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Improving CNN's application in the early identification of skin cancer and its types

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Abstract
Skin cancer is a prevalent and possibly dangerous disorder that requires accurate classification and early discovery in order to be properly treated. This article explores the application of convolutional neural networks (CNNs), a state-of-the-art method, to address these problems. The goal of this research is to develop a trustworthy CNN-based model that can recognize lesions associated with skin cancer and accurately classify them into many categories, including benign moles, malignant melanomas, squamous cell carcinomas, and basal cell carcinomas. In order to do this, we will gather a substantial set of dermatological images representative of various racial backgrounds, age groups, and skin types. The trained CNN model will undergo a thorough evaluation utilizing a number of measures, including area accuracy, precision, recall, and F1-score. A very accurate skin cancer detection and classification algorithm, with the potential to revolutionize dermatological diagnosis, is one of the predicted outcomes of this study. Our method may lead to better patient outcomes by providing early and accurate skin cancer type identification. The results of this study have important ramifications for dermatology and healthcare, opening the door to the creation of automated diagnostic tools that may be included in mobile apps and telemedicine platforms for increased accessibility. The effect of this innovative method for skin cancer detection and classification will be further increased by future work that involves collaboration with dermatologists for clinical validation and practical deployment.

Keywords: CNN, Skin cancer, Skin cancer classification, patient data

Introduction
Skin cancer is a set of disorders collectively referred to as skin cancer and is characterized by the unchecked proliferation of aberrant skin cells. It happens when genetic changes in skin cells cause them to divide rapidly and uncontrollably, resulting in tumors or lesions. Exposure to ultraviolet (UV) radiation from the sun or artificial sources, such as tanning beds, is the leading cause of skin cancer. The prevention of the spread of malignant cells to other bodily areas depends on early identification and treatment. There are three main types of skin cancer that are most common [1-2]:

Basal Cell Carcinoma (BCC)
the form of skin cancer that occurs most frequently. The basal cells, which are found in the deepest layer of the epidermis (the top layer of the skin), are where it starts. BCC generally manifests as a sore that doesn't heal or a raised, pearly lump. It frequently appears on exposed skin, including the hands, neck, and face. Although BCC seldom poses a life-threatening threat and typically grows slowly, it should be swiftly treated to avoid local harm.

B. Squamous Cell Carcinoma (SCC)
Like basal cells, squamous cell carcinoma develops from cells in the epidermis but at a higher level. SCC often manifests as an ulcerated sore or a red, scaly area that may heal and reappear. SCC can appear on other regions of the body in addition to sun-exposed places, like BCC does. It is more likely to spread than BCC and, if handled, can become hazardous.

C. Melanoma
Melanoma is a more dangerous and severe type of skin cancer that develops in the melanocytes, the cells that produce the color in the skin known as melanin. A new mole or a

change in the size, shape, or color of an existing mole are frequent manifestations of melanoma. The palms, soles, and nail beds are examples of places where it might appear where there is little sun exposure. Melanoma must be found early because it can spread quickly to other places of the body.

In addition to these three primary kinds, there are a few uncommon skin cancers, Vascular lesion, including cutaneous lymphoma, Merkel cell carcinoma, and Kaposi sarcoma.

For the early identification and effective treatment of skin cancer, routine skin examinations and seeking medical attention for worrisome lesions are crucial. Dermatologists and other medical professionals frequently use a variety of diagnostic methods, such as dermoscopy, visual examination, and, increasingly, computer-aided classification utilizing Convolutional Neural Networks (CNNs), to correctly detect and categorize different forms of skin cancer.

Skin cancer, one of the most common and fatal diseases, affects millions of people all over the world. For successful treatment and better patient outcomes, skin lesions must be identified early and classified properly. Traditional techniques for diagnosing skin cancer always rely on a primitive method that takes a long time and effort by new doctors, but the use of convolutional neural networks may greatly speed up the diagnosis of the disease. It is considered one of the techniques of artificial intelligence and has great potential for classifying these skin lesions, which allows us to diagnose them accurately. More accurate and faster than the traditional method [3]

Using deep learning techniques such as CNN to classify images is considered a good way to classify and recognize images. It can be said that pathology and other diseases that rely on the imaging industry to diagnose treatment and that rely directly on images to diagnose this disease can rely heavily on CNN for the purpose of building a reliable method for diagnosing these lesions and diseases more effectively and accurately [4, 10-11].

