An AutomaticSkin Melanoma Detection Based on Convolution Neural Network

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Abstract. Cancer that develops in the tissues of the skin is referred to as skin cancer. This form of cancer can damage the tissues that are nearby, lead to disability, and even result in death. After cervical and breast cancer, the most common type of cancer seen in Indonesians is skin cancer, which ranks third overall. The detrimental effects of skin cancer can be minimized and brought under control if an accurate diagnosis and prompt, appropriate treatment are given. As a result of the comparable appearance of the disease among malignancy and benign tumor lesions, medical professionals spend significantly more time trying to diagnose these types of lesions. Utilizing the Convolutional Neural Network, the system that was constructed for this study had the capability of automatically identifying skin cancer as well as benign tumor lesions (CNN). The model that has been presented has three hidden layers, each of which has an output channel that ranges from 16 to 32 to 64. With a learning rate of 0.001, the model that has been suggested makes use of a number of optimizers including Adam, and Nadam. The Adam optimizer achieves the greatest results, with an accuracy value of 93.9 percent, when it comes to classifying the skin lesions from the ISIC dataset into the following four categories: dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanomas. The accuracy of the existing technique for classifying skin cancer has been outperformed by the findings that were obtained.

Keywords. Deep Learning, Machine Learning, Skin Melanoma, CNN Algorithm, Melanoma Detection

1. Introduction

Skin cancer is a condition that is caused when normally occurring skin cells undergo changes in their characteristics that cause them to become cancerous. Due to the fact that their DNA has been damaged, the cells in this situation will continue to alienate and will take on erratic and uncontrollable forms as they do so.When looked at from the point of view of histology, skin cancer has an uneven structure, with cell differentiation happening at differing stages of chromatin, nucleus, and cytoplasm [1]. In addition to breast and cervix cancer, skin cancer is yet another form of malignancies that is frequently detected in Indonesia's population. Cervix cancer is also a common form of the disease. 5.9 to 7.8 percent of people diagnosed with skin cancer per year across all forms of skin cancer. In Indonesia, basal cell carcinoma is responsible for 65.5% of all instances of skin cancer, which also includes malignant melanoma (23%), malignant melanoma (7.9%), as well as other types of skin cancer [2]. However, the death rate from metastatic melanoma appears to be higher, and it is responsible for more than 70 percent of all deaths associated with skin cancer [1]. Although the prevalence rate of squamous cell carcinoma is lower than that of squamous cell carcinoma and squamous cell carcinoma, the death rate from malignant melanoma is still relatively high. Melanoma, the most aggressive form of skin cancer, carries a high risk of death, particularly if it is not discovered in its early stages and treated promptly. Even though they have a lower risk of metastasizing to other organs and causing death or disability, cancers of both the skin that are not melanoma, such as basal cell carcinoma and squamous cell carcinoma, are much more common than melanoma. Examples include squamous cell carcinoma as well as squamous cell carcinoma. Accurate assessment and early discovery of skin cancer are both beneficial to the healing process, as well as to receiving the appropriate medical therapy and avoiding the disease's most severe side effects. As a result, there is a requirement for an early identification framework that can enhance and significantly improve community understanding in the process of acknowledging type of skin cancer or other problems of the skin, such as with a benign growth upon that skin that looks very similar to skin cancer. That's because there is the need for an early intervention system that can facilitate and augment public awareness in the process of acknowledging type of skin cancer.

