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Convolutional Neural Network (CNN) for Automatic Skin Cancer Classification System

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Abstract. Skin cancer is a type of cancer that grows in the skin tissue, which can cause damage to the surrounding tissue, disability, and even death. In Indonesia, skin cancer is the third leading for most cancer cases after cervical and breast cancer. The accuracy of diagnosis and the early proper treatment can minimize and control the harmful effects of skin cancer. Due to the similar shape of the lesion between skin cancer and benign tumor lesions, physicians consuming much more time in diagnosing these lesions. The system was developed in this study could identify skin cancer and benign tumor lesions automatically using the Convolutional Neural Network (CNN). The proposed model consists of three hidden layers with an output channel of 16,32, and 64 for each layer respectively. The proposed model uses several optimizers such as SGD, RMSprop, Adam, and Nadam with a learning rate of 0.001. Adam optimizer provides the best performance with an accuracy value of 99% in identifying the skin lesions from the ISIC dataset into 4 classes, namely dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma. The results obtained outperform the performance of the existing skin cancer classification system.

1. Introduction

Skin cancer is a disease caused by changes in the properties of normal skin cells to become malignant, in which cells will continue to divide into abnormal shapes that are uncontrolled due to DNA damage. Based on histopathology view, skin cancer has an irregular structure with cell differentiation in various levels of chromatin, nucleus, and cytoplasm [1]. Skin cancer is a malignancy disease that is often found in Indonesia in addition to cervical cancer and breast cancer. Skin cancer found 5.9 to 7.8% for all types of skin cancer per year. The most common skin cancers in Indonesia are basal cell carcinoma (65.5%), followed by squamous cell carcinoma (23%), malignant melanoma (7.9%), and other skin cancers [2]. Even though the number of Malignant Melanoma incidents is smaller than Basal Cell Carcinoma and Squamous Cell Carcinoma, the death rate tends to be greater, which causes 75% of deaths from skin cancer [1]. The most invasive skin cancer is melanoma, which has a high mortality rate, especially if it is not early detected. Non-melanoma skin cancers, such as basal cell carcinoma and squamous cell carcinoma are more common but less metastatic, and only partially leads to disability or death. Accurate diagnosis and early detection of skin cancer can help the healing process, proper medical treatment, and avoid the worst effects of skin cancer. Therefore, an early detection system is needed that can facilitate and increase public awareness in identifying types of skin cancer or other skin disorders such as a benign tumor on the skin that look very similar to skin cancer.

The automatic skin disorders classification can help people in identifying skin disorders that occur and immediately consult with medical personnel to get appropriate medical treatment. Several related studies based on digital image processing for the detection and classification of skin cancers were developed as a tool for medical personnel to diagnose skin disorders more accurately with fast computing time. The previous research [3] was developed using an edge detection method with K-NN and C-NN algorithms provide an accuracy of 75% and 75.6% respectively to classify skin disorders that potentially benign cancer and skin disorders that have the potential to be malignant cancer by using the International Skin Imaging dataset Collaboration (ISIC). In research [4], using the ISIC dataset for the conditions of skin cancer and skin benign tumors, an automatic skin disease classification system was developed based on deep learning with PNASNet-5-Large architecture which gives the best performance accuracy of 76%. Furthermore, other studies using CNN for the detection of skin diseases [5] [6] [7] provide performance accuracy of 80.52%, 86.21%, 87.25% respectively. To increase the amount of data and to improve the performance of the skin cancer detection system, the ISIC data augmentation process was performed [8]. The best accuracy was obtained by 95.91% using Alexnet. In the study [9], the CNN method with random regulators gave performance accuracy of 97.49% to distinguish some lesions of skin disorders such as nevus lesions, carcinomas, and melanomas. In this study, augmentation data from the ISIC dataset will be used to recognize the condition of skin cancer lesions or benign tumor lesions that look similar to cancer. The proposed method in this study uses CNN with various optimizer methods such as SGD, RMSprop, Adam, and Nadam optimizer to find out which optimizer provides the best performance.

2.   Skin Cancer ISIC Dataset

This study uses the International Skin Imaging Collaboration (ISIC) data set shown in Figure 1 [10]. The data set consists of squamous cell carcinoma and melanoma for skin cancer, while for tumor conditions, there are dermatofibroma and nevus pigmentosus.

