DOI: 10.15849/IJASCA.240330.15

Int. J. Advance Soft Compu. Appl, Vol. 16, No. 1, March 2024
Print ISSN: 2710-1274, Online ISSN: 2074-8523

Skin Cancer Classification from Dermatoscopy Images Using Deep Neural Network

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Abstract

Skin cancer is one of Indonesia's most common malignant cancers and can cause death. A dermatologist uses a sample and microscope procedure to diagnose skin cancer manually. Nevertheless, this procedure is laborious, and there is a chance that the biopsy will be done incorrectly. More than 90% of cases can be cured with an early diagnosis. However, less than 50% can be fixed with a late diagnosis. This study suggests a convolutional neural network (CNN) approach to classify skin cancer using an Alexnet architecture. A dataset called HAM10000 ("Human Against Machine with 10000 training images") was taken from the International Skin Imaging Collaboration (ISIC) dataset and used in the experiment. We employed 9000 data points in this investigation that were suitable for identification after preprocessing. With a percentage distribution of 80% training data and 20% validation data, the dataset will be used for both training and validation. Thus, 7200 photos of skin cancer were used as training data. Simultaneously, 1800 photos are used as validation data. The test findings demonstrate that the system has an accuracy rate of 80% and a loss value of 0.5459 in classifying skin cancer based on its type. According to system performance data, the generated model may substitute early skin cancer detection.

Keywords: Skin Cancer Classification, Deep Learning, Artificial Intelligence, Dermoscopy Images.

1. Introduction

Skin cancer is a disease caused by changes in the characteristics of cells that make up the skin from normal to malignant, which causes these cells to divide uncontrollably and damage DNA [1], [2], [3]. Skin cancer can cause defects in the skin and, in some cases, can even result in death if not treated or treated. [4], [5], [6]. There are many types of skin cancer, from less dangerous to very dangerous.

Currently, seven types of skin cancer are commonly found [7], [8]. The World Health Organization (WHO) estimates that the use of sunbeds causes around 66,000 deaths each year from malignant melanoma and other skin cancers and increases the risk of contracting skin cancer [9]. As seen in Fig. 1, based on sunburst analysis, it shows the percentage of countries that have cases of skin cancer.

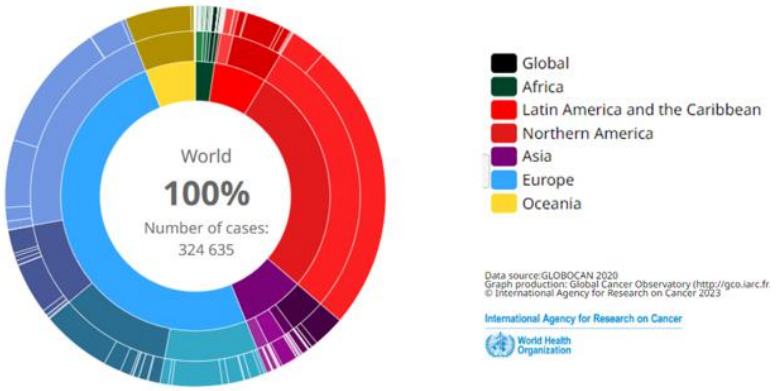

Figure 1. Cases of skin cancer from WHO.

The organ that is attacked is the outermost human skin, so the initial symptoms of a rash from each skin cancer are almost the same and difficult to recognize with the naked eye. Skin cancer can be identified based on the symptoms it causes. The doctors call the symptoms of this skin cancer "ABCDE," which is Asymmetry, Border that is irregular, uneven Color, Diameter, and Evolving [10], [11]. A unique examination is using a Biopsy method to diagnose skin cancer [12]. The process involves taking samples of small pieces of skin tissue and then examining them in the laboratory [13], [14]. Biopsy costs are relatively expensive and this method can injure or scratch human skin [15]. We hope that with computer-based skin cancer diagnosis method using digital images, faster and more accurate results can be obtained.

Dermoscopy can help visualize structures under the skin's surface down to the superficial dermis and show the morphology of lesions that are difficult to observe with the naked eye[16], [17]. Dermoscopy is a skin imaging modality for the identification of skin cancer. In response to ISIC's challenge to make expertise more accessible, the International Skin Imaging Collaboration (ISIC) has built an archive of dermoscopy images for research and clinical training[18], [19], [20].

