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Skin Cancer Diagnosis Based on the Convolutional Neural Network: a Comparative Study Jane J. Stephan University of Information Technology and Communications <u>janejaleel@uoitc.edu.iq</u> Muhammed Kadhim Hussein Iraqi Commission for Computers and Informatics Informatics Institute for Postgraduate Studies

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Abstract

Skin cancer is one of the leading causes of death in humans, however, it is treatable if caught early. Therefore, early detection of skin cancer contributes to saving many patients. Skin cancer is divided into two types, benign tumor, and malignant tumor that leads to the death of a person if not treated early, and both are similar in appearance only a dermatologist can classify cancer as malignant or benign.

The proposed system consists of several basic stages. The first stage is the creation and provision of a large database, the second stage is the use of data compression techniques (images), and the third stage is the use of artificial intelligence by applying an artificial neural network to image processing technology, specifically in the field of deep learning approach. The database used in the proposed system consists of a set of skin cancer images from the International Skin Imaging Cooperation (ISIC) and a set of images also brought from the Medical City in Iraq (Dermatology Consultation Department). Be clear and free of distortion at a good rate.

Huffman technology is used to compression images while preserving image information from loss, reducing image size, saving storage space, saving time, and thus increasing system speed, as a neural network (deep

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learning) was used with the SVM classifier for the support machine. Also, a set of deep learning models VGG16, AlexNet, ResNet-50 and Inception v3 were used only without any modifications to the models except the last layer of each model. Finally, a special model that detects skin cancer (SkinNet) was proposed.

The method used in detecting skin cancer is deep learning that works by inserting compressed images and then splitting the images 70% for the training process, 30% for the testing process, and the proposed model (SkinNet) performed better with accuracy, and the performance was with 98.2% accuracy.

Keywords : Skin diseases, technology, classification, features, deep learning, CNN.

1-Introduction

The skin in the human body is the most important part, and its weight is estimated at (6-8) kilograms, and its area is estimated at (1.5-2) square meters. The skin protects the body from extreme temperatures, harmful UV rays, and harmful chemicals. It protects tissues from harmful sunlight and acts as a waterproof shield [1]. Approximately 13 million cases of skin cancer occur worldwide each year. This is stated by the World Health Organization [2]. This means that skin diseases are increasing rapidly and dramatically among the factors responsible for the occurrence of skin diseases such as pollution, UV rays, weak immunity and unhealthy lifestyle. Skin diseases can be classified into two main categories: benign and malignant skin lesions. Most skin diseases or lesions are benign and not serious. At the same time, lesions of malignant diseases are represented by melanoma [3].

Human skin consists of three main layers. These differ in their functions, anatomy, or composition: the thinner outer layer of the epidermis, the thicker middle layer, the dermis, and a deeper layer called the subcutaneous tissue layer. Also, the first layer, the epidermal layer, is made

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up of cells called surface cells and melanocytes, which give the color pigment to normal skin. Figure (1) shows the layers of the skin [4].

Usually the epidermal layer is the target of such an insidious disease; Skin cancer can be fatal if not treated early. Skin cancers begin as precancerous lesions that are not malignant but become malignant over time.

During these years and after the remarkable development in technology, the use of automated (computer) diagnostic systems in the detection of skin cancer has become very important, especially in these recent years [5].

Deep learning models have achieved remarkable results in how to analyze and classify medical images, especially skin cancer, in this paper the proposed system SkinNet was used to detect skin cancer.

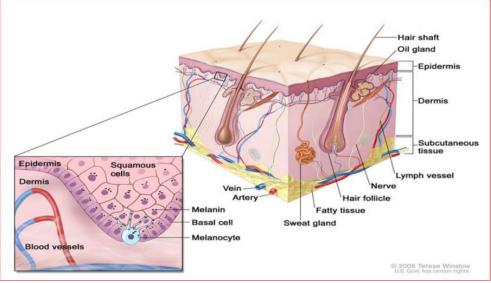


Figure (1): Skin Layers [4]

2- Dataset Collection

HAM10000 is a dataset of 10000 training images for detecting pigmented skin problems. This dataset was obtained from the international skin imaging cooperation archive. In this thesis, 2360 images are used, 2000

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of which were abnormal and 360 normal. Figure(2) depicts a selection of images from the dataset.