2.1. Dermatofibroma

Dermatofibromas include the category of benign tumors caused by an overgrowth of a mixture of various types of cells in the dermis layer of the skin. The skin growth that causes dermatofibroma usually occurs after experiencing several types of minor trauma to the skin, such as stab wounds caused by glass splinters or insect bites. Characteristics of dermatofibromas measuring around 2-3 mm, purplish brown, hard structure, and painful when pressed [11].

2.2. Nevus Pigmentosus

Nevus pigmentosus is a benign tumor originating from melanocytes, dendritic cells that produce pigment, normally found between keratinocytes in the basal layer of the epidermis. The developing Nevus Pigmentosus is very dangerous and quite difficult to handle. Nevus Pigmentosus has characteristics such as birthmarks or moles, if not early detected and exposure to pollution, ultraviolet light, and harmful chemicals, its potential to develop into melanoma which is very deadly skin cancer. Other effects of this disease for patients affected by complications will experience nerve disorders, such as seizures, fainting, and vomiting [12].

2.3. Squamous Cell Carcinoma

Squamous Cell Carcinoma is a type of skin cancer that attacks parts of the body that are often exposed to sunlight, such as legs, arms, lips, ears, face, neck, and head [13]. This disease is not too aggressive as like as other skin cancers. This disease tends to grow slowly and it can be treated easily through non-surgical therapy if early diagnosed. The benign

tumor can continue to grow to be cancer which can spread to bones, tissues, and even lymph nodes due to the lateness of treatment. The more widespread the spread, the more difficult the cancer is to be treated.

2.4. Melanoma

Melanoma is a type of skin cancer that is very dangerous. This condition starts with human skin and can spread to other organs in the body. This disease is a type of skin cancer originating from melanocyte cells, melanin-producing cells that are usually found in the skin. Melanoma has an irregular shape and more than one color. Moles affected by melanoma can feel itchy and can bleed, also, their size can exceed normal moles [14].
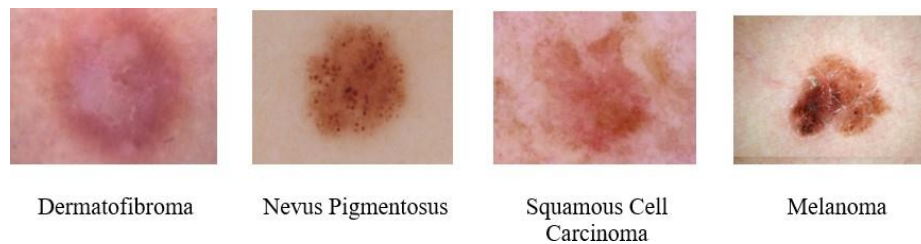

Dermatofibroma   Nevus Pigmentosus   Squamous Cell   Melanoma
                                                    Carcinoma

Figure 1. ISIC Dataset

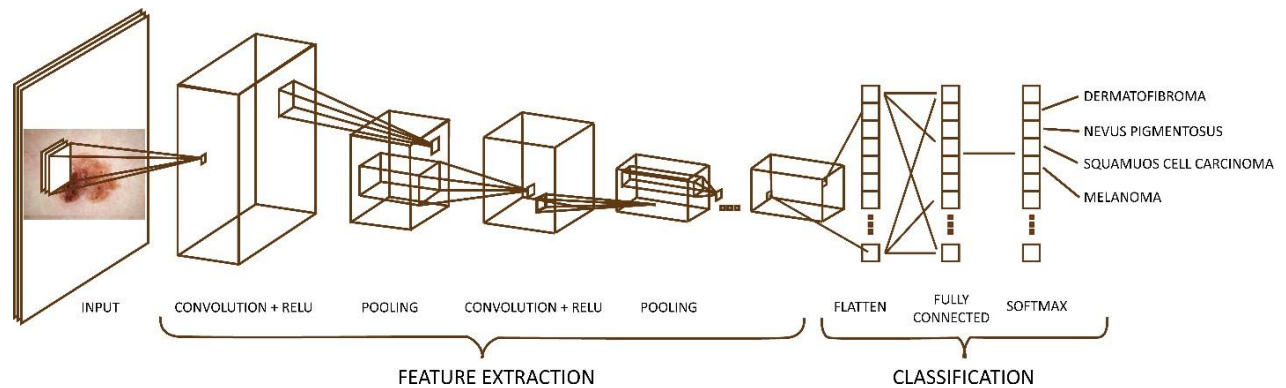### 3.   Convolutional Neural Network (CNN)