Previous studies on image analysis using Artificial Intelligence (AI) in skin cancer detection have attracted the attention of dermatologists. Artificial Intelligence (AI) methods have been widely used as a skin cancer identification method [21], [22], [23]. These methods can process uncertain, imprecise data and can be implemented at a low cost (low-cost solution). Research by Murugan et al. [24] uses machine learning methods such as SVM (Support Vector Machine), kNN (k Nearest Neighbor), and Random Forest for skin cancer detection using imagery. Anas et al. [25] used a clustering technique to detect skin cancer. This study proposes an automated medical image classification method to classify two main types of skin cancer: melanoma and non-melanoma. Brinker et al. [26] used deep

learning techniques such as Convolutional Neural Network (CNN) with Alexnet architecture to classify melanoma and melanocytic nevi skin cancers. The use of Deep Learning algorithms reduces the need for human labor, such as manual feature extraction and data reconstruction for classification purposes.

Previous research related to digital image processing using computer technology is an essential breakthrough in improving the ability of Artificial Intelligence (AI) to solve problems. Research topics related to skin cancer identification have been widely researched, and new developments have been made in classifying the disease. This can be a basis for researchers in conducting research on skin cancer identification by considering previous research to improve the recognition process to obtain optimal and accurate classification results.

The dataset used in this study is a contains dermatoscopy image, namely HAM10000 ("Human Against Machine with 10000 training images"), A challenge hosted by the International Skin Imaging Collaboration (ISIC), 2018 [9]. Researchers used a dataset from HAM10000. In the data used, there is image data that was cropped manually, and CNN-segmented image data sets from photographs of skin disease. This study aims to create an alternative model for the early identification of skin cancer types. The main goal of this project is to achieve maximum skin disease prediction accuracy. Deep learning techniques are applied to detect skin diseases at an early stage based on dermoscopic images.

2. Related Work

Recently, deep learning-based approaches for detecting and categorizing skin lesions into several types of skin cancer have been created. This issue has previously been addressed using a variety of deep learning system methodologies and approaches. These techniques include unsupervised learning, supervised learning, transfer learning, and hybrid approaches. Younis et al. [27] proposed using deep learning to classify skin cancer. The Transfer Learning method used the HAM10000 skin lesion data set to train a pre-tuned MobileNet convolution neural network. Ali et al. [28] proposed a model for feature extraction and automatic identification of boundary irregularities from skin lesion images combining a Gaussian Bayes ensemble with a Convolutional Neural Network. When tested against a data set of skin lesion photographs, the system yielded values for accuracy, sensitivity, specificity, and F-scores of 93.6%, 100%, 92.5%, and 96.1%, respectively.

El-Khatib et al. [29] used the transfer learning method to train the CNN model on data from ImageNet and Places365. Other pre-trained models were used, including GoogleNet, ResNet-101, and NasNet-Large. A transfer learning approach to detect skin lesions was then used to refine these models on skin lesion data sets. With the respective values obtained, accuracy reached 88.33%, specificity reached 88.24%, coefficient of the dice 88.46%, and the combined model reached 86.79% on skin lesion image data. Aljohani et al. [30] compared deep learning models that fit on a graphics processing unit using several convolutional neural networks (CNN) architectures, including DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, and GoogleNet (GPU). According to

experimental findings, GoogleNet can achieve maximum performance accuracy on the training and test sets (74.91% and 76.08%, respectively).

Alqudah et al. [31] used transfer learning, gradient-optimizing adaptive momentum learning rate (ADAM), GoogleNet, and AlexNet for skin lesion image classification. This method was used to classify images from the 2018 ISBI database into three main categories: benign keratosis, melanoma, and seborrheic, using two different classification approaches for segmented and non-segmented lesion images. Classification accuracy for segmented data sets is 92.2% and for unsegmented, it is 89.8%. Lesion images undergo preprocessing techniques such as lesion image enhancement, screening, and segmentation to provide Region-of-Interest (ROI) data. Deep learning features, as well as handcraft features, are both extracted. Shape, color, and texture features are extracted using ABCD rules, while deep learning features are extracted using CNN [32].

