A Novel Skin Cancer Detection Approach Using Deep Learning Algorithm with Image Segmentation Filters

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***Abstract*—Skin cancer is considered one of the most common and dangerous diseases in the world because so many people do not pay attention to it. In addition, skin cancer is a medical condition that a doctor cannot accurately diagnose from imaging data during a manual examination. Therefore, there is a great need to apply deep learning methods for early detection of skin cancer, as these methods are excellent in the field of medical image processing. This paper presents a deep learning model based on the convolutional neural network algorithm to provide automatic detection of skin cancer. The model basically consists of two scenarios: binary classification (benign and malignant) of the data set without an image segmentation process and binary classification of the same data set after applying four image segmentation methods (threshold-based segmentation, edge-based segmentation, binary fill holes technique, and removing small objects). The input images in the first scenario are three channels and one channel in the second scenario. These image segmentation techniques have significantly improved the accuracy of the proposed model, as the proposed model achieved 92.18% before applying segmentation and 96.83% after applying image segmentation.**

***Index Terms*—Computer vision, Deep learning, Edge, Neural Network, Skin cancer, Threshold.**

I. Introduction

Skin cancer is an abnormal growth of skin cells and often develops on the face, especially in areas frequently exposed to sunlight. However, this Widespread type of cancer can also develop on areas of the skin that are not frequently exposed to sunlight, (Hosny, et al., 2018; Gouda, et al., 2022a). This disease is prevalent worldwide, as skin cancer is one of the most common diseases globally. Skin cancer is mainly divided into four types: melanoma cancer, basal cell carcinoma, squamous cell carcinoma, and Merkel cell carcinoma. The most dangerous form of skin cancer is melanoma (Schaefer, et al., 2013), which is responsible for most skin cancer-related deaths worldwide (Gouda, et al., 2022b), as 100,000 new cases of melanoma are detected in the United States each year, and the death rate from them reaches 9,000 deaths each year, and in Australia, there are about 13,000 new cases each year and about 1,200 deaths (Codella, et al., 2017). Skin cancer is a very common disease in rural areas of developing countries such as India, Bangladesh, and Sri Lanka. According to Oxford Journals, there are about 1.5 million cases of skin cancer in Bangladesh (Rahi, et al., 2019a). Skin cancer occurs when a problem develops in skin cells that cause them to divide repeatedly and uncontrollably, causing cancer cells to spread to other parts of the body if the disease is not detected early, which is life-threatening. Early detection of skin cancer can reduce the mortality rate by 90%. This percentage drops dramatically to 62% after the disease reaches the lymphatic vessels, and then the percentage drops further to 16% when the disease spreads to other parts of the body (Tan, Zhang and Lim, 2019). The great similarity between many skin diseases makes it difficult to detect skin cancer by visual inspection (Swapno et al., 2025). Of 20,000 skin lesions surgically removed for suspected cancer, 0.1% tested positive for the disease (Tan, Zhang and Lim, 2019). Therefore, there is a constant need for an artificial intelligence system that can detect and distinguish skin cancer from other skin lesions. Deep learning techniques have been widely used in the medical field in the past decade. Convolutional neural network (CNN) algorithms are one of the best models in medical image processing, and recently, researchers have used a lot of deep learning and machine learning techniques to detect skin cancer cases.

The challenges facing most models for detecting skin cancer in its early stages are described as follows:

1. Sometimes, noise obscures many important features that affect the model's accuracy in its prediction, so noise must be eliminated, and the areas of high-quality artifacts must be preserved.

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2. Another challenge is the presence of hairs in areas of cancer presence that affect the accuracy of detecting between benign and malignant cancer.
3. Many studies rely on the principle of using pre-trained models that contain many parameters and require a large amount of time and memory in addition to powerful computers.

In this article, the research questions are defined as follows:

1. Is there an artificial intelligence system capable of automatically detecting skin cancer?
2. Is the system effective in automatically detecting skin cancer?

After a long search in the literature to answer these questions, the researchers found that many other researchers have taken this field extensively, which gave us the moral motivation to try to participate in this vital field. This study focuses on building an automated system for automatically detecting skin cancer using deep learning techniques; it also presents an approach based on reducing the training parameters to approximately one and a half million parameters. This system consists of two stages: The first one is pre-processing images by segmenting the images, improving, normalizing, and resized. The second one is training the deep learning model using a CNN, taking into account the time used in training by reducing the number of parameters as much as possible.