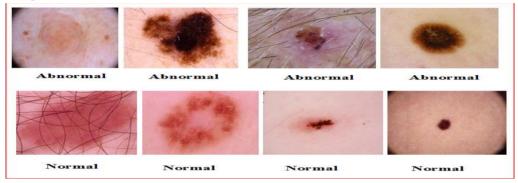


Figure (2): A Sample of Dataset

3- Convolutional Neural Networks (CNN)

A CNN has many important uses, particularly in image processing. This network has been widely developed in many applications, including text detection, scene tagging, object tracking, object recognition, and other applications.

CNN consists of three basic layers, the convolutional layer, the pooling or subsample layer, and the fully connected layer. You can add other layers, but these layers are the main layer of this network. Figure (3) shows these layers [6].

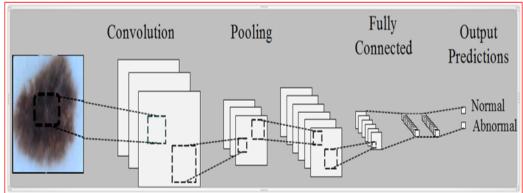


Figure (3): Layers of CNN [6]

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CNN can self-learn by extracting features through the process of wrapping layers and the collector layer. The network learns its layers on the characteristics and features of the images. After identifying the characteristics and features in the network, the network can identify the object in the images [7].

The data entered into this bypass neural network are digital (images) that you convert into a matrix for the network to understand. The input (images) if it is of the (RGB) type, then the input matrix will be of three dimensions ($512 \times 512 \times 3$). Width, height, and three colors (red, green, and blue), but if the entered data is of gray type, i.e. ($512 \times 512 \times 1$), width x height and 1 is grayscale.

4- The Architecture of Deep Learning Models

The data entered into the system is reduced in size through the data compression process. Then comes the stage of extracting features from the data through the process of deep learning, specifically the convolutional neural network and its models (AlexNet, Densenet-201, Inceptionv3, ResNet-101, VGG16, ResNet50) Divide the data into two groups, the first to train the network and the second to test it. This process is used to extract features from the data for this data to be classified through the classifier (SVM) Figure (4).

- 1. Deep learning with SVM.
- 2. Deep learning without SVM.
- 3. Proposed Model (SkinNet)

Figure (4) shows the mechanism by which the hybrid system works, Figure (5) shows deep learning without SVM.

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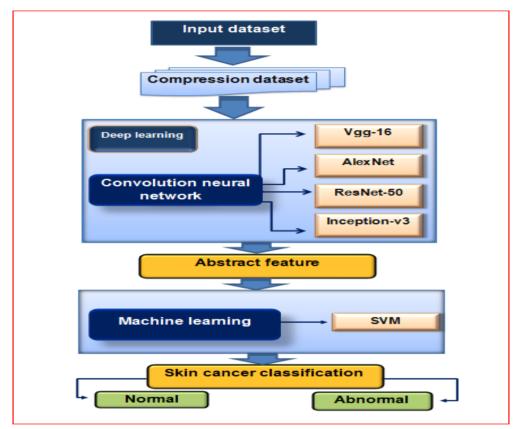


Figure (4): The Proposed Architecture of The System (Deep learning & Machine Learning)

This Figure (5) shows the deep learning mechanism without the SVM classifier, and the outcomes of this mechanism were better than the hybrid mechanism after implementation.