Figure 2. The Architecture of CNN

Convolutional Neural Network (CNN) is a development of the Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the type of Deep Neural Network because it has a high network depth and has been widely applied to image data [15]. CNN has an architecture as like as neural networks in general, neurons in CNN have a weight, bias, and activation function. CNN architecture as shown in Figure 2, which consists of the convolution layer with ReLU activation, pooling layer as feature extraction layer, and fully connected layer with softmax activation as classification layer.

3.1. Convolution Layer

In the Convolution layer, the convolution process is the main process that underlies CNN. Convolution layer is the first layer that will process the image as an input system model. The image will be convoluted with a filter to extract features from the input image that is called the feature map. Figure 3 shows an illustration of the convolution process.
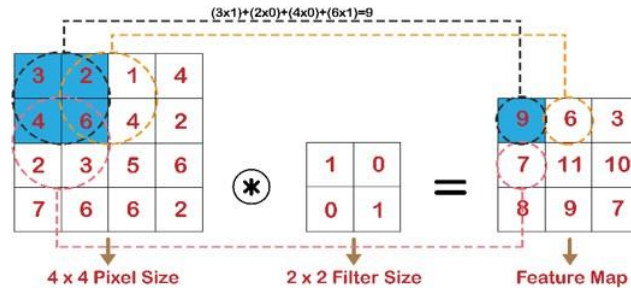
Figure 3. Illustration of the convolution process

3.2. Activation Rel-U

ReLU (Rectified Linear Unit) is an activation layer in CNN to increase the training stage on neural networks that have advantages to minimize errors. Rel-U activation makes all pixel values to be zero when a pixel image has a value of less than zero [16].

$$f(x) = \begin{cases} x\,, x > 0 \\ 0, x \le 0 \end{cases} \qquad (1)$$

3.3. Activation Rel-U

Polling layers in the CNN method usually will be inserted regularly after several convolution layers, There are several advantages of the pooling layer, which can progressively reduce the size of the output volume on the Feature Map so that it can control over-fitting [15]. Pooling Layer is used to reduce data using max-pooling or mean Pooling. The max-pooling will select the maximum value, whereas the main pooling finds the average value. The pooling process illustration using the four by four-pixel input image is shown in Figure 4.
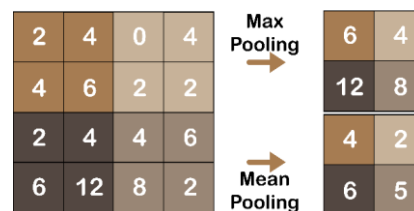

Figure 4. Pooling Process Illustration

3.4. Fully Connected Layer

The Fully-Connected Layer is the layer at the end of the architecture used in the multi-layer perceptron. This layer will connect all the neurons of the previous activation layer. In this stage, all neurons in the input layer need to be transformed into one-dimensional data (flatten process) [17]. After that softmax activation as another form of the logistic regression algorithm can be used to classify more than two classes.

3.5. Hyperparameter

Hyperparameter has variable values that remain during the model training process and can affect the performance of the model trains. In this study, the hyperparameter that used is   an optimizer, such as Stochastic Gradient Descent (SGD), Root Mean Square Propagation (RMSprop), Adaptive Moment Estimation (Adam), and Nesterov-accelerated Adaptive Moment Estimation (Nadam). Stochastic Gradient Descent (SGD) is a repetitive optimization method that functions to optimize the model using better functions such as differential or subdifferential [18]. SGD uses each training sample as a new parameter. Root Mean Square Propagation (RMSprop) is widely used in the design

of deep learning models [19]. This optimizer is an improvisation from Root Propagation (Rprop). Initially, Rprop cannot be used on files with large amounts of data. The essence of RMSprop is moving the average gradient at the time of the model. Adam optimizer is a combination of RMSprop and momentum. This optimizer also uses an average gradient of weight [20]. The advantage of Adam over other optimizers is efficient in computing time, consume less memory, and can handle sparse gradients on noisy problems. Nadam (Nesterov-accelerated Adaptive Moment Estimation) thus combines Adam and NAG (Nesterov accelerated gradient).