The main scientific contributions of this study can be summarized as follows:

1. To improve the accuracy of detecting and classifying images containing skin cancer, reduce distractions, and draw attention to key features. Several methods were included to extract the most important features (threshold-based segmentation, edge-based segmentation, binary fill holes technique, and removing small objects).
2. With the help of AI, develop a novel CNN model to detect and classify skin cancer in the images.
3. The number of parameters has been reduced for the classifier to save time and computation consumption during training the model to 1.6 million parameters.
4. The proposed model has obtained 92.18% without applying segmentation and 96.83% after applying image segmentation.

The rest of this paper is arranged as follows. In the second section, the literature review is discussed. The third section describes the methodology that was used in this study. In the fourth section, the results are listed and discussed briefly. In the final section, the conclusion of this study is presented.

II. Literature Review

Many works over many years have attempted to diagnose melanoma from skin imaging. In this section, we will review the most prominent works in the literature.

Adegun and Viriri (2019) proposed a multi-stage deep learning method for classifying skin cancer into malignant and non-malignant based on pixel-wise image classification called Lesion-classifier. The model was tested on two different datasets and achieved 95% accuracy. Ech-Cherif Misbhauddin and Ech-Cherif (2019) presented a CNN model called MobileNetV2 for the automated detection of skin malignancies. The proposed model was trained on 48,373 skin imaging images collected from three different datasets. The proposed model achieved 91.33% accuracy. Rahi, et al. (2019b) developed a deep neural network-based automated system for skin cancer detection. The proposed model achieved an accuracy of 80%. Then, pre-trained deep learning models, such as VGG11, RESNET50, and DENSENET121 were tested. The performance accuracy increased to a maximum accuracy of about 90%. Guan, et al. (2019) trained two deep-learning networks, VGG-16 and Inception-v3, for thyroid tumor detection. In this paper, thyroid images were randomly rotated four times at different angles (0, 90, 180, and 270) to augment the training data, where the training data were augmented 8 times. The proposed model achieved an accuracy of 97.66% using VGG-16 and 92.75% using Inception-v3. Reis, et al. (2022) proposed a deep learning-based CNN model called InSiNet for automatic skin cancer detection. The proposed model was trained on three different datasets and achieved more than 94% accuracy. Gouda, et al. (2022c) used a deep learning network (CNN) to detect two main types of malignant and benign tumors automatically. The proposed model was trained on the ISIC2018 dataset consisting of 3,533 images. In the pre-processing stage, the images were enhanced, enhanced, and resized using ESRGAN. The proposed model achieved an accuracy rate of 83.2%. (Kandhro, et al., 2024) In this paper, we enhanced the E-VGG19 model by incorporating max pooling and a dense layer to improve skin cancer prediction. The model extracts feature from skin lesions and classifies them as either malignant or benign. These extracted features are then fed into various machine learning classifiers, including Linear support vector machine, k-Nearest neighbors, decision tree, and logistic regression (LR). Our results show that integrating the E-VGG19 model with traditional classifiers significantly enhances classification accuracy for skin cancer detection. The proposed approach achieved an accuracy of 88%. (Ozdemir and Pacal, 2025) This study introduces a novel, lightweight, mobile-friendly hybrid model that integrates ConvNeXtV2 blocks with autofocusing mechanisms. The model focuses on extracting local features in the initial two stages, while autofocusing is employed in the later stages for enhanced feature refinement. When tested on the ISIC 2019 dataset, the model achieved an impressive accuracy of 93.60%.

When reviewing previous studies, the researchers noted gaps in several studies, including the lack of effective use of image processing techniques or the failure to reduce the number of parameters to reduce training time. For these reasons, the researchers decided to use two scenarios in this study: The first scenario without pre-processing the images and without reducing the number of parameters, and the second scenario after applying pre-processing and reducing the number of parameters. The researchers noted that this study successfully filled the gap in the literature.

We conclude from this section that many studies have tried to detect skin cancer automatically by applying different types of deep learning algorithms. Table I shows some of these studies in the literature.

III. Materials and Methods

This section will summarize all the steps of building the proposed skin cancer detection system in this study. This study is specifically built on two main scenarios: The first scenario is data classification before pre-processing (three input channels), and the second scenario is the classification of the same data set after applying several image segmentation and cleaning processes (one input channel). This method aims to know the extent to which image segmentation affects the result. After these two separate scenarios, three evaluations were used: accuracy, sensitivity, and objectivity to determine the reliability of the proposed model. Fig. 1 shows the general structure of the study.

A. Dataset

The ISIC-Archive dataset used in this study consists of 3,297 images of size 224 × 224 RGB (1,800 benign images and 1,497 malignant images). This dataset was obtained from Kaggle https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign?resource=download&select=train accessed August 30, 2024.