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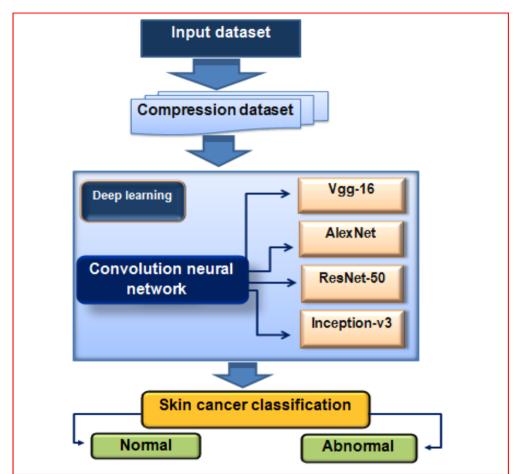


Figure (5): The Architecture of the System (Deep Learning)

5- Proposed Methodology SkinNet model

SkinNet, a new deep CNN design, is presented for improving the extraction of main features related to skin cancer classification. It was built using the Directed Acyclic Graph (DAG) concept in notion Figure 6 illustrates this concept.

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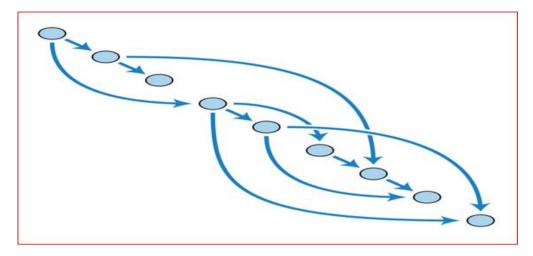


Figure (6): Methodology for Model Working

A DAG is a diagram that represents a set of activities. The order of the activities is represented by a graph, which is visually presented as a group of circles, each of which represents an activity, and some of which are connected by lines, which represent the flow from one activity to the next. Each circle is referred to as a "vertex," whereas each line is referred to as a "edge." "Directed" implies that each edge has a distinct direction, implying that each edge reflects a discrete directional flow from one vertex to the next. The term "acyclic" refers to the absence of loops (i.e., "cycles") in the graph, which indicates that for any given vertex, if you follow an edge connecting that vertex to another, there is no path in the graph back to that initial vertex[8].

When using this type of network, there are two basic issues to consider. The first problem is that addition of convolutional layers in a

conventional CNN model to improve accuracy is good in a limited number of layers but might lead to a drop-in performance as more layers are added. A network with a few layers and a simple structure is suitable for some tasks. skin cancer classification requires a network with a more advanced Technique, in order to extract more information and differentiate

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between normal and abnormal classes. The proposed model has the good advantage of allowing the model width to be increased without significantly increasing the processing cost. This enhances not only the details that can be learned, but also the validity and accuracy of the information. The Figure 7 shows the construction of the model.

Figure (7): Proposed Architecture of the System (SkinNe)

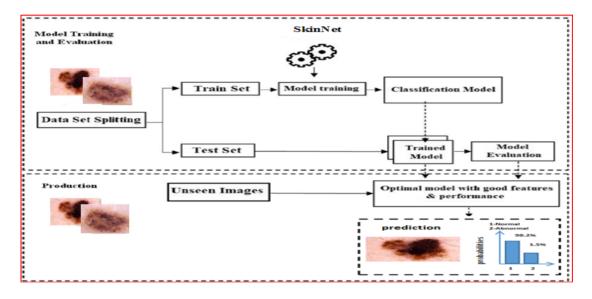


Figure 7 is divided into two parts: the upper portion depicts the model and metrics training process, while the process prediction is depicted in the lower portion. In the model training process The dataset which includes 2360 images, is provided to the training process and has been compressed, making the data ready for use. The dataset is split into two classes (normal and abnormal), and the model is trained 70% of the data and 30% of the testing process.

