S. Chapman, and F. Andres, “Machine learning on mobile: An on-device inference app for skin cancer detection,” 2019 4th Int. Conf. Fog Mob. Edge Comput. FMEC 2019, pp. 301–305, 2019.

[9] S. Bassi and A. Gomekar, “Deep Learning Diagnosis of Pigmented Skin Lesions,” 2019 10th Int. Conf. Comput. Commun. Netw. Technol. ICCCNT 2019, pp. 1–6, 2021.

[10] S. Albawi, T. A. M. Mohammed, and S. Alzawi, “Layers of a Convolutional Neural Network,” Ieee, 2017.

[11] Institute of Electrical and Electronics Engineers, “2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA 2017) : March 10-12, 2017, Beijing, China.,” pp. 721–724, 2021.

[12] G. S. Jayalakshmi and V. S. Kumar, “Performance analysis of convolutional neural network (CNN) based cancerous skin lesion detection system,” ICCIDS 2019 - 2nd Int. Conf. Comput. Intell. Data Sci. Proc., pp. 1–6, 2021.

[13] E. Jana, R. Subban, and S. Saraswathi, “Research on Skin Cancer Cell Detection Using Image Processing,” 2017 IEEE Int. Conf. Comput. Intell. Comput. Res. ICCIC 2017, 2021.

[14] K. Pai and A. Giridharan, “Convolutional Neural Networks for classifying skin lesions,” IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON, vol. 2019-Octob, pp. 1794–1796, 2021.

[15] A. Budhiman, S. Suyanto, and A. Arifianto, “Melanoma Cancer Classification Using ResNet with Data Augmentation,” 2019 2nd Int. Semin. Res. Inf. Technol. Intell. Syst. ISRITI 2019, pp. 17– 20, 2021.

[16] E. H. Mohamed and W. H. El-Behaidy, “Enhanced Skin Lesions Classification Using Deep Convolutional Networks,” Proc. - 2019 IEEE 9th Int. Conf. Intell. Comput. Inf. Syst. ICICIS 2019, pp. 180–188, 2021.

[17] B. Harangi, A. Baran, and A. Hajdu, “Classification of Skin Lesions Using An Ensemble of Deep Neural Networks,” Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, vol. 2018- July, pp. 2575–2578, 2018,2021

[18] V. Singh and I. Nwogu, “Analyzing Skin Lesions in Dermoscopy Images Using Convolutional Neural Networks,” Proc. - 2018 IEEE Int. Conf. Syst. Man, Cybern. SMC 2018, pp. 4035–4040, 2021.

[19] A. Ech-Cherif, M. Misbhauddin, and M. Ech-Cherif, “Deep Neural Network Based Mobile Dermoscopy Application for Triaging Skin Cancer Detection,” 2nd Int. Conf. Comput. Appl. Inf. Secur. ICCAIS 2019, pp. 1–6, 2021.

[20] A. H. Shahin, A. Kamal, and M. A. Elattar, “Deep Ensemble Learning for Skin Lesion Classification from Dermoscopic

Images," 2018 9th Cairo Int. Biomed. Eng. Conf. CIBEC 2018 - Proc., pp. 150–153, 2019.

[21] S. Kaymak, P. Esmaili, and A. Serener, "Deep Learning for TwoStep Classification of Malignant Pigmented Skin Lesions," 2018 14th Symp. Neural Networks Appl. NEUREL 2018, pp. 1–6, 2021.

[22] R. Jain, P. Nagrath, G. Kataria, V. Sirish Kaushik, and D. Jude Hemanth, "Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning," Meas. J. Int. Meas. Confed., vol. 165, p. 108046, 2021.