Convolutional neural network for classification of skin cancer based on image data using google colab

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Abstract. Climate change causes the world's weather to become hotter and has an impact on human health. The direct impact that can be seen is the increase in skin cancer cases due to rising temperatures. This study aims to perform digital image data classification modeling by implementing the Convolutional Neural Network (CNN) method in skin cancer cases using Google Colab software. Research on deep learning applications for identifying and classification image data has been carried out in many recent articles. We used secondary skin cancer image data obtained by a dermoscopy consisting of malignant and benign skin cancer. From 3297, there are 1,800 images of benign skin cancer and 1,497 images of malignant skin cancer. For modeling purposes, it was divided into 2967 training data and 330 testing data. The training process uses variations of the epoch and learning rate to determine the best results. The accuracy value obtained is 99.60% and the validation accuracy value is 92.12%. These results were obtained using 100 epochs and a learning rate of 0.00001. Based on the prediction results using a confusion matrix for testing data, the accuracy value is 90%.

1. Introduction
The risk of skin cancer is determined by multiple factors, the most important being exposure to ultraviolet radiation. Strong circumstantial evidence supports the hypothesis that climate change factors, including stratospheric ozone depletion, global warming, and ambient air pollution, are likely to contribute to a global increase in the incidence of skin malignancy and will continue to negatively affect the incidence of skin cancer for many decades to come. These extreme weather changes are caused by the increase in vehicles, the wasteful use of electricity and the use of glass buildings. The impact of global warming is due to rising global temperatures as well as the greenhouse effect [1-4].

It is important to understand that cancer is one of the main mortality rates in Indonesia and global health danger. In Indonesia, skin cancer malignancy ranks third after cervical cancer and breast cancer. According to Wibawa et al. [5], out of 263 cases of skin cancer, basal cell carcinoma (BCC; 66.9%) was the most common skin cancer followed by squamous cell carcinoma (SCC; 27.4%), and malignant melanoma (MM; 5.7%). Most skin cancers were predominantly in the female population. In BCC and SCC, the majority of patients were older than 60 years of age. In MM, the incidence is higher in the age group of 41–50 years. For BCC and SCC, the lesion distribution sites were mostly in sun-exposed areas, while the MM distribution sites were mostly in sun-exposed areas. The mean diameters of BCC, SCC and MM were 2, 4, and 6.5 cm, respectively. The incidence of BCC was increased from 1996 to 2017.
Cancer is an abnormal growth of cells in the body that can interfere with cell performance. The growth of skin cells would be abnormal, usually because of excessive exposure of UV. There are two types of abnormal cell growth: benign (benign) and malignant (malignant tumor). Benign tumor is an abnormal cell which grows very slowly and rarely causes death. Unlike benign, malignant growth is fast and can attack other body tissues. Malignant can lead to a high death rate. Early identification between the diagnosis of benign and malignant skin lesions enables appropriate management regimes to achieve the best long-term prognosis. A presumptive diagnosis may be made by considering the risk factors of the patient, the history of the lesion and the location and appearance of the lesion. The definitive diagnosis is made by the histological examination of the specimens of the biopsy. The three common types of malignant skin lesions are basal cell carcinoma, squamous cell carcinoma, and malignant melanoma. Generally, benign skin lesions do not require definitive treatment. Treatment for primary skin malignancies includes surgical excision with adjuvant therapy, if necessary [6].

Skin cancer can be detected by the use of a dermoscopy tool to identify objects in a picture [7-9]. Dermoscopy is a tool for the doctor to check the layer of skin. Deep learning is a subset of machine learning and, in turn, is a subset of artificial intelligence. The input, several hidden and output layers consist of neural networks consist of deep learning. It increases efficiency by increasing the dataset, i.e. it learning much better than machine learning with more data sets.

It is possible to model the classification of skin cancer images using google colab. Google has created google collaboratory (google colab), the online forum for publishing, running, and improving machine learning codes. Google colab is a coding environment using the Python programming language. Various python versions and different runtime environments are available here. More data sets can also be copied directly from servers to high-speed google drives. Google also discusses the amount of memory and calculation provided by the user. It offers high-speed simulations and then saves the learning model. The best model can be used for forecasts. In this study, skin cancer classification was carried out based on image data using the convolutional neural network method.