Through this work, we focus on how to use convolutional neural networks in the field of skin disease diagnosis, especially in skin cancer classification.

We are building a system capable of diagnosing these diseases and dividing them into their categories in a more accurate and efficient way by training a neural network on sets of these images. In order to know the accuracy of this model and its ability to distinguish between these categories, it can also be said that the main goal of this system is to create a system capable of helping doctors make decisions quickly in the field of diagnosing skin cancer, as the speed of detecting this disease helps in the healing process or gives Great opportunity to cure this disease.

After completing the work, we will evaluate this project, and we will note the difficulties. We will look into the difficulties in classifying skin cancer, including changes in lesion appearance, lighting, and imaging quality. We intend to contribute to ongoing efforts to improve skin cancer detection and lessen the impact of this illness on people and healthcare systems by tackling these issues and making use of CNN capabilities [7-9].

We will go over the methods utilized, the dataset used for training and validation, the architecture of the CNN model, the outcomes, and the ramifications of our findings in the parts that follow. We want to create a significant impact on the area of dermatology and healthcare overall by adopting cutting-edge technology and working with medical experts, furthering the cause of early identification and prompt intervention in the battle against skin cancer.

Previous Work

Here is a condensed table that summarizes some important earlier research on utilizing convolutional neural networks (CNNs) to classify skin cancer. The topic, methodology, and key findings of several research are briefly summarized in this table. This table offers a succinct summary of a few significant research in the area of Skin Cancer Classification Using CNNs. The variety of techniques, the focus on CNN performance, and the overriding objective of enhancing skin cancer diagnosis with AI-powered systems are all highlighted.

Table 1: Literatrue Review Table

References	Objective	Methodology	Findings
[15]	Skin cancer categorization according to dermatologists	Using a vast collection of skin image training data, we trained a CNN to perform at an expert level.	Shown how CNNs may be used for dermatological diagnoses
[16]	Performance of CNN in comparison to dermatologists	Dermatologists and CNN were compared for diagnosing accuracy.	Showed the capacity of AI systems to compete with human skills
[17]	Collaboration on International Skin Imaging (ISIC)	Held a contest for deep learning systems that detect melanoma	Presented numerous skin lesion classification methods based on CNN
[18]	For melanoma, deep learning versus dermatologists	CNN beat numerous specialists when performance was compared to dermatologists.	Emphazized CNN's prowess with melanoma classification tasks
[19]	Using computers and people to combat skin cancer	Looked at dermatologists and CNNs working together for diagnosis	Collaboration between AI and humans is advised as a successful diagnostic technique
[20]	Challenge for Skin Lesion Analysis (ISBI)	Organized a competition for CNN-based skin lesion analysis	Shown the flexibility of CNNs in examining different types of skin lesions
[21]	dermatologists vs. CNN in the fight to diagnose skin cancer	Compared CNN's performance to dermatologists, it performed with great accuracy.	Demonstrated potential for CNNs to match or surpass human diagnostic skills

Proposed Method

We created an integrated system for classifying skin diseases using deep learning to facilitate the diagnosis of the doctor because the process of rapid diagnosis of the disease increases the chance of recovery from skin cancer. Since we have collected a large collection of photos of skin cancer patients, we have classified them. Where each part of this classification contains images related to this disease, and we processed all these images using CNN to reach the diagnosis of each type through the images entered into the system. In the images resulting from this process, we compare them with the new images so that the system can determine the type of disease that belongs to any of these categories. Where do we build this system first, then we go through the

process of training this system, then we test this system to see its efficiency in diagnosing these diseases, and we compare the system that we have with another system from previous research so that we can know the extent of the difference between our system and other systems.
There are several various layers that makeup CNN architectures. The layers always accept a 3D volume as input, convert it using differential equations, and then output a 3D volume. Some layers need their hyperparameters adjusted, while others do not.