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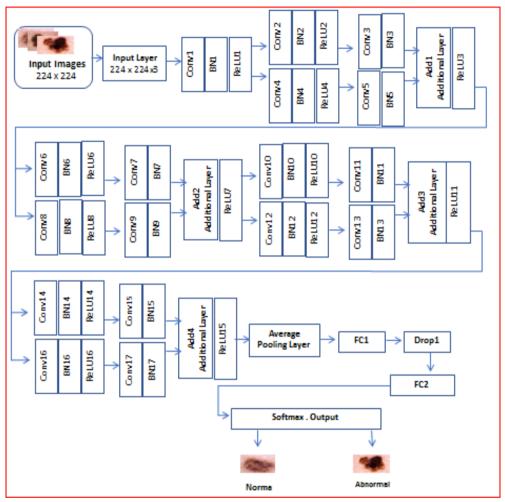


Figure (8): The Architecture for The SkinNet CNN Classification Model

Figure 8 shows the proposed system, with Table 3.1 summarizing the layers. The system consists of 58 layers, which are distributed as follows. This system are 17 bypass layers (CNN) and 17 layers in (BN). In addition, four 2D convolutional layers that modify the filter size attributes were built. each layer (CNN) and (BN) has a (Relu) layer that works to correct errors. In addition to the Average pooling layer, Dropout Layer and a Fully Connected (FC) two layers.

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Name of Layer	Kernel size and stride	Activations
Input layer	-	224×224×3
Conv1,BN1,ReLU1	Conv1: Kernel1 size=3 ×3,	$224 \times 224 \times 32$
	stride=1	
Conv2,BN2,ReLU2	Conv2: Kernel2 size= 3×3 ,	$112 \times 112 \times 32$
	stride=2	
Conv3, BN3	Conv3: Kernel2 size= 3×3 ,	$112 \times 112 \times 32$
	stride=1	
Conv4,BN4,ReLU4	Conv4: Kernel2 size= 3×3 ,	$112 \times 112 \times 32$
	stride=2	
Conv5, BN5	Conv5: Kernel2 size= 3×3 ,	$112 \times 112 \times 32$
	stride=1	
Add1	Addition of two inputs	$112 \times 112 \times 32$
ReLU3	Activation Function	$112 \times 112 \times 32$
Conv6,BN6,ReLU6	Conv6: Kernel size= 3×3 ,	$56 \times 56 \times 64$
	stride=2	
Conv7, BN7	Conv7: Kernel size= 3×3 ,	$56 \times 56 \times 64$
	stride=1	
Conv8,BN8,ReLU8	Conv8: Kernel size= 3×3 ,	$56 \times 56 \times 64$
	stride=2	
Conv9, BN9	Conv9: Kernel size= 3×3 ,	$56 \times 56 \times 64$
	stride=2	
Add2	Addition of two inputs	$56 \times 56 \times 64$
ReLU7	Activation Function	$56 \times 56 \times 64$
Conv10,BN10,ReLU10	Conv10: Kernel size= 3×3 ,	$28 \times 28 \times 128$
	stride=2	
Conv11, BN11	Conv11: Kernel size= 3×3 ,	$28 \times 28 \times 128$
	stride=1	
Conv12,BN12,ReLU12	Conv12: Kernel size= 3×3 ,	$28 \times 28 \times 128$
	stride=2	
Conv13, BN13	Conv13: Kernel size= 3×3 ,	$28 \times 28 \times 128$
	stride=1	
Add3	Addition of two inputs	$28 \times 28 \times 128$
ReLU11	Activation Function	$28 \times 28 \times 128$
Conv14,BN14,ReLU14	Conv14: Kernel size= 3×3 ,	14 imes 14 imes 256

Table (1): Summary for the Proposed CNN Model (SkinNe)

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	stride=2	
Conv15, BN15	Conv15: Kernel size= 3×3 ,	$14 \times 14 \times 256$
	stride=1	
Conv16,BN16,ReLU16	Conv16: Kernel size= 3×3 ,	$14 \times 14 \times 256$
	stride=2	
Conv17, BN17	Conv17: Kernel size= 3×3 ,	$14 \times 14 \times 256$
	stride=1	
Add4	Addition of two inputs	$14 \times 14 \times 256$
ReLU15	Activation Function	$14 \times 14 \times 256$
Average Pooling Layer	Kernel size=8×8, stride=1	$7 \times 7 \times 256$
FC1	100 fully connected	$1 \times 1 \times 100$
Drop1	Drop1 layer with learning	$1 \times 1 \times 100$
	rate:0.5	
FC2	2 fully connected	$1 \times 1 \times 2$
Softmax layer	0=Normal, 1=Abnormal	$1 \times 1 \times 2$

The proposed system (SkinNet) structure is made up of multiple layers, namely:

6- Deep Learning Proposal Model (SkinNet)

SkinNet is a proposed model that was designed using a CNN and distinguished by its accuracy and speed in identifying skin cancer. The results of the training and testing model are depicted in Figure (9).