People will be better able to recognise skin disorders when they use the automatic skin disorders classification, which will allow them to more quickly consult with medical professionals and receive the proper medical treatment. The classification and detection of skin cancers was developed as a tool for medical workers to use in order to make more accurate diagnoses of skin illnesses within a shorter amount of computer time. This tool is based on several similar studies that use digital image processing. An edge recognition system with K-NN and C-NN algorithms was used in previous research [3] to classify skin disorders that possibly harmless cancer and skin dissociative symptoms that have the potential to be cancerous growth by using the Worldwide Skin Imaging dataset Collaboration. This method was used to classify skin disorders that possibly harmless cancer. The accuracy of this study's classification of skin problems that potentially lead to benign cancer was 75%, and the accuracy of its classification of skin disorders that may lead to malignant cancer was 75.6%. (ISIC). In the study [4], an autonomous skin sickness classification system was developed by utilising the ISIC dataset for the circumstances of skin cancer and epidermal benign growths. This allowed for the construction of a classification system for skin diseases. Deep learning with the PNASNet-5-Large architecture formed the foundation for this system, which achieves an accuracy rating of 76 percent and gives the best performance. In addition, the performance accuracy of CNN for the diagnosis of skin illnesses was found to be 80.52 percent, 86.21 percent, and 87.25 percent, respectively, in a number of studies [5, 6, 7] that used CNN for the purpose of making the diagnosis. The ISIC data augmentation method was carried out in order to increase the total amount of data as well as to contribute to the overall success of the skin cancer detection system [8]. We were successful in attaining a level of accuracy that was 95.91 percent thanks to the employment of Alexnet. The CNN approach using random regulators was able to reach a performance accuracy of 97.49 percent in the study [9] when differentiating some lesions of skin illnesses such as nevus lesions, carcinomas, and melanomas. In order to differentiate between these lesions, this strategy was applied. The augmentation information from the ISIC dataset, which will be utilised in this study, will be used to identify cases of skin cancer lesions or benign tumor lesions that have the appearance of cancer. The strategy that has been suggested as a result of this research makes use of CNN in conjunction with a variety of different optimizers, such as the Adam optimizer and the Nadam optimizer, in order to identify which optimizer delivers the maximum degree of performance possible.

2. ISICDataset for SkinCancer

The International Skin Imaging Collaboration (ISIC) data collection, which is depicted in Figure 1, was employed for this work [10]. Melanoma and squamous cell carcinoma are the two types of skin cancer that are included in the data collection. Dermatofibroma and nevus pigmentosus are the two types of malignant diseases that are included.

2.1. Dermatofibroma

Dermatofibromas are benign tumours generated by an expansion of mixed skin cells. Dermatofibroma commonly develops after mild skin trauma, such as glass splinter or insect bite wounds. Dermatofibromas are 2-3 mm, purplish coloured, rigid, and painful [11].

2.2. NevusPigmentosus

Nevus pigmentosus is a benign tumour from pigment-producing melanocytes in the epidermis' basal layer. Nevus Pigmentosus is hazardous and hard to treat. Nevus Pigmentosus can develop into melanoma if not discovered early and exposed to pollution, UV light, and hazardous chemicals. Nerve abnormalities, such as seizures, dizziness, and vomiting, are further consequences [12].

2.3. SquamousCellCarcinoma

Squamous Cell Carcinoma affects the legs, limbs, lips, ears, face, neck, and head [13]. This skin cancer isn't aggressive. If caught early, this condition can be managed non-surgically. Due to late treatment, a benign tumor might become cancer and spread to bones, tissues, and lymph nodes. Spreading cancer makes it harder to treat.

2.4. Melanoma

Melanoma is a serious skin cancer. This skin disorder can extend to organs. This skin cancer begins in melanocyte cells, which produce melanin. Melanoma is uneven and multicolored. Melanoma moles are itchy, bleed, and are larger than usual [14].