Convolutional Layers
Imagine you are looking at a picture, but instead of looking at the picture as a whole, you start by gazing at the top left corner and move to the right until you get to the conclusion of the picture. As you go down the line, you switch back to left-to-right scanning. You learn something new about the contents of the image each time you go to a different area of it. This is essentially how convolution functions.
Convolutional layers are the basic building blocks of CNNs. The filters that make up these layers each have a width, height, and depth. Convolutional layers are constructed from 3-dimensional neurons, as opposed to the thick layers of traditional neural networks. Convolutional Neural Networks are a reasonable option for picture categorization because of this property

Filters
Convolutional Layers are composed of weighted matrices called Filters, sometimes referred to as kernels. Filters use only part of the image (the receptive field) as input as they move across the image from left to right. We will observe how this local connection between the active nodes and the weights enhances the functionality of the neural network as a whole. The size of the filter may be different depending on the method of work in which we will work and according to the accuracy with which we need the work to be such as 3 x 3, 5 x 5, etc.

a) Padding works: Padding works by expanding the region of an image that a convolutional neural network analyzes. The neural network filter known as the kernel traverses the image, inspecting each pixel and resizing the data into a smaller, or occasionally bigger, shape. Padding is added to the image's frame to provide the kernel additional room to process the picture. This helps the kernel process the image more quickly. For more precise image analysis, padding can be added to a CNN-processed picture.

b) Stride: Stride designates and specifies the appropriate step size for the convolutional product. A big stride value may lead to a smaller output size, and vice versa.

Pooling: We employ a pooling layer to lower the image's dimensionality, which reduces the image's features by condensing the data. This pooling process is carried out across every single channel, and it makes sure to only modify the dimensions (nh, nw) while maintaining the prior state of nd. Given an image, we apply a function to the chosen elements by sliding a kernel over the picture while maintaining a predetermined stride value. We write p for the pool's size.

The Fully-Connected Layer
Keep in mind that fully linked neural networks consist of layers of nodes, each of which is associated with every node in the layer preceding it. To produce predictions using our learned and set features, this type of network was added to the end of our CNN design.
Making class predictions is the fully connected layer's objective. A flattened vector of nodes that were active in the preceding convolutional layers will be the input for the fully connected layer. Before being delivered to the output layer, the vector input will go through two to three dense layers, and occasionally more. It will also go through a final activation function. It is not necessary for the activation function used for prediction to be a rectified linear unit. Depending on the classification issue, there are two typical activation functions that can be chosen:

1. Given that it is a logistic function, sigmoid is typically utilized for binary classification tasks.
2. SoftMax may be applied to both binary and multi-class classification issues and assures that the output layer's value sums equal 1.

Deep Learning Model
Architecture Work
The CNN model used here for melanoma classification consists of 16 layers and all images used in this work will be of fixed size. We will enter the images that we have that we brought from the database into our model and we will pass them on 16 layers and extract the characteristics of each image and then process it. The size of the filter passed over the layers will be 3 x 3. I will explain how our model works through the table shown below.

Table 2: Proposed Models to Solve

Layer	The number of filter cycles	Filter size	Stride	Output
Conv_2d	64	3 x 3	1	320x 320x 64
Conv_2d	64	3 x 3	1	320x 320x 64
Maxpooling_2d	64	2 x 2	1	160 x 160x 64
Conv_2d	128	3 x 3	1	160 x 160x 64
Conv_2d	128	3 x 3	1	160 x 160x 128
Maxpooling_2d	128	2 x 2	1	80 x 80x128
Conv_2d	256	3 x 3	1	80 x 80x256
Conv_2d	256	3 x 3	1	80 x 80x256
Conv_2d	256	3 x 3	1	80 x 80x256
Conv_2d	256	3 x 3	1	80 x 80x256
Maxpooling_2d	256	2 x 2	1	40 x 40x256
Conv_2d	512	3 x 3	1	40 x 40x512
Conv_2d	512	3 x 3	1	40 x 40x512