The dataset was divided into three Groups: training, testing, and prediction, as shown in Table II. In the testing folder, 600 images were placed (300 benign and 300 malignant); in the prediction folder, 40 images were placed (20 benign and 20 malignant), and the rest of the images were placed in the training folder.

B. Pre-Processing Image

The second scenario pre-processing is the most important stage in the proposed model, where the color images (RGB) are converted to grayscale images and then followed by using two image segmentations (threshold-based segmentation and edge-based segmentation), and two filtering methods (binary fill holes technique, and remove small objects). The goal of using image segmentation techniques is to reduce the number of features for the images so that the model is trained on the melanoma region only without the need to focus on other parts of the image, such as hair and others. Figs. 2 and 3 show the segmentation methods used in the study on benign and malignant cancer images, respectively.

C. Threshold-Based Segmentation

Threshold is one of the most common image segmentation techniques. It is useful to know the difference

TABLE I
Some Skin Cancer Detection Work in the Literature

Recent work	Data size	Techniques used	Number of classes	Data set	Accuracy (%)
Adegun and Viriri (2019)	2,000	Deep convolutional encoder-decoder network (DCNN)	Two	ISIC 2017	95
Ech-Cherif, Misbhauddin and Ech-Cherif (2019)	48,373	MobileNetV2	Two	DermNet, ISIC Archive	91.33
Muzahidul Islam Rahi, et al. (2019a)	450	ResNet50	Seven	HAM10000	90
Guan, et al. (2019)	279	DCNN VGG-16	Two	H&E-stained images	97.66
Reis, et al. (2022)	1,323	InSiNet	Two	ISIC 2018, 2019, and 2020	94.59
Gouda, et al. (2022c)	1,000	CNN	Two	ISIC 2018	83.2
Nawaz, et al. (2022)	1,280	RCNN	Two	ISIC-2016, ISIC-2017, and PH 2	95.6
(Kandhro, et al., 2024)	33,126	E-VGG19	Two	ISIC 2020	88
(Ozdemir and Pacal, 2025)	25,331	ConvNeXtV2	Eight	ISIC 2019	93.60

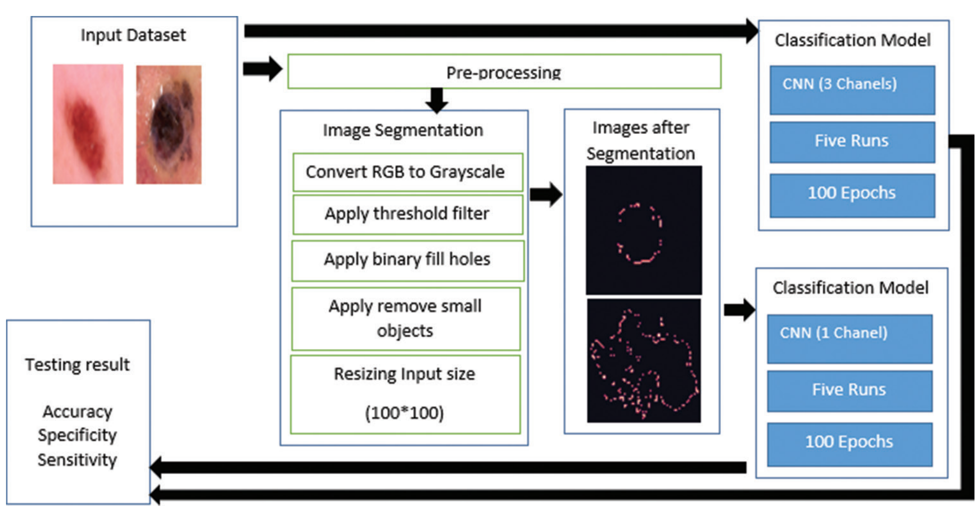

Fig. 1. The flow chart used in this study.