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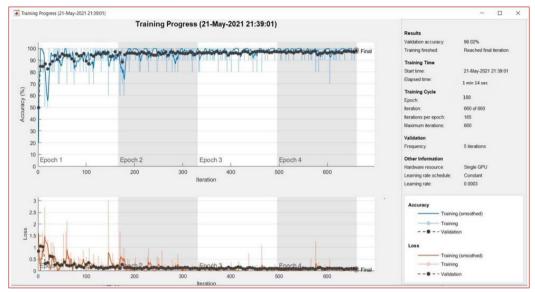


Figure (9): Training Results of the Proposed Model (SkinNet)



Figure (10): Test Results of the Proposed Model (SkinNet)

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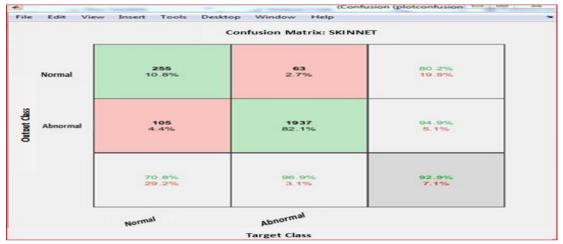


Figure (11): Confusion Matrix of the Proposed Model (SkinNet)

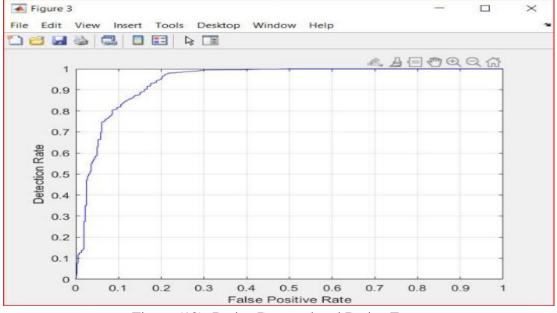


Figure (12): Ratios Detected and Ratios Errors

Table (2): Test Results of the Proposed Model (SkinNet)

 · · · · · ·
Performance Measurement

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CNN (model)	Type Image	Number image	Time	Accuracy	Sensitivity	Specificity	Precision	F-Measure
SkinNet	Dermoscopic	2360	1 min 14 sec	98.2%	75%	98%	89%	8 9 %

As a result, the proposed system (SkinNet) achieves the best results compared to deep learning systems, whether with or without SVM.

7- Deep Learning Strategy of Classifying Skin Diseases

The approach is based on deep learning, which is a subset of machine learning, and it can be said that deep learning has become a semi-pioneer in many scientific, security, and other fields, including medicine because it has strong capabilities and requires big amounts of information; these are some studies related to this work.

Sun et al. 2016 [8] proposed a technique based on the Convolutional Neural Network (CNN) to classify the clinical image. They trained those CNN technologies that have been designed (Caffeine, VGG, and VGGNet), and among these technologies (VGGNet) have proven their success with very high accuracy. The accuracy of VGGNet technology is excellent and was established by the following methods, Local binary patterns (LBP), Scaleinvariant feature transform (SIFT), As well as a classifier (SVM).

Esteva et al. 2017 [9] He was the first to report on CNN's ability to classify images. The results were similar or identical to that of 20 dermatologists who are experts in the field. Malignant, benign and non-neoplastic skin diseases were classified using an algorithm. If carefully trained and tuned to the data, InceptionV3 CNN's modern architecture for classifying skin lesions has allowed it to outperform human specialists.

InceptionV3 has also been used by Zhang et al. 2018 [10]. Also, Zhang and those who followed him in this technique were those wrong

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classifications can occur due to multiple diseases in one picture. By training the model designed by Zhang on two nearly identical data sets from dermatoscopy images.