Conv_2d	512	3 x 3	1	40 x 40x512
Conv_2d	512	3 x 3	1	40 x 40x512
Maxpooling_2d	512	2 x 2	1	20 x 20x512
Conv_2d	512	3 x 3	1	10 x 10x512
Conv_2d	512	3 x 3	1	10 x 10x512
Conv_2d	512	3 x 3	1	10 x 10x512
Conv_2d	512	3 x 3	1	10 x 10x512
Maxpooling_2d	512	2 x 2	1	5 x 5x512
Convolutional	5 x 5x512			
flatten	12,800			

Through the above table, we will notice that each image will be included in 16 layers from which the characteristics in this image can be extracted so that we can classify it within any of the categories of this disease.

Dataset

For this project we use more 25,000 images for many kinds of caner as shown in the Fig. 1. This dataset contains the training data for the ISIC 2019 challenge, note that it already includes data from years (2018 and 2017) [28].

The dataset for ISIC 2019 contains 25,331 images available for the classification of dermoscopic images among nine different diagnostic categories: Melanoma, Melanocytic nevus, Basal cell carcinoma, Actinic keratosis, Benign keratosis (Solar lentigo / seborrheic keratosis / lichen planus-like keratosis), Dermatofibroma, Vascular lesion, Squamous cell carcinoma. The distributions of image in the dataset between all provided kinds of cancer can be seen clearly in Fig.1.

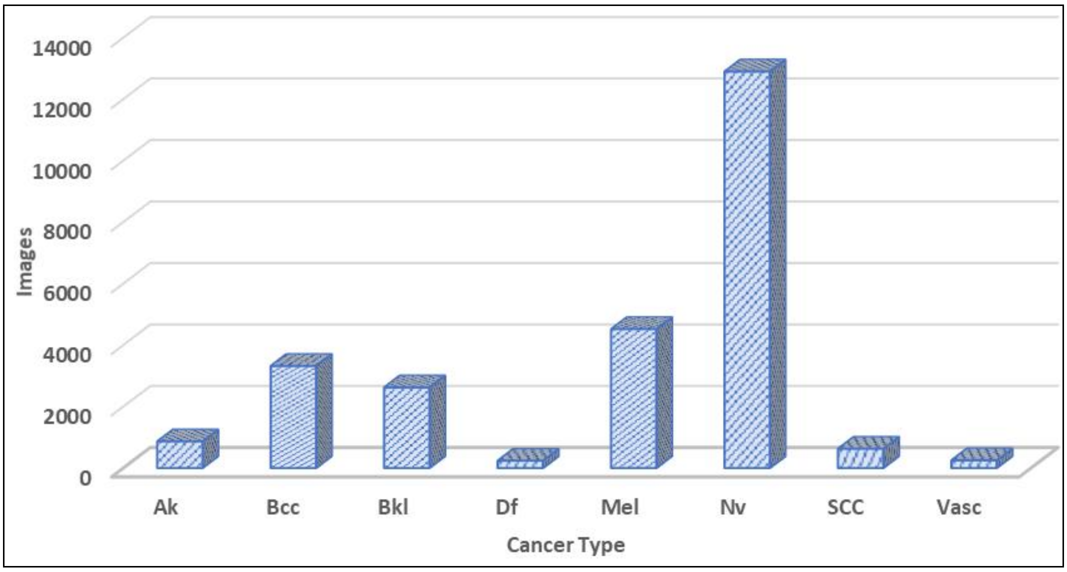

Fig 1: Shows the distributions of image in the dataset between the kinds of cancer.

Performance

We have worked on applying this proposed model on more than 25000 images to determine the efficiency of this system, and we have determined through simple mathematical operations a mechanism to know the criteria accuracy evaluating recall, accuracy, and F1-score of this system. By estimating the anticipated image among four subsets True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) it is possible to assess the performance matrix. The proportion of successfully categorized positive instances is denoted by TP. The TN indicator shows how many accurately identified negative instances there were. The proportion of positive instances designated as incorrect, or FP. FN, the number of falsely labeled negative instances.