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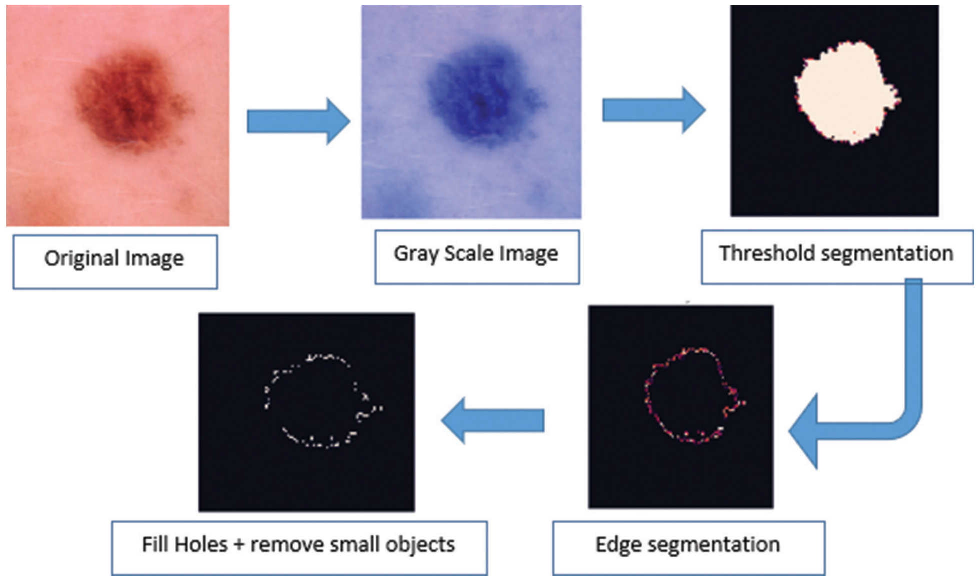

Fig. 2. The segmentation process used in this study (benign image number 26).

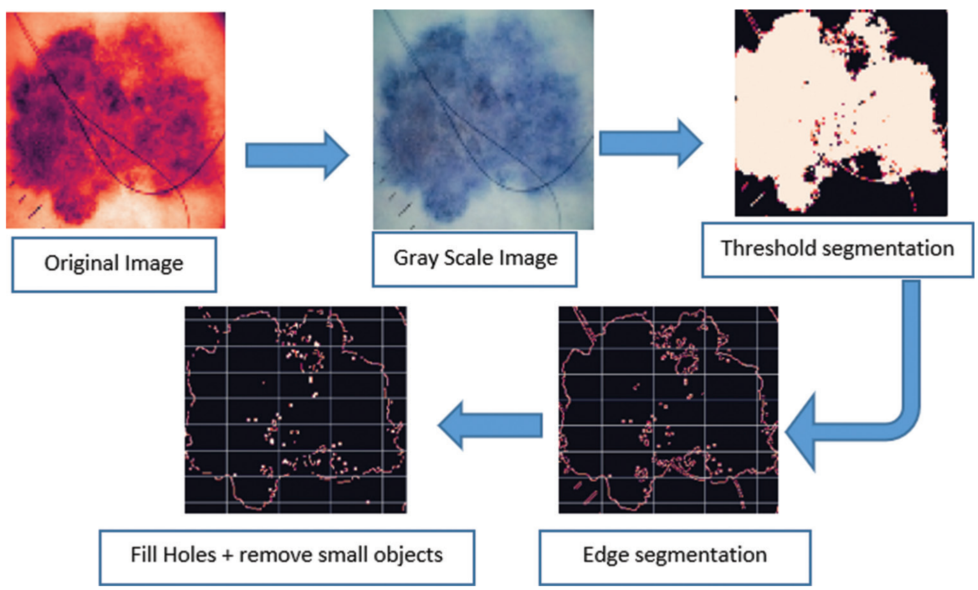

Fig. 3. The segmentation process used in this study (malignant image number 52).

TABLE II
Distributing Images to Folders used in the Study

Folder	Benign images	Malignant images
Training folder	1480	1177
Testing folder	300	300
Prediction fodder	20	20
Total	1800	1497

between front and back. By choosing a sufficient threshold value, T, the gray-level image can be converted into a binary image. The two images should contain all the necessary information about the position and shape of the objects of interest (front) (Abdulrahman and Varol, 2020). The advantage of having two images in advance is that it reduces the complexity of the data and simplifies the process of detection and classification. The most common way to convert a gray-level image to two images is to choose a threshold value (T). All gray level values below this T will then be classified as black (0), and those above the T will be white (1). The segmentation problem is to choose an appropriate value for the threshold T. The most common way to choose T is to examine the histogram of the images to be segmented. The best is when the histogram uses only two dominant channels that is, a clear valley (bimodal) is active. In this case, the value of T is chosen as the valley between the two modes (Al-Amri and Kalyankar, 2010).