Skin lesions were divided into melanoma and nevi using the Higuchi 2D fractal surface feature by Simona Moldovanu et al. [33]. Based on the fractal skin surface characteristics and the average percentage of relevant color area features, they conducted a study to classify skin lesions. The results show that when the resulting color features are correctly coupled to fractal features, the radial basis function neural network (RBF-NN) [34] classifier can obtain good classification accuracy. Khalid M. Hosny et al. [35] classified three different lesions using AlexNet: melanoma, common nevus, and typical nevus. They used the PH2 data set and found that the overall accuracy was 98.61%, the sensitivity was 98.33%, the specificity was 98.93%, and the precision was 97.73%. In this study, we propose to use the DL technique with the Convolutional Neural Network method. It will use the Alexnet Architecture with modifications.

3. METHOD

The designed and implemented system consists of four main stages, namely image input, preprocessing, model training, and classification, as presented in Fig. 2. In preprocessing, the skin image will be normalized to remove needed objects such as noise. Cropping is used to remove the edges of the image so that it does not have a size larger than the main object, and then resizing is used to equalize the size of each skin image. This whole process is carried out to suit research needs. The output of the preprocessing process will be training to obtain a classification model. The classification system in this research will introduce skin images through two stages, namely the training and validation stages, and then classify them according to class.

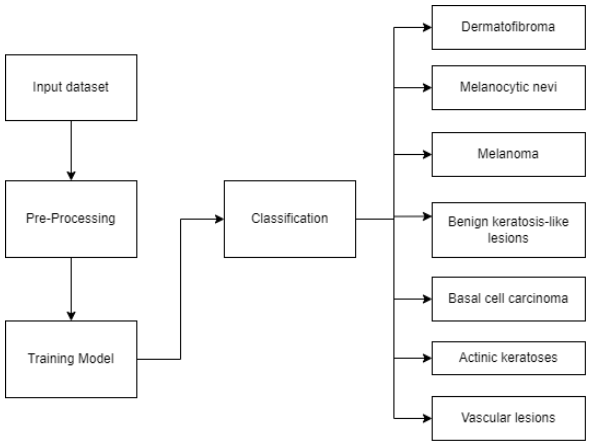

Figure 2. System flow chart.

3.1. Data Source

In this research, the image data used is the HAM10000 ("Human Against Machine with 10000 training images") dataset, a challenge hosted by the International Skin Imaging Collaboration (ISIC) 2018 [36]. The entire collection of multi-sources dermatoscopy images of pigmented lesions. Dermatoscopy images were collected from different populations, obtained, and stored by different modalities. The final data set consists of 10015 dermatoscopy images. The dataset features seven different types of skin cancer, including actinic keratosis, basal cell carcinoma, benign keratosis-like lesions, melanocyte nevi, melanoma, vascular lesions, and dermatofibromas, as seen in Fig. 3.

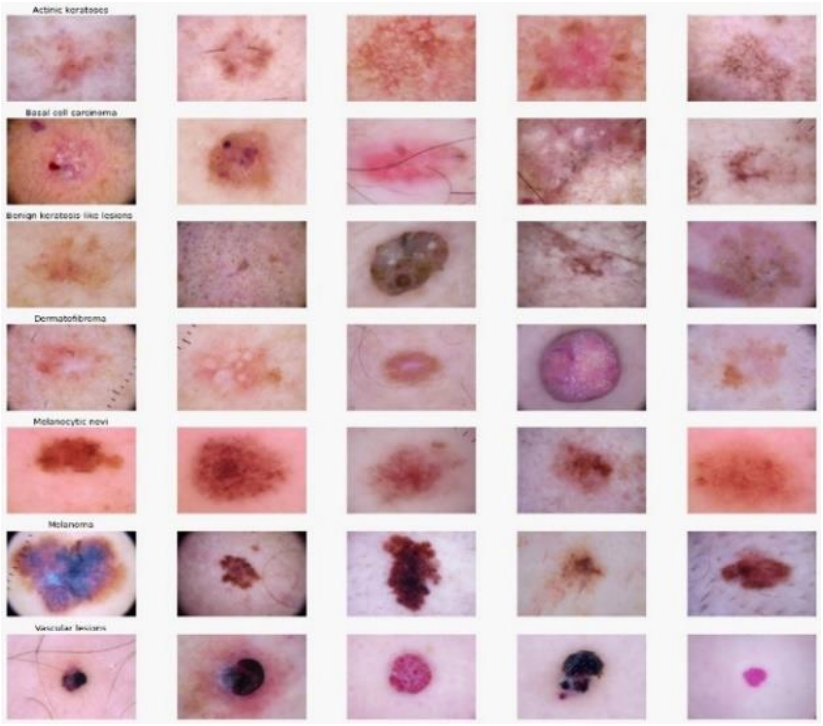

Figure 3. Seven types of skin cancer.