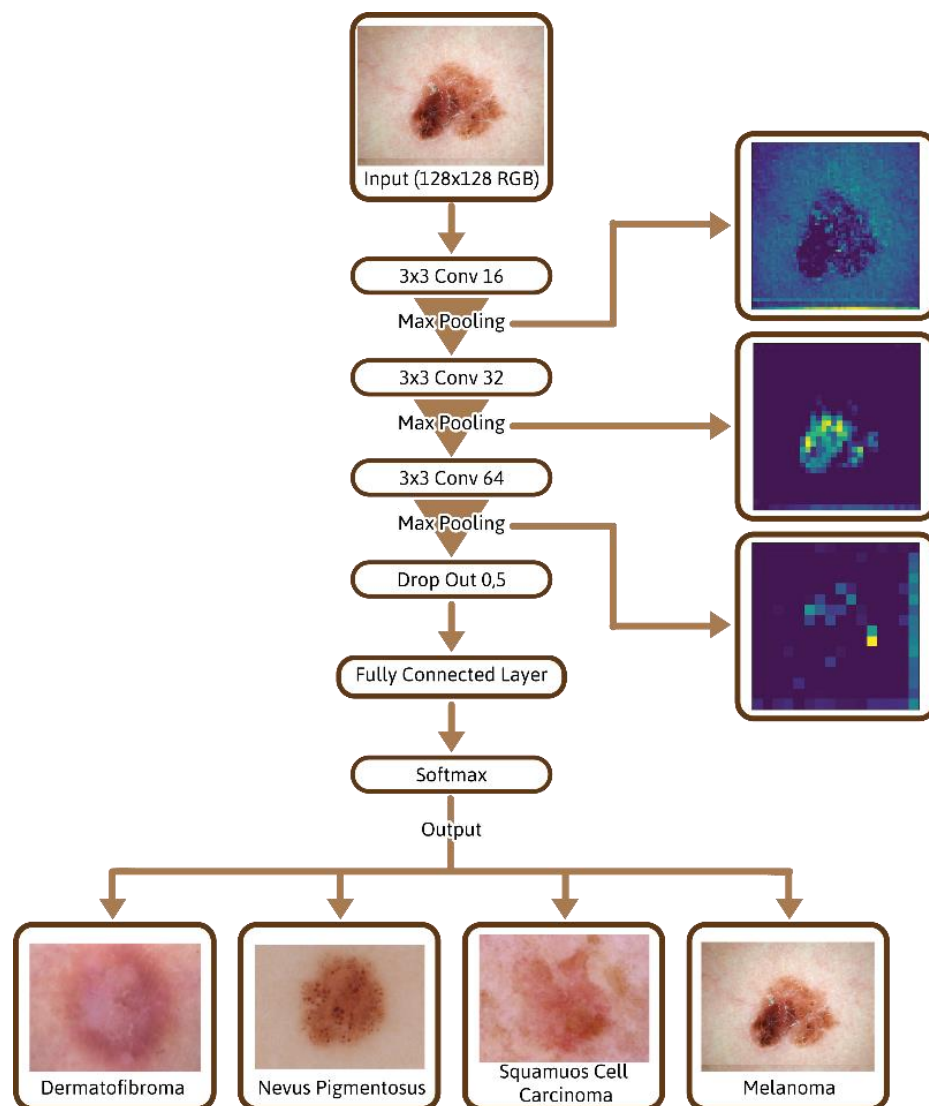## 4.   System Design

4.1.   Proposed System Model

Figure 5. The Proposed System Model

In this study, the dataset used is an augmentation of the ISIC dataset for the conditions of dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma. Dermatofibroma and nevus pigmentosus are benign tumors, while squamous cell

carcinoma and melanoma are skin cancers. The total amount of augmentation data is 4000 images consisting of 1000 images for each class. The distribution of training data and validation data were 75% and 25% so that the training data used were 3000 images and the validation data used were 1000 images.