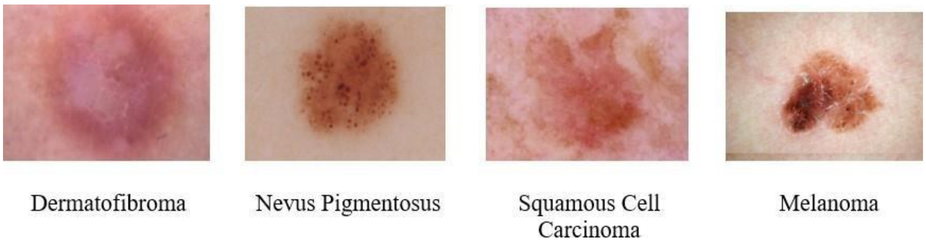

Figure1.ISICDataset

3. Architecture of ConvolutionalNeuralNetwork(CNN)

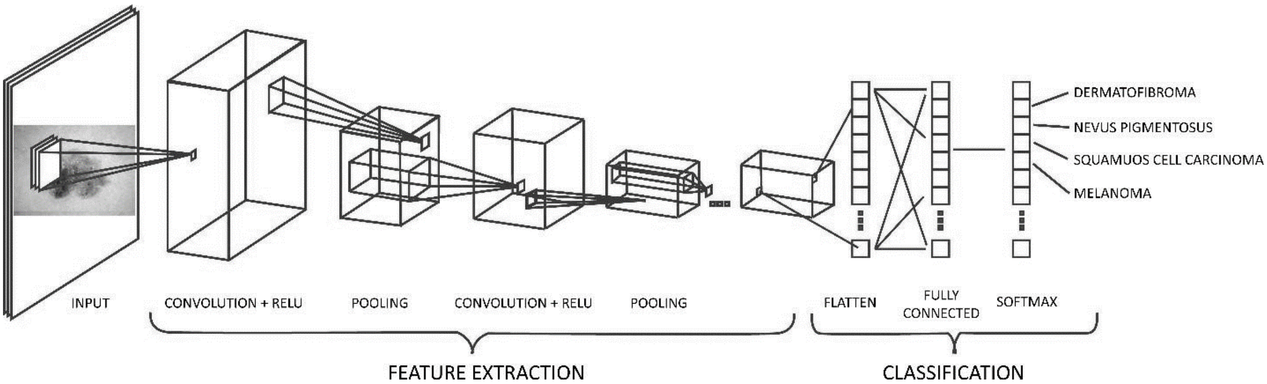

Figure2.CNNArchitecture

The Multilayer Perceptron (MLP), which is meant to handle input in two dimensions, gave rise to the Convolutional Neural Network (CNN), which was developed from the MLP. CNN is classified as a sort of Deep Neural Network due to the fact that it possesses a large network depth and has found widespread use in the analysis of picture data [15]. The design of CNN is quite similar to that of neural networks in general; similarly, the neurons that make up CNN each have their own weight, bias, and transfer functions. The design of the CNN is shown in Figure 2, and it consists of three layers: the convolution layer, which uses ReLU activation; the pooling layer, which serves as the feature extraction layer; and the fully-connected layers, which use softmax activation as the classification layer.

3.1. ConvolutionLayer

The convolutional process is the primary one that underpins CNN and is carried out in the Convolution layer of the network. The image will first be processed using the convolution layer, which is the first layer of an input system model. In process of extracting features from the input image, which is referred to as the feature map, the picture will be complicated with a filter first. The process of convolution is depicted in Figure 3, which offers an example of the process.

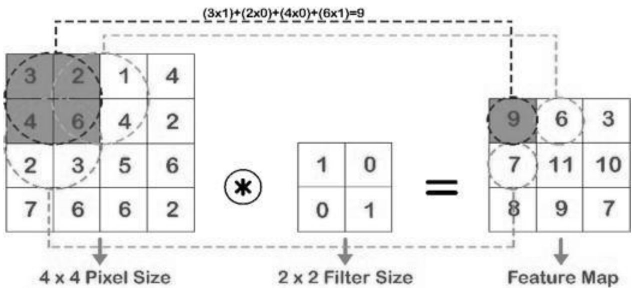

Figure3.ConvolutionprocessDiscription

3.2. ActivationRel-U

Rectified Linear Unit, often known as ReLU, is an activation layer that is used in CNN. Its focus is to maximize the training stage of neural networks, which has the benefit of reducing error. When a pixel image contains a value that is less than zero, the Rel-U activation causes all of the adjacent pixels to be reset to zero [16].

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

3.3. ActivationRel-U

After multiple convolution layers, CNN adds polling levels. The pooling layer might gradually reduce the Feature Map's resulting volume to prevent overfitting [15]. The Convolution Operation can reduce data by using mean or maximum pooling. Max-pooling chooses the greatest possible value, while main pooling determines the average. Figure 4 presents an illustration of the pooling process making use of an input image consisting of four pixels by four pixels.