Classification of images is an important activity for many different applications of medical imaging. Their classification performance is greatly influenced by image segmentation and the characteristics of the classification process. The recent development of a deep learning algorithm, such as a convolutional neural network (CNN), allows image classification without image segmentation and manual properties and provides high performance with sufficient data [10-13]. We propose to categorize melanoma images into benign and malignant groups in a deep CNN.

2. Research methods
This study uses the Convolutional Neural Network (CNN) method. CNN according to Dewi in 2018 is a deep learning method that is widely used to solve problems related to object detection and image classification. CNN is able to recognize an object in the form of images, sounds, text, etc. In this study, the implementation of CNN was carried out in a google colab environment. The detection phase of CNN includes data input, data visualization, data preprocessing, and CNN modelling. In the training process, experiments were carried out using variations in the epoch parameter and the learning rate. The best model is obtained through evaluation using test data based on the results of the confusion matrix.

The first stage is to import the packages used in the test and enter the data using the installed drivers to be entered into the google colab. Furthermore, the data visualization stage shows that skin cancer data has been adjusted to a size of 224x224 and using RGB images. The preprocessing stage divides the data into 90% training data and 10% test data. The formation of the CNN model uses the RELU activation function and the softmax activation function. The next process is to test the training data to get accuracy on several variations of the epoch. The final stage is to evaluate the test data using a confusion matrix to produce accuracy values based on TP, FP, FN, and TN values.

3. Results and discussion
The data used was obtained from the International Skin Imaging Collaboration (ISIC) via Kaggle. The data consists of malignant and benign skin cancer images obtained by a dermoscopy tool. There were
3297 image data with 1,800 images of benign skin cancer and 1497 images of malignant skin cancer. Each image is labeled 0 or 1. Label 0 indicates that the image data is benign skin cancer, while label 1 is for malignant skin cancer image data.

**Table 1. Research data.**

| Type of Data | Data Training (90%) | Data Testing (10) |
|--------------|---------------------|------------------|
| Skin cancer  | 2967                | 330              |

Based on Table 1, we divide 2967 images as training data and 330 images as testing data. In Figure 1 below, we illustrate a visualization of 20 skin cancer images. Each existing skin cancer image has been labelled and displayed in the following visualization.

![Image of skin cancer visualization](image)

**Figure 1. Visualization of skin cancer images.**

Based on Figure 1, we can see an image visualization with 20 images consisting of 7 columns and three rows. The visualization image consists of 20 images of skin cancer hyperplasia and malignant skin cancer with a size of 224x224 that have been formed. We built a CNN model with an image input of 224x224 and a kernel size of 3x3. This modelling uses the Keras library with a Sequential model of the convolutional layer. The process continues to be convolutional and max-pooling to the classification layer. Several layers that are needed in CNN modelling are convolutional layer, max-pooling, dropout, flatten, and dense.
Table 2. CNN model parameters.

| Layer          | Output Shape | Parameter |
|----------------|--------------|-----------|
| conv2d         | 224x224x8    | 224       |
| max_pooling2d  | 112x112x8    | 0         |
| conv2d_1       | 112x112x8    | 584       |
| max_pooling2d_1| 56x56x8      | 0         |
| conv2d_2       | 56x56x32     | 2336      |
| max_pooling2d_2| 28x28x32     | 0         |
| conv2d_3       | 28x28x32     | 9248      |
| max_pooling2d_3| 14x14x32     | 0         |
| dropout        |              |           |
| flatten        | 6272         | 0         |
| dense          | 128          | 802994    |
| dropout_1      | 128          | 0         |
| dense_1        | 2            | 258       |
| Total Parameter|              | 815.954   |

The number of parameters in the CNN model formed was 815,594. All parameters are derived from the number of elements for each layer. The results of the max-pooling, dropout, and flatten parameter values are 0 because they do not have parameter elements that can be learned. In this study, a training experiment was conducted to evaluate several CNN models produced. We process training data for several variations of the learning rate and variations of the epoch. In the first experiment, we used a variation of the epoch 25, 50, 75, and 100, with each epoch using a learning rate parameter of 0.00001. The results obtained are summarized in Table 3.