The technique of the threshold can be defined as in equation 1, and the threshold image g (x, y) can be defined as in equation 2:

$$T = T\,[x, y, p\,(x, y), f\,(x, y)] \quad (1)$$

Where: T means the value of the threshold, x, y means the threshold coordinate point, p (x, y), f (x, y) means the point of the gray level images.

$$g(x,y)=\begin{cases}1 if\ f(x,y)>T\\0 if\ f(x,y)\le T\end{cases} \quad (2)$$

D. Edge-Based Segmentation

There is much research devoted to edge detection to develop optimal edge detection that provides a good balance between detection and localization performance. Searching for performance-optimizing filters is a common approach in designing such edge processors, and this requires three parameters: Good detection, good localization, and unique edge response (Canny, 1986). The best edge detector is the Cani method, which the first derivative of the Gaussian algorithm can approximate. Detecting edges by rotating the image with this filter is equivalent to finding the maximum gradient of a properly smoothed Gaussian image (Deriche, 1987). Finding and merging edges at multiple scales is another important aspect of edge detection. The scale-space method introduced by Witkin involves smoothing the original images using Gaussian smoothing kernels (Ma and Manjunath, 2000). Edge image G can be defined as in equation 3, and Fig. 4 shows how segmentation works using edges.

$$G=\sqrt{G_x^2+G_y^2}\ angle(\theta) \quad (3)$$

Where: G(x) means the horizontal direction of the image, and G(y) means the vertical direction of the image.

E. Fill Holes and Remove Small Objects

The segmentation techniques were used to extract important features as in the previous two steps, but some areas were missing in the image, so the Fill holes technique from the SciPy library in Python was used to fill those missing points in the image to improve the image quality. In this Article, the binary fill holes function (Abdulrahman, et al., 2022; Ramadhan and Baykara 2022). The method of filling the holes depends on the type of function used. There are several types of hole-filling methods, including Interpolation, Extrapolation, and fixed filling (Somasundaram and Kalaiselvi, 2010). In this study, the last type was used, where a fixed value of 0.5 was specified. As for removing small parts of the image, the remove_small_objects function from the scikit-image library in Python was used. The technique of removing small and unwanted objects from images is one of the common techniques for improving image quality. A value is specified for the function, and then the function removes any object that contains a number of pixels less than the specified value (Yang, et al., 2024).

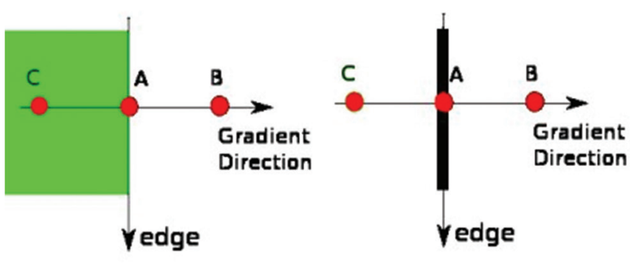

Fig. 4. Edge segmentation mechanism (Hong, et al., 2021).

F. Proposed Model

The model is built from scratch rather than using pre-trained architectures and features fewer layers compared to models, such as VGGNet, GoogLeNet, MobileNet, ResNet, and VGG16. The first stage consists of convolutional layers, which apply a set of filters to extract low-level features from images. Before training, all images are resized to 100 × 100 pixels as shown in Fig. 5.

The network structure comprises seven convolutional stages using "conv2d" layers as shown in Fig. 6. Initially, the model includes two convolutional layers, each with 32 kernel filters, separated by a MaxPool2D layer and a Dropout layer. The MaxPool2D layer performs down-sampling by selecting the maximum value from neighboring pixels, reducing computational complexity and mitigating overfitting.

In the second stage, the number of filters doubles to enhance feature extraction, while MaxPool2D and Dropout layers remain. The third stage expands to 128 filters, again incorporating MaxPool2D and Dropout layers. In the fourth, fifth, and sixth stages, the number of filters increases to 256, maintaining the same pooling and dropout mechanisms.

Finally, the seventh stage introduces two fully connected dense layers with 128 and 256 neurons, respectively, followed by a Dropout layer that connects to the output layer.

As for some of the features that were used in this model, ADAM optimizer was used. Each convolution layer contains a kernel size of 3 × 3 and a "ReLU" activation function. Furthermore, the learning rate annealing (LR) function was used. LR is a process by which the optimizer explores the "loss region." The Batch size value was changed five times in each experiment (2, 4, 8, 16, and 32). The rest of the features used in this study are shown in Table III and Table IV shows the total parameters.