3.2. Data Preprocessing

Pre-processing is a technique for preparing data so that it is more ready to be carried out further in the knowledge extraction framework. Classification is an approach in data science that is also known as a supervised algorithm. Of course, the data type in the classification technique requires a data label. The pre-processing carried out in this study is divided into data cleaning, exploratory analysis, and image processing.

3.2.1 Data Cleaning

Data cleaning is a procedure to ensure data correctness, consistency, and usability in a dataset [37]. The data cleaning carried out on the dataset used removes Null values in the data. As seen in Fig. 4, there are 57 Null values in the age feature. It will affect the analysis process that is carried out next. So the data cleaning process is carried out to remove the Null value.

```
lesion_id        0
image_id         0
dx               0
dx_type          0
age             57
sex              0
localization     0
```

Figure 4. Data Null.

3.2.2. Image Preprocessing

The following process is to resize the image. Because the original dimension of the image on the dataset is 450 * 600 * 3, it takes a long time to process. It requires preprocessing the image, which divides each skin cancer image into several smaller parts [38], can be seen in Fig. 5. The original image measuring 600 x 450 pixels, is divided into several image fragments with a size of 125 * 100 so that the images are compatible with the training model created. The results of image preprocessing can be seen in Fig. 3.

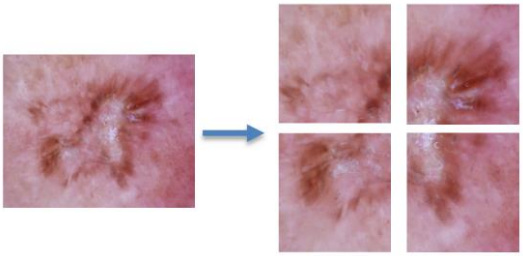

Figure 5. Preprocessing Patch on Skin Cancer Images.

3.2.3. Exploratory Data Analysis

Conduct exploratory analysis, with univariate and bivariate analysis, to determine the suitable analysis model. Exploratory data analysis can help detect obvious errors, identify outliers in data sets, understand relationships, find out important factors, find patterns in data, and provide new insights. Data exploration was carried

out using univariate analysis. Analysis was carried out based on age, gender, location of the lesion, and type of cancer. The analysis results can be seen in Fig. 7. Skin disease is found maximally in people aged around 45, whereas it is minimally present for persons of age of ten and under. We also observed that the probability of developing skin diseases increases with age. Skin disease is more prominent in men than in women. Skin disease is more pronounced on the "back" of the body and least on the "acral surfaces" (such as the limbs, fingers, or ears). The most common type of cancer found in humans is Melanocytic nevi, while the least found is Dermatofibroma.

3.3. Evaluation Measure

To evaluate our classification model, we use Accuracy (Acc). Accuracy is a measure of the value that becomes the determination of a system in correctly classifying true positives and negatives. A significant accuracy value indicates that more data is classified correctly. Accuracy calculations are carried out for each part by making predictions using a classification model first. These results can then be used to compare the predicted output with the dataset labels and calculate accuracy for each group of objects. As for calculating the level of accuracy, we are using the following equation [39].

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \quad (1)$$

3.4. Confusion Matrix

A confusion Matrix is a helpful method for comparing the misclassification of data expressed in a matrix form. The Confusion Matrix has various performance parameters such as True Positive, True Negative, False Positive, and False Negative, as in Fig. 6 [40], [41]. The definition of elements of the confusion matrix, such as True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP) is as follows:

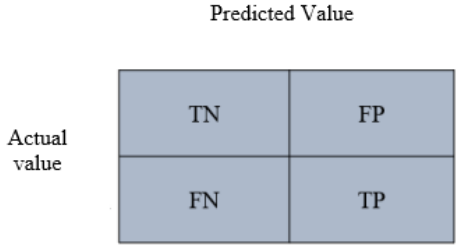

Figure 6. Confusion matrix.

1. True Positive (TP) is a condition where the data image of malignant skin cancer correctly predicts malignant skin cancer according to its class.
2. True Negative (TN) is a condition where the data image of benign skin cancer predicts true benign skin cancer according to its class.
3. False Negative (FN) is a condition where the data image represents a malignant skin cancer but detected benign skin cancer does not match its class.

4. False Positive (FP) is a condition where the data image belongs to a benign skin cancer but detected malignant skin cancer does not match its class.