Table 3. Loss results and accuracy of epoch variations.

| Epoch | Loss | Accuracy | Val. Loss | Val. Accuracy |
|-------|------|----------|-----------|---------------|
|       | Min  | Max      | Min       | Max           | Min | Max | Min | Max |
| 25    | 0.2107 | 0.5808 | 0.6899 | 0.9066 | 0.2444 | 0.4022 | 0.7909 | 0.9091 |
| 50    | 0.0863 | 0.7033 | 0.5642 | 0.9670 | 0.2274 | 0.6913 | 0.5788 | 0.9152 |
| 75    | 0.0420 | 0.6559 | 0.6151 | 0.9845 | 0.2772 | 0.5290 | 0.7758 | 0.9212 |
| 100   | 0.0130 | 0.5776 | 0.6828 | 0.9960 | 0.2384 | 0.5490 | 0.7758 | 0.9212 |

Based on Table 3, the highest accuracy results are 99.60% and the validation accuracy value is 92.12% at epoch 100. The results using epoch 100 are the best results compared to other epoch results. At this level, the maximum loss values are 57.76% with a validation loss value of 54.90%. Based on these results, it is concluded that increasing the epoch will increase the accuracy value.

In the second experiment, we used a variation of the learning speed of 0.0001; 0.00001; 0.000001; and 0.0000001. Each learning speed uses epoch 100. Based on Table 4 for variations in learning rates, the highest accuracy value is 99.60% and the highest accuracy validation is 92.12% at a learning rate of 0.00001. The smallest loss value can be seen at 1.2% at a learning rate of 0.000001. From Table 4, it can be concluded that changes in the learning rate value do not linearly affect the accuracy value. If you are using the more extensive epoch, you should use a small learning rate value to produce optimal values.

Table 4. Loss results and accuracy of epoch variations.

| Epoch   | Loss | Accuracy | Val. Loss | Val. Accuracy |
|---------|------|----------|-----------|---------------|
|         | Min  | Max      | Min       | Max           | Min | Max | Min | Max |
| 0.0001  | 0.0180 | 0.6515 | 0.6100 | 0.9956 | 0.2317 | 0.6368 | 0.7030 | 0.9152 |
| 0.00001 | 0.0130 | 0.5776 | 0.6828 | 0.9960 | 0.2384 | 0.5490 | 0.7758 | 0.9212 |
| 0.000001| 0.0120 | 0.5817 | 0.7165 | 0.9966 | 0.2093 | 0.5788 | 0.7848 | 0.9061 |
| 0.0000001| 0.0173 | 0.6048 | 0.6606 | 0.9943 | 0.2234 | 0.5612 | 0.7758 | 0.9091 |
Based on the results of the analysis above, the variation that produces the best accuracy in the training process is obtained using 100 epochs and a learning rate of 0.00001. The accuracy and loss models plots for training data and testing data set are given in Figures 2 and 3, respectively.

![Figure 2. The plot of train and test accuracy.](image1)

![Figure 3. The plot of train and test loss.](image2)

For the model validation process, a total of 330 data were used. Based on the confusion matrix, an accuracy value of 90% was obtained with a true positive (TP) value of 123, false positive (FP) 11, false negative (FN) 22, and true negative (TN) 174.

### 4. Conclusion

In this paper, CNN modeling is carried out with an input of 224x224 and a kernel size of 3x3. In this CNN modeling estimated 815,594 parameters. The training process uses epoch 100, learning rate 0.00001, batch size 64, training data 2967, and testing data 330. Experiments are carried out for two variations, namely variations of epoch and variations of learning rate. In the epoch variation, epoch 25, 50, 75, and 100 are used, with each epoch using a learning rate of 0.00001. In the first experiment, the highest accuracy value was 99.60% and the validation accuracy was 92.12% at epoch 100, with the lowest loss value of 1.3% and validation loss of 23.84%. It appears that the difference in the epoch value can affect the accuracy value, so it is necessary to adjust the epoch value to get optimal results. The
second experiment uses a learning rate variation of 0.0001; 0.00001; 0.000001; and 0.0000001 using 100 epochs, respectively. We obtained the highest accuracy of 99.66%. However, the losses were quite high, namely 58.17%; then, using an accuracy of 99.60% with a learning rate of 0.00001. Furthermore, the model validation was carried out using 330 test data to predict the image error rate. From the validation results, 123 images of benign cancer were predicted to be correct, and 11 images were wrong. There were 174 images of malignant skin cancer that were predicted correct and 22 images were incorrectly predicted. Based on these results, an accuracy value of 90% and an error value of 10% is obtained.

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