IV. Results and Discussion

The results section consists of three subsections: Evaluation methods, results, and discussion and comparison with other studies:

A. Evaluation Metrics

To evaluate the performance of the proposed model, several metrics were used: global accuracy, sensitivity, specificity, and confusion matrix. Equations 4-6 give us the method for calculating each of the metrics used in this study (Baykara and Abdulrahman, 2021; Ramadhan and Baykara, 2022).

$$Accuracy=\frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$

TABLE III
Parameter setting details in our method

Experimental parameters	Setting
Image size	(100×100×3)–(100×100×1)
Batch size	2, 4, 8, 16, 32
Optimizer	Adam
Epoch	100
Learning rate (LR)	0.0001
Loss	binary cross entropy

TABLE IV
The total parameters used in this study

Layer (type)	Output shape	Param#
Convd_7 (Conv2D)	(None, 100, 100, 32)	320
Max_poolingd_6 (Maxpooling2D)	(None, 50, 50, 32)	0
Dropout_7 (Dropout)	(None, 50, 50, 32)	0
Conv2d_8 (Conv2D)	(None, 50, 50, 32)	9,248
Conv2d_9 (Conv2D)	(None, 50, 50, 64)	18,496
Max_pooling2d_7 (Maxpooling2D)	(None, 25, 25, 64)	0
Dropout_8 (Dropout)	(None, 25, 25, 64)	0
Conv2d_10 (Conv2D)	(None, 25, 25, 128)	73,856
Max_pooling2d_8 (Maxpooling2D)	(None, 12, 12, 128)	0
Dropout_9 (Dropout)	(None, 12, 12, 128)	0
Conv2d_11 (Conv2D)	(None, 12, 12, 256)	295,168
Max_pooling2d_9 (Maxpooling2D)	(None, 6, 6, 256)	0
Dropout_10 (Dropout)	(None, 6, 6, 256)	0
Conv2d_12 (Conv2D)	(None, 6, 6, 256)	590,080
Max_pooling2d_10 (Maxpoolind2D)	(None, 3, 3, 256)	0
Dropout_11 (Dropout)	(None, 3, 3, 256)	0
Conv2d_13 (conv2D)	(None, 3, 3, 256)	590,080
Max_pooling2d_11 (Maxpooling2D)	(None, 1, 1, 256)	0
Dropout_12 (Dropout)	(None, 1, 1, 256)	0
Flatten_1 (Flatten)	(None, 256)	0
dense_3 (Dense)	(None, 128)	32,896
dense_4 (Dense)	(None, 256)	33,024
Dropout_13 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 1)	257

Total params: 1,643,425 (6.27.MB)
Trainable params: 1,643,425 (6.27 MB)
Non-trainable params: 0 (0.00 B)
None

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

Where TP means the value of true positive, TN means the value of true negative, FP means the value of false positive, and FN means the value of false negative.

B. Results

Table V shows all the results obtained after executing the proposed model 5 times, each time changing the Batch size value (doubled) from 2 to 32.

The researchers notice from the table that there is a noticeable superiority of the proposed model in image segmentation over the first model before segmentation. In the first run of the model (32 Batch_size), this study achieved an accuracy of 92.18% before the image segmentation process, and then the researchers repeated the same experiment with the image segmentation process (Second scenario) and achieved a performance accuracy of 96.66%. Furthermore, the sensitivity and specificity have a better accuracy rate for the proposed model.

TABLE V
The total results obtained from the CNN model

Run	Batch_size	Filter	Accuracy (%)	Sensitivity (%)	Specificity (%)
Run 1	Batchsize 32	First Scenario	92.18	94.81	89.64
		Second Scenario	96.66	98	95.33
Run 2	Batchsize 16	First Scenario	91.81	94.07	86.07
		Second Scenario	96.33	98	94.66
Run 3	Batchsize 8	First Scenario	89.45	94.44	84.64
		Second Scenario	96.5	97.33	95.66
Run 4	Batchsize 4	First Scenario	92.18	93.33	91.07
		Second Scenario	96.83	98.1	95.66
Run 5	Batchsize 2	First Scenario	90	94	86.09
		Second Scenario	95.83	95.66	96

In addition, we noticed that the training time was reduced by 80%. For example, in the first run (Batchsize 32) before pre-processing, the training time was approximately 126 s per epoch, while after applying pre-processing, the training time became approximately 28 s per epoch.

Then, the same experiment was repeated before and after segmentation, and each time the batch value was changed, the performance of the proposed model was still superior to the first model. The highest accuracy is obtained in the fourth run, with an accuracy of 96.83%, and the best sensitivity accuracy is 98.1%. As for the specificity, the highest accuracy was obtained in the fifth run, with a value of 96%.

Fig. 7 shows the confusion matrix of the fourth run after applying image segmentation. Fig. 8 shows the accuracy curve of the second run after applying image segmentation. Fig. 9 shows the loss function curve of the third run before applying image segmentation.

C. Discussion and Comparison

After reviewing the results achieved using the proposed model, it became clear that it is possible to use deep learning techniques in the field of automatic detection of skin cancer using medical image processing techniques. The result obtained is somewhat good but needs improvement because, from our point of view, not all the images used in the experiment have the same shooting resolution or the same shooting angle, and some images have pen writing on them, from our point of view led to some impact on the final result of the model. In future studies, we will try to use other methods to process and clean images before training them.