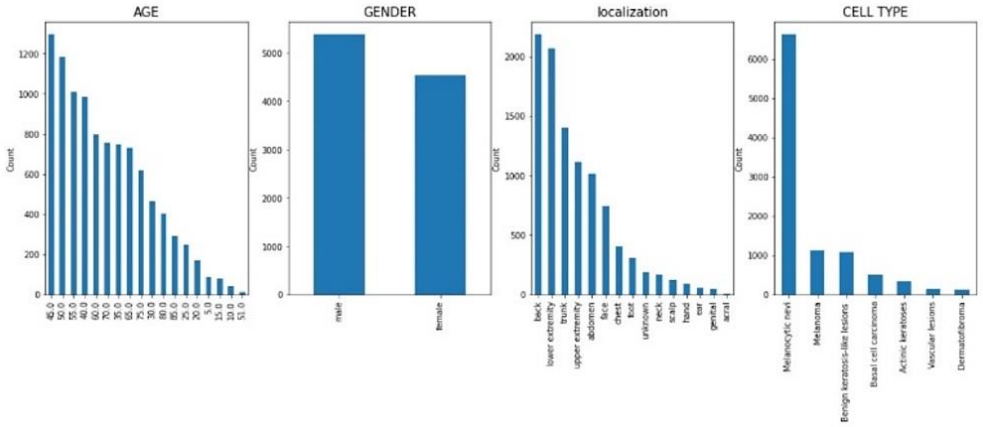

Figure 7. Image data analysis based on age, gender, localization, and cell type.

3.5. Convolutional Neural Network (CNN)

Convolutional Neural Networks are part of deep learning and are effectively used for visual image analysis and object or image detection [42]. Convolutional Neural Network consists of a set of layers that can be grouped based on their function. CNN consists of two major parts: the feature extraction layer and the classification layer. The Feature Extraction Layer consists of several parts: the Convolutional Layer with ReLU activation and the Pooling layer, which functions as a feature extraction layer, and a fully connected layer with softmax activation as a classification layer.

In the Feature Extraction Layer, there is an encoding process of input in the form of images into features in the form of numbers representing those images. The classification of each neuron extracted at the previous layer is carried out at the Classification Layer. This layer consists of a flattened, fully connected layer and softmax. The classification process uses the Alexnet architecture. The Alexnet model used in this study is described in Fig. 9. The proposed CNN architecture contains 6 Convolutional layers, Dropout, Pooling, followed by Flatten, Dense, Dropout, and Dense layers. Table I shows the layer type and output shape used for each layer.

3.5.1. Mathematical Models

The clinical diagnosis of several disorders consistently demonstrates the efficacy of all variations of CNN. The mathematical background of some of the CNN building pieces is explained in the next section.

A) Convolution Layers

This stage is a layer that performs the convolution process between the input image matrix and the filter matrix to produce an output in the form of a feature map. The formula for the convolution operation can be written as follows:

$$Conv[i]_{j,k} = \sum_m \sum_n N_{[j-m,k-n]} F_{[m,n]} \quad (2)$$

Where, Conv[i] is the ith feature map matrix, j,k is the pixel position in the input image matrix, m,n is the pixel position in the convolution filter matrix, N is the input image matrix, F is the convolution filter matrix.

B) Activation Function

The next step a Rectified Linear Unit (ReLU). All pixels in the feature map are entering into the ReLU function, where this activation function works to sort out pixels that have a value less than 0 and then change the value to 0, with the formula f(x) = max (0, x).

C) Pooling Layer

To speed up processing, the pooling method is used to reduce the image size. The subsampling step follows each convolution step, decreasing the dimension of the feature map by 2. The subsampling level is 2x2 pooling layers. Image data is resized using average and maximum pooling. The pooling process that is often used is max pooling, and it selects the maximum value in a certain area.

$$Pool_{x,y} = max(Conv_{x,y}, Conv_{x+1,y,} Conv_{x,y+1}, Conv_{x+1,y+1}) \quad (2)$$

Where $Pool_{x,y}$ is the resulting value of the pooling layer, and $Conv_{(x,y)}$ is the pixel value of the result of the convolutional layer. Fig. 8 is an example of the Max Pooling process.