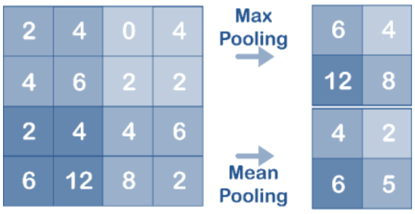

Figure4. Illustration of PoolingProcess

3.4. FullyConnectedLayer

The final layer of the multi-layer perceptron design is called the Fully-Connected Layer, and it is located at the very end of the structure. All of the neurons that were activated in the layer below will be connected to one another via this layer. At this point, all of the neurons in the hidden layer need to be flattened into one-dimensional data (the process is called "flattening") [17]. After then, an additional variation of the regression analysis technique known as softmax activation can be utilised to categorise more than two different types of data.

3.5. Hyperparameter

The values of the hyperparameter are subject to change throughout the process of model training, which in turn can have an impact on how well the trained model performs. A recurring optimization method known as stochastic gradient descent (SGD) serves the purpose of optimizing the model by making use of superior variables including such differentially or sub differential [18]. Each training sample is treated as a separate parameter by SGD. Root Mean Square Propagation, or RMSprop for short, is a technique that is frequently utilised in the construction of deep learning techniques [19]. This optimization is a modification of Root Propagation's original design (Rprop). At this time, Rprop cannot be applied to files that include a significant amount of data. The pivoting of the averaged gradients there at moment of the model is the heart of the RMSprop technique. The RMSprop and momentum optimizers are combined to create the Adam optimizer. This optimizer additionally makes use of a weight gradient that is averaged over [20]. Adam has several advantages over other optimizers, including its ability to handle sparse gradients on noisy situations, its efficient use of processing time, and its low memory use. Adam and NAG are also components of Nadam, which stands for Nesterov-accelerated Dedicate Some time Estimation (Nesterov accelerated gradient).