Fig. 10 shows a comparison of the results achieved with some results of other studies conducted to detect skin cancer using deep learning techniques. We note from this figure that

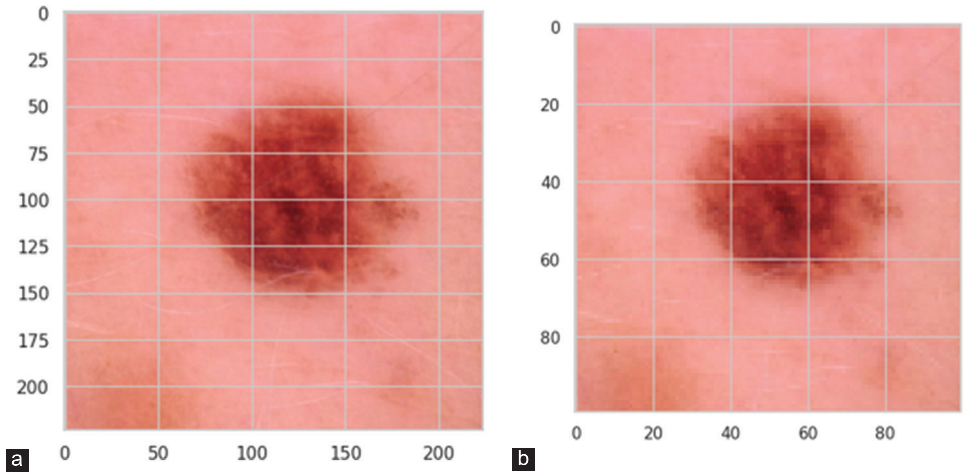

Fig. 5. Image resized (a) the original Image 224×224 RGB (b) the Image after resized it 100×100 RGB.

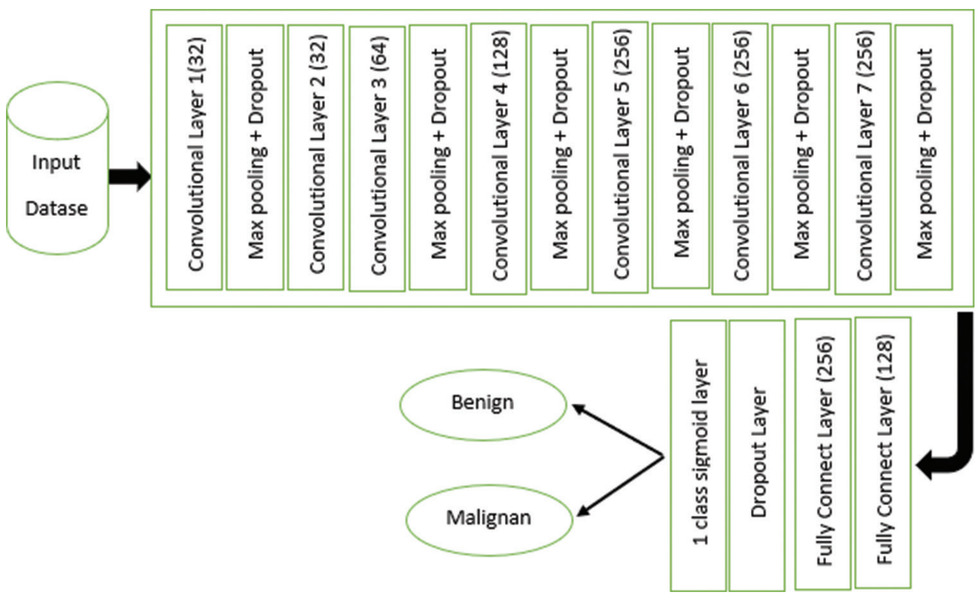

Fig. 6. The structure of the modified CNN model.

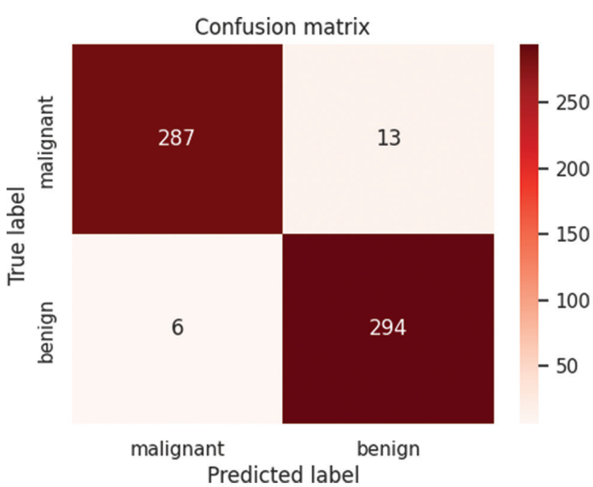

Fig. 7. Run4 Batch_size 4 after applying image segmentation process.