Based on Figure 5 and Table 1, the resolution of skin images is changed to 128×128 pixels as an input of the CNN model which consists of 3 hidden layers. The image is convoluted using 3×3 filters on each hidden layer with the number of output channels on each layer is 16, 32, 64 respectively. At each layer, the activation process uses Rel-U activation and Max pooling. The result of Maxpooling reduces the size of the image as can be seen in Figure 5 and Table 1. After that, the flatten process will change image features from 3 dimensions became 1 dimension. The last, softmax activation function will be used to classify the condition of skin image into four classes namely, dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma.

Table 1. Details of CNN Model Proposed

Layer (type)	Output Shape	Parameter
Input Image	128,128,3	0
Convolution	128,128,16	448
ReLU	128,128,16	0
Max-Pooling	64,64,16	0
Convolution	64,64,32	4640
ReLU	64,64,32	0
Max Pooling	32,32,32	0
Convolution	32,32,64	18496
ReLU	32,32,64	0
Max Pooling	16,16,64	0
Dropout	16,16,64	0
Flatten	16384	0
Dense	4	65540
Softmax	4	0

4.2. System Performance

System performance in classifying the conditions of dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma was measured using a confusion matrix to obtain accuracy, recall, precision, and F1 scores. The equation is used to determine the accuracy of the system in classifying skin cancer lesions and benign tumor lesions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \tag{5}$$

True Positive (TP) indicates the condition while the data is positive and correctly predicted as positive. True Negative (TN) indicates the condition where the data is negative and correctly predicted as negative. False Positive (FP) indicates the conditions where the data is negative but incorrectly detected as positive. Whereas False Negative (FN) indicates the conditions where the data is positive, but incorrectly detected as negative.

5.   Result and Discussion

In this study, 3000 training images and 1000 validation images were used in the training model. The images obtained from the ISIC dataset, consist of four classes; dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma. These images were trained using the CNN model with various optimizer methods such as SGD, RMSprop, Adam, and Nadam optimizer with a learning rate of 0.001, and use loss categorical cross-entropy. The performance parameters measured in this study are accuracy, recall, precision, F1 scores, and loss. After training with 100 iterations (epoch), it can be seen the comparison of the accuracy and loss performance of the proposed model for each optimizer used in Figure 6.

Figure 6. Confusion Matrix

Table 2. Details Performance of Model Proposed

Class	Precision	Recall	F1-Score	No of Images
Dermatofibroma	1.00	1.00	1.00	257
Nevus Pigmentosus	0.98	0.98	0.98	246
Squamous Cell Carcinoma	1.00	1.00	1.00	255
Melanoma	0.98	0.98	0.98	242
Total	0.91	0.91	0.91	114

Based on the results shown in Figure 7, it shows the performance comparison of each optimizer used, Adam optimizer provides the best accuracy performance and loss performance when compared to other optimizers. The performance accuracy using SGD, RMSprop, and Nadam optimizer for training and validation data can decrease suddenly so that the loss also rises at certain epochs. This is indicated by the appearance of many spikes on the accuracy and the loss graph. Whereas, the system model that uses Adam optimizer

continues to show an increase in accuracy at each iteration (epoch) and the difference in accuracy between the training data and the validation data is not much different, as well as for the system loss continues to decrease at each iteration. This condition shows that the proposed model is not overfitting and the system model used can recognize the condition of dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma with the best accuracy performance of 99% and loss of 0.0346.