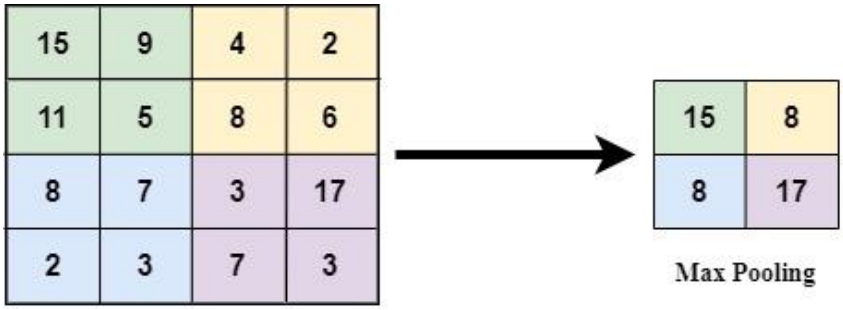

Figure 8. Max pooling.

D) Fully Connected Layer

Multi-Layer Perceptron has several (hidden) layers, activation functions, and output layers. The fully connected layer functions to classify input data. The output generated from the pooling layer is still in the form of a multidimensional array, so a flattening process is needed first to convert the data into vectors before it is inputted into the fully connected layer. The equations to be used at this stage are as follows:

$$Fully_i = \sum_j^{Length(flatten)} W_{i,j} * flatten_j + b_i \quad (3)$$

Where $Fully_i$ is the calculation result of the fully connected layer, $W_{i,j}$ is the weight value in the convolutional layer, $flatten_j$ is the value of the j-th vector, vector values are obtained from the results of max pooling in the convolution layer, and i is the i-th class (i=1, 2,3,4,5,5,7). The result of fully will be activated again by using the ReLU function and the SoftMax function. The SoftMax function is used because the number of classes is more than two, which is commonly called multi-class.

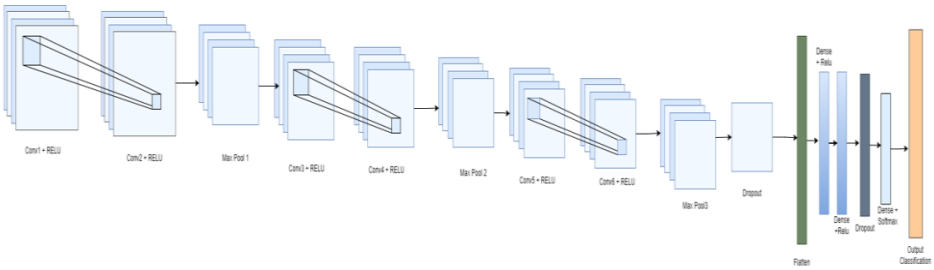

Figure 9. CNN model modification.

Table 1. Optimizer test results.

Layer (type)	Output Shape	Param #
Conv1	(None, 100, 125, 32)	896
Conv2	(None, 100, 125, 32)	9248
Max_pooling1	(None, 50, 62, 32)	0
Conv3	(None, 50, 62, 32)	9248
Conv4	(None, 50, 62, 32)	9248
Max_pooling2	(None, 25, 31, 32)	0
Conv5	(None, 25, 31, 64)	18496

Conv6	(None, 25, 31, 64)	36928
Max_pooling3	(None, 12, 15, 64)	0
Dropout	(None, 12, 15, 64)	0
Flatten	(None, 11520)	0
Dense	(None, 256)	2949376
Dense	(None, 128)	32896
Dropout	(None, 128)	0
Dense	(None, 7)	903

The architecture of the classification model used for optimal testing is shown in Table 1. The input of a CNN model is a 4D array with a 3-dimensional batch size (*batch_size, height, width, depth*), which changes depending on the filter value, kernel size, and padding used. In the Output Shape section, the first dimension represents the batch size, which does not exist in this study. This is because the network does not know the batch size beforehand. The output data from CNN is a 4D array consisting of *batch_size, height, width, depth*.

In the layer section, *Conv* is a convolutional layer consisting of neurons arranged in such a way as to form a filter with pixel length and height. *Max_pooling* contains the kernel that takes the most significant value of the kernel dimension. Meanwhile, *Dropout* prevents overfitting, thereby reducing connections from neurons by determining a threshold value as an input parameter. *Flattern* makes input with many dimensions into one dimension and is often used before fully connected. Then, *Dense* is an architectural model layer that contains neurons and can be inserted into the convolution section. *Param#* (Parameter) is the value obtained from the calculation *(shape of width of filter*shape of height filter*number of filters in the previous layer + 1) * number of filters*. This is the first step if the layer has a number like *Conv1*. If *Param#* has a value of 0, it has no parameters.