4. SystemDesign

4.1. ProposedSystemModel

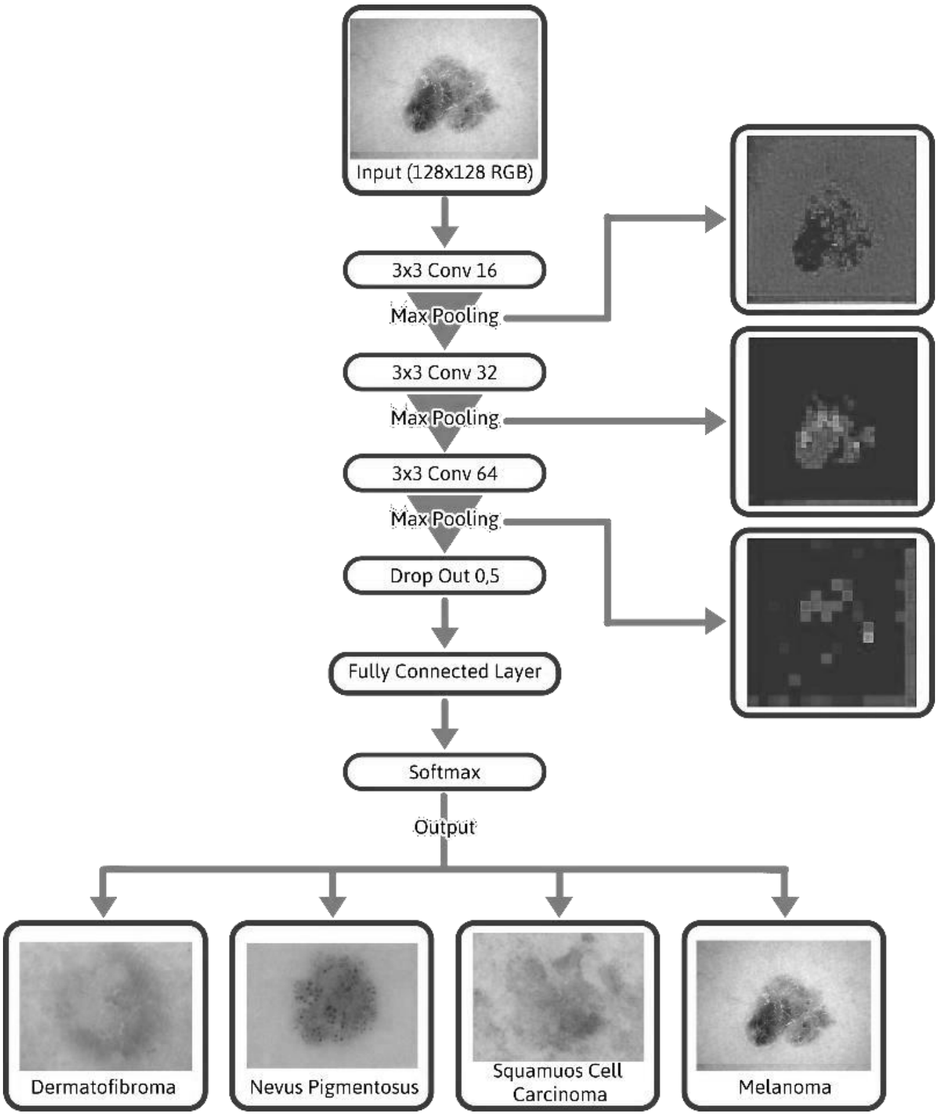

Figure5. Schematic representation of ProposedModel

An expanded version of the ISIC dataset was utilised for the purpose of this investigation. Both dermatofibroma and nevus pigmentosus are considered to be benign tumours, but squamous cell carcinoma and melanomas are considered to be malignant forms of skin cancer. There are a total of 4000 photographs included in the augmentation data set, with each class having its own set of 1000 images. The ratio of training data to validation data was 75% to 25%, and the total number of images used for training was 3000, while the total number of images used for validation was 1000.

The resolution of skin images was modified to 128 by 128 pixels so that they could be used as an input into the CNN model, which has three hidden layers and can be shown in Figure 5 and Table 1. The image is distorted by applying three identical filters to each of the three hidden layers, with the number of output channels increasing from 16 to 32 to 64 for each of the three layers. The Rel-U activation and Max pooling processes are used at each layer of the activation process. As can be seen in Figure 5 and Table 1, the output of Maxpooling results in a reduction in the overall size of the image. After then, the process of flattening the image will change the features of the image such that it has only one dimension instead of three. The condition of the skin image will be classified into one of four categories using the softmax activation function as the final step. These categories include dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanomas respectively.

Table1. Description ofCNNModelParameters

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. SystemPerformance

Using a prediction model, accuracy, recall, precision, and F1 scores were used to evaluate the system's sink cancer categorization performance. These scores measure the system's accuracy. The equation measures how well the system classifies skin cancer and benign tumors.

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

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

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

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

True Positive (TP) describes a circumstance in which the data are positive and the condition has been accurately forecasted as positive. True Negative, abbreviated TN, refers to the circumstance in which the data are in fact negative and have been accurately forecasted as negative. The term "false positive" (FP) refers to situations in which the data should be negative but are instead mistakenly identified as positive. While False Negative (FN) describes situations in which the data should be positive but is mistakenly interpreted as negative, the opposite is true of True Positive (TP).

5. ResultandDiscussion

Figure 7 depicts the results of the performance analysis. Graph. On the basis of spam sensitivity and specificity, we offer a summary of the findings obtained by using the three machine learning algorithms presented in this paper. As demonstrated in Table 2, the measurement from which the graph in Fig.7 is formed may be found in the previous paragraph. In the effectiveness graph, we can see that the SVM technique is by far the most accurate, but that the k nearest - Neighbor method has a lower accuracy percentage than the SVM approach. As shown in Figure 6, the deep Convolutional neural algorithm outperforms the SVM and CNN with softmax algorithms in terms of accuracy when compared to the spam precision graph. In the following graphs, the x-axis shows different classification approaches, while the y-axis displays percentages of the total population.