Rahman et al. 2018 [11] suggested a CNN strategy by designating 16 different 7 * 7 core-size filters with sampling layers. The proposed model is trained on the benign and malignant diseases of melanoma. The outputs of this matrix (7*7) are inputs to the (CNN) for extraction. Moreover, ANN consists of a 3-layer well-connected layer that classifies the skin lesion as toxic or malignant.

(Gessert) and et al. 2019 [12] have introduced a correction method to obtain accurate differences between different skin diseases through images. The high-resolution image is divided into counted spots, and these spots are input into (CNN). Three strategies were used by the designers (DenseNet) (Inception v3) (SE-Resnet50) to predict diseases through images.

(Kulhalli) et al. 2019 [13] suggested a hierarchical strategy consisting of 5 phases, 3 phases, and 2 phases to identify and classify diseases with InceptionV3 CNN. To solve the problem of balance between categories, they used the image enlargement technique the classifier consisting of 5 stages certainly had better results than the 3 and 2 hierarchy.

referenc e	Type image	Numbe r images	dataset	Architectur e CNN	Performance Measurement
Sun et al. 2016	Clinical	6584 5619	SD-198[14] SD-128[14]	Fine-tuned VGG19	Accuracy 50.27%
Esteva et al. 2017	Clinical Dermoscopic	129450 3374	[9-15]	Inception v3	Accuracy: 72 %
Zhang et al. 2018	Dermoscopic	1067	Dataset [14]A Dataset [14]B	Inception-v3	Accuracy: 87 %

Table (3): Deep Learning-Based Skin Disease Classification Summary

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		522	-		Accuracy: 86 %
Rahman	Dermoscopic	379	ASIC-2016[15]	(CNN) With	Accuracy: 90.32
et al.				Conv:	%
2018				16 filters of	Sensitivity:
				7*7, pooling	88.15%
				layer:16 FC:	Specificity:
				100*50*5	82.41%
(Gessert)	Dermoscopic	1279			Accuracy:
and et al.			ISBI-16[15]	1-ResNet50	90.20%
2019		2790		2-	
			ISBI-17[15]	ResNet101	
		10000	HAM10000[15		Accuracy:95.60
]		%
					Accuracy:89.8%
(Kulhalli)	Dermoscopic	10015	HAM10000[15	Inception v3	Accuracy: 90
et al.]		
2019					

8- Results Comparisons with Other Studies

Several criteria were utilized to compare the proposed system's performance in skin cancer classification with other studies. Table 3 shows the results of related studies with the suggested model (SkinNet).

Reference	Number of images	Images Compression	Number of Models	Number of Model Suggestion	Accurac y
[17]	6584	No	1	No	50.27%
[18]	1067	No	1	No	87.25%

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[19]	3374	No	1	No	72.1%
[20]	379	No	No	1	90.32%
[21]	1279	No	3	No	90.20%
[21]	2790	No	3	No	95.60%
[21]	10000	No	3	No	89.8%
[22]	10015	No	1	No	90%
SkinNet (Proposed)	2360	Yes	5	1	98.2%

Table (3): Comparison between the SkinNet and other Studies

Table 3 includes several comparison criteria and demonstrates that the proposed system addressed an important point that was not covered in previous studies, which is the process of data compression. It also overcomes previous studies in terms of the number of models and accuracy. Therefore, a system was presented for detecting skin cancer with high accuracy and less execution time.

9- Conclusions

In this paper, deep learning was used because it has a very great potential in image analysis, specifically a convolutional neural network (CNN) that can analyze and classify thousands of images quickly and with very high accuracy. After all, a neural network can analyze images. The ability to analyze and classify thousands of images quickly and with high accuracy. Many models have many layers that contain many filters and other features that make them a leader in many areas today.

Four models were used on a data set (images) after adjusting the last layers for each model, and then a special model for detecting skin cancer was

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proposed and then the results were compared between these models to choose the best model for the image classification process in the field. from skin cancer.

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