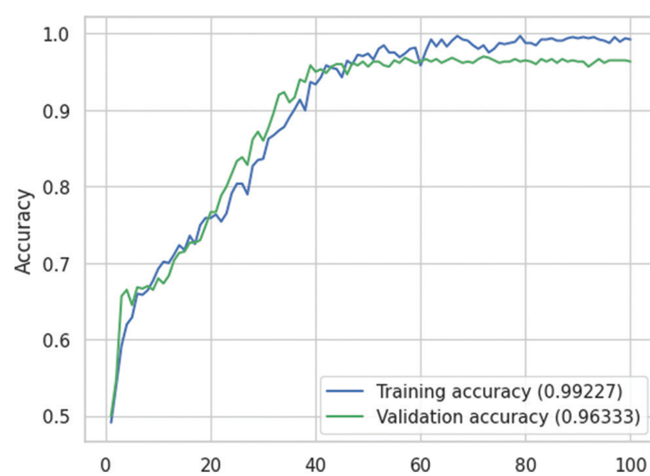

Fig. 8. The accuracy curve of Run 2 after applying image segmentation.

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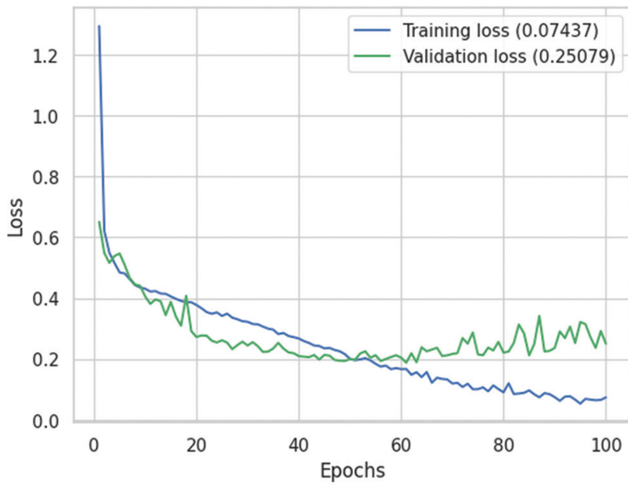

Fig. 9: Loss function curve for Run 3 before applying image segmentation.

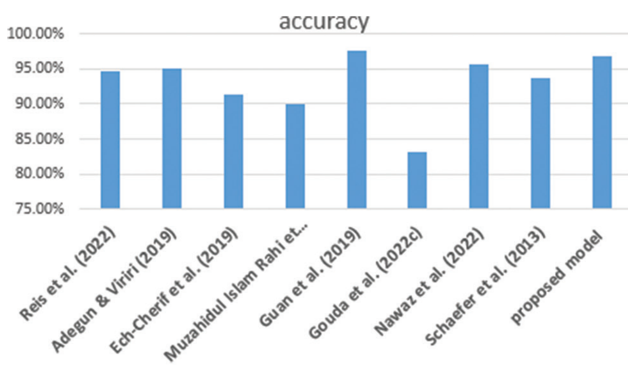

Fig. 10. A comparison with the newest studies.

the proposed model achieved satisfactory results and can be adopted in detecting melanoma cancer.

V. Conclusion

Skin cancer is one of the most dangerous diseases, especially melanoma skin cancer. Because most people do not pay attention to this dangerous disease and do not see a doctor when skin pigmentation appears, delaying the diagnosis of the disease leads to very negative results. Artificial intelligence and computer vision researchers have tried to help in this vital and dangerous field by finding an automated system that detects skin cancer early and reduces the death rate. Because early detection of the disease leads to an increase in the recovery rate to a percentage that may reach 90%.

In this study, a deep learning system derived from a CNN was built. It consists of two stages: The first stage involves training a model without pre-processing the images, and the second stage involves pre-processing the images by segmenting them using two image segmentations (threshold-based segmentation and edge-based segmentation), and two filtering methods (binary fill holes technique, and remove small objects). In both stages, training time and model accuracy were considered by reducing the number of parameters used.

The study achieved a performance accuracy of 96.83%. The results achieved in this study are satisfactory and can be built upon in future studies to develop early detection of skin cancer.

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