Table 2. Performance parameters reading

Algorithms	AC	Sensitivity	Specificity
CNN (Softmax)	0.87	0.63	0.914
SVM	0.882	0.59	0.81
CNN (Proposed)	0.939	0.479	0.88

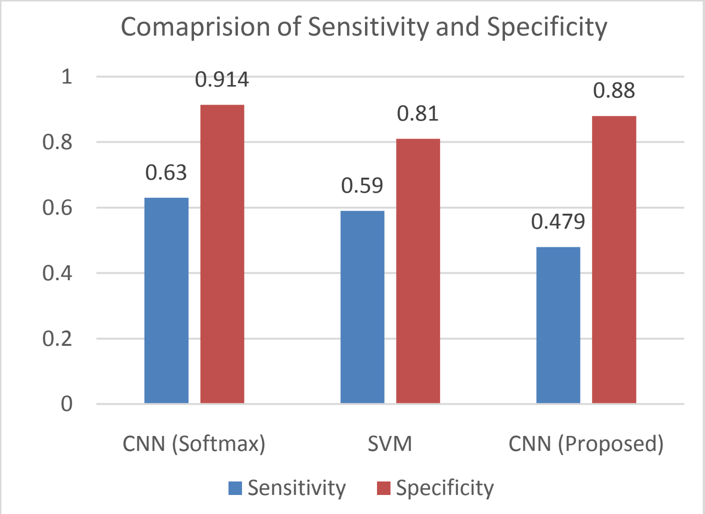

Figure 6: Specificity and Sensitivity Graph

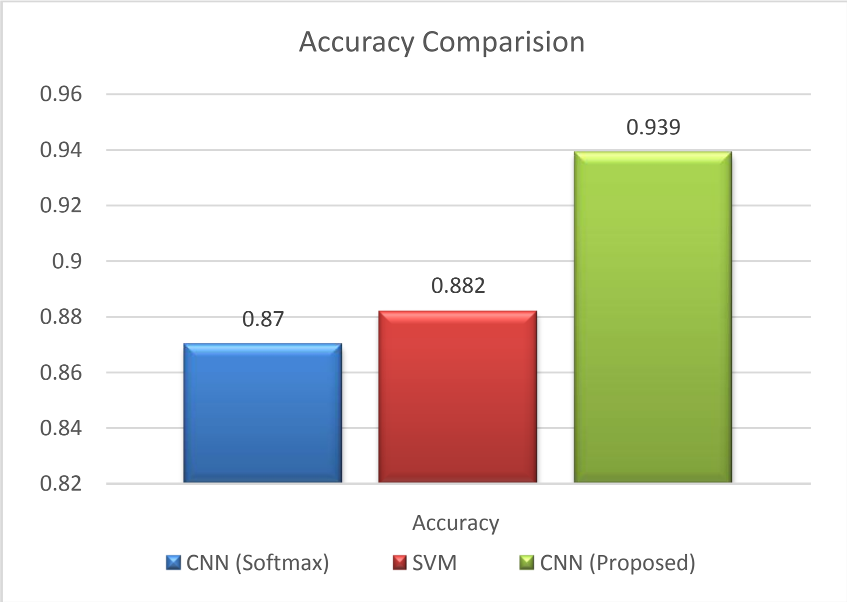

Figure 7: Accuracy Comparison Graph

6. Conclusion

Experts in the field of medicine believe that melanomas are among the most deadly forms of cancer, despite the fact that they are also among the cancers that may be avoided with the most ease. During the course of the inquiry, it was suggested that a novel method that is based on CNN may be used to diagnose skin cancer from photographs. It has been clearly demonstrated that the approach can successfully collect features of skin cancer through the use of concurrent convolution blocks to acquire the feature and character of basal cell carcinoma through the use of parallel convolution blocks to capture this same characteristic and character of skin cancer. This has been accomplished by using concurrent convolution blocks to acquire the feature and character of basal cell carcinoma. As a consequence of this research, a computer-assisted dermoscopy image classification system is currently in the process of being built. This system combines many different deep neural network topologies, transfer learning algorithms, and segmentation in order to classify skin lesions. Other pre-processing and augmentation processes were applied so that the influence of the ISIC's unbalanced data, which was a distinctive element of the study's design, could be reduced. This was accomplished through the usage of the ISIC. In addition, the CNN classifier was utilised to differentiate between the diagnosis of melanoma and other types of skin lesions.

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