Confusion Matrix for system models with Adam optimizer can be seen in Figure 6. It can be seen that from 1000 validation images used, 990 images were successfully classified according to their class. The error occurs in four images on nevus pigmentosus detected as melanoma and six images on melanoma detected as nevus pigmentosus. Other parameters used to evaluate system
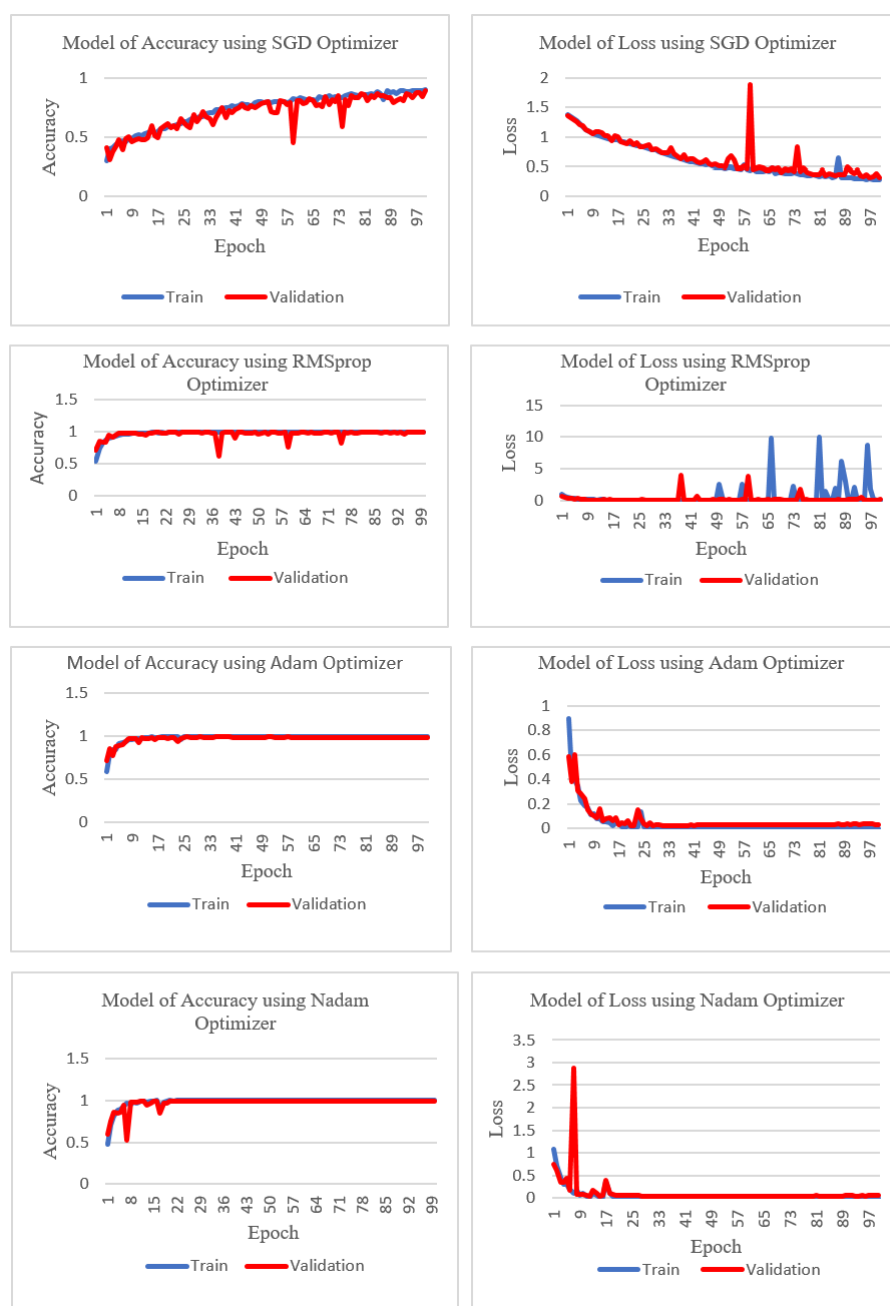
Figure 7. System Performance Comparison

performance are Precision, Recall, and F1-score, which has a range of values from 0 to 1 (a value of 1 indicates no error). Based on the data shown in Table 2, the value of system performance parameters obtained is close to 1, so it can be concluded that the CNN model proposed can classify the conditions of dermatofibroma, nevus pigmentosus, squamous cell carcinoma and melanoma with high accuracy and provides a minimum error.

6.   Conclusion

In this study, an automatic system was designed to classify the conditions of dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma based on digital image processing. The CNN model used in this study consists of 3 hidden layers, using 3×3 filter sizes with 16, 32, and 64 channel outputs in sequence, a fully connected layer, and softmax activation. The optimization is performed on the proposed model using SGD, RMSprop, Adam, and Nadam optimizer. Based on testing that has been carried out the CNN model proposed with Adam optimizer provides the best performance in classifying the dataset of skin cancer lesions and benign tumor lesions with 99% accuracy, loss of 0.0346 and the value of precision, recall, F1- score is almost 1. Based on the performance results, the system shows that the proposed model is promising to use as an existing tool for medical personnel in determining the diagnosis of skin cancer or benign tumors. In further research, systems can be developed to classify the various types of skin cancer and other skin diseases.

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