4. Results and Discussion

In this research, the Alexnet architecture has been modified by adding the Max_pooling function to each convolution layer. This function is added to obtain the most significant value of the kernel dimensions, thereby obtaining more accurate data information and reducing dimensions in the following process. Dimensionality reduction helps predict model performance so that each process in the convolution layer does not experience overfitting. The model in this study uses nine layers divided into six convolution layers and three fully connected layers for each neuron. With this modification, researchers aim to optimize to obtain high accuracy values.

To validate our model, we divided our data (9000 images) into training and validation data. The dataset used is 9000 images, divided into 7200 for training data

and 1800 images for testing data (80:20). System testing is carried out using predetermined test parameters, as seen in Table 2.

Table 2. Optimizer test results.

Scenario Description	Optimizer	Learning Rate	Iteration (*epoch*)	Size Batch	Training Accuracy
Scenario 1	Adam	0,0001	10	16	0.7287
Scenario 2	Adam	0,0001	20	16	0,7660
Scenario 3	Adam	0,0001	30	16	0,7764
Scenario 4	Adam	0,0001	40	16	0,7956
Scenario 5	Adam	0,0001	50	16	0.7759
Scenario 6	Adam	0,0001	60	16	0.8018

In the scenario of Table 2, we set fixed values for the Adam optimizer, a learning rate of 0.0001, and a batch size of 16. However, we varied the number of iterations (epochs). The training results showed that the sixth scenario had optimal results with the Adam optimizer, learning rate 0.0001, epoch 60, and batch size using 16.

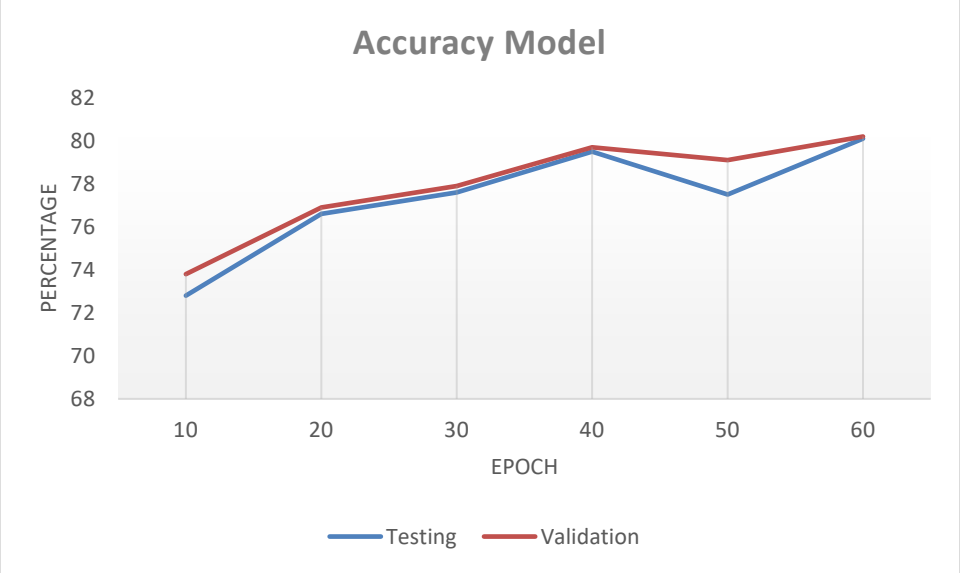

Figure 10. Percentage of testing and validation accuracy values.

The results of the training and validation processes carried out with different numbers of epochs show that epochs affect the accuracy obtained. It can be seen from the varying training results and model validation values. The more epochs, the higher the accuracy results obtained, as seen in Fig. 8. the loss in the model testing process is shown in Fig. 9. The more iterations used (epoch), the lower the error made by the model during testing. The training results can be seen from the

resulting confusion matrix to determine the amount of data successfully detected correctly or incorrectly by the system. Fig. 10 shows the confusion matrix of system performance results with the best scenario.

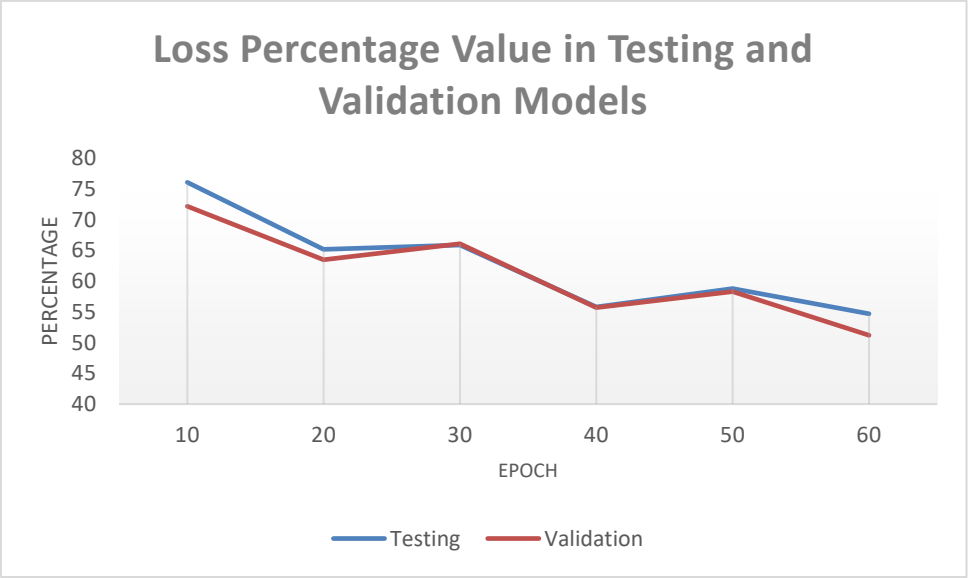

Figure 11. Loss percentage value.

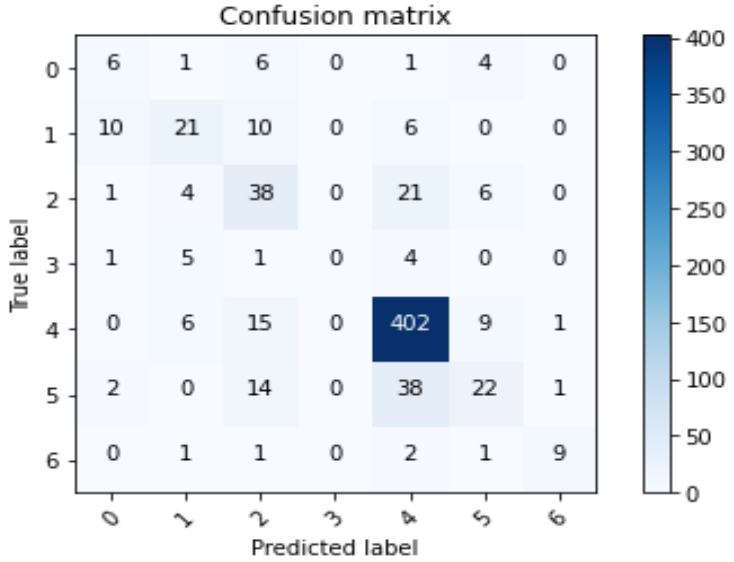

Figure 12. Confusion matrix.

As shown in Table 3, the test results are compared with the transfer learning method and other methods to determine the model's accuracy. The results of the accuracy values above are the average of 6 trials. However, this study obtained the best model from the configuration proposed in the sixth experiment. Our model can produce a relatively high accuracy value of up to 80% from the comparison results with other scenario. It makes our model an alternative that can be used to classify skin cancer.

Table 3. Method comparisson result.

Metode	Accuracy (%)	Loss
Transfer Learning	80%	0.543251
Artificial Neural Network	65%	1.0809
Proposed Model	80%	0.5459

5. Conclusion

The classification system used deep learning techniques, namely the Convolutional Neural Network with the Alexnet architecture. The technique can be used to detect skin cancer and help reduce the risk of delays in early diagnosis of seven classes of skin cancer with system performance that is an accuracy rate of 80% and a loss value of 0.5459. This research uses a classification system, Adam optimizer, learning rate 0.0001, epoch 60, and batch size 16. System testing results also prove that the greater the number of iterations used, the greater the accuracy. Further research suggests developing research in the field of skin cancer treatment based on classification results. This method can be applied as a decision-making expert system model.

6. Acknowledgments

The research team would like to thank the University of Tanjungpura for its assistance in funding and provision of laboratory facilities for the study. Also, we wish to thank Kaggle for providing the databases used in this study for comparison.

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