We will now evaluate the level of performance of the proposed model through the following equations:

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

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP+FP})} \tag{2}$$

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

$$\text{F1-score} = 2\left(\frac{(\text{Precision}*\text{Recall})}{(\text{Precision+Recall})}\right) \tag{4}$$

Results

We implemented our own model based on a dataset of more than a thousand images to be able to differentiate skin cancer diseases and classify them according to their type. And by applying the system to a set of images, we were able to diagnose the disease more clearly using the CNN algorithms, and through this work we can diagnose the disease early so that the disease does not worsen and makes it difficult for us to treat it and avoid the risks associated with these diseases. Where our system consists of 16 layers, that is, each image must pass through 16 layers, so that we can extract its characteristics and the advantages of these images, so that we can determine which type this disease belongs to. Where it consists in the beginning of dividing the data into parts, the first part is the stage of training and building the system, and the second part is the stage of testing the accuracy of the work of this system, where the results obtained indicate high accuracy in the process of diagnosis and classification of images for each disease, and we also compared our work With other work so we can improve this algorithm to get as much benefit as possible from this search.

Table 3: The results of training and testing models

Method	Precision	Recall	F1−score	Accuracy
[1]	0.79	0.83	0.77	79.45%
[9]	0.818642	0.80509	0.82797	83.04%
[23]	0.91	0.89	0.89	90%
[30]	0. 92	0.91	0. 9	91%
Proposed	0. 937	0.92	0.915	92.4%

We will now show some diagrams to illustrate the working mechanism of the special system.

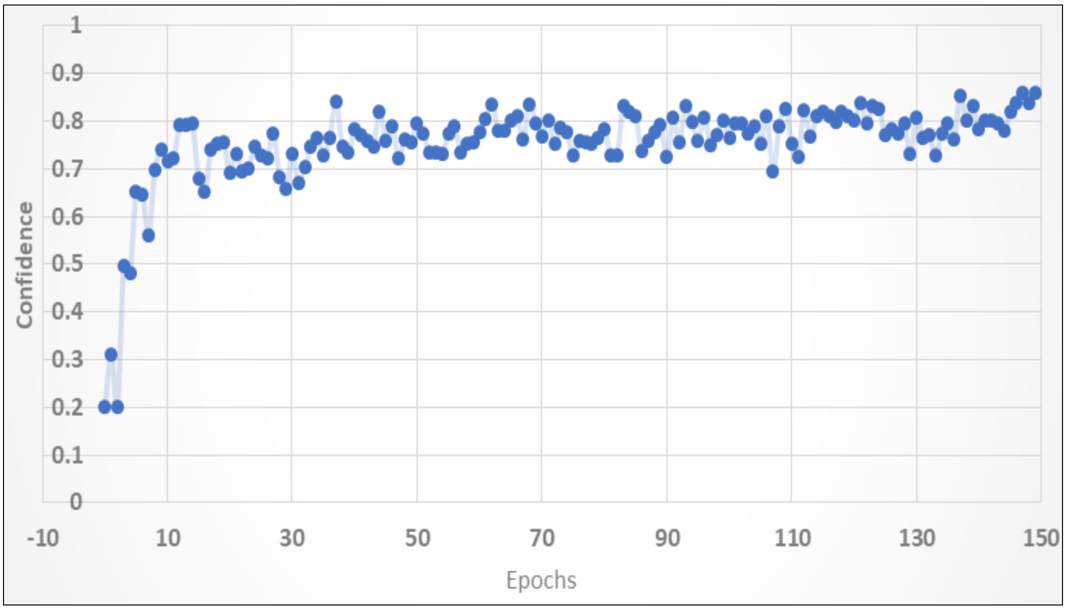

Fig 2: The Recall chart as shown after 100 epoch, the confidence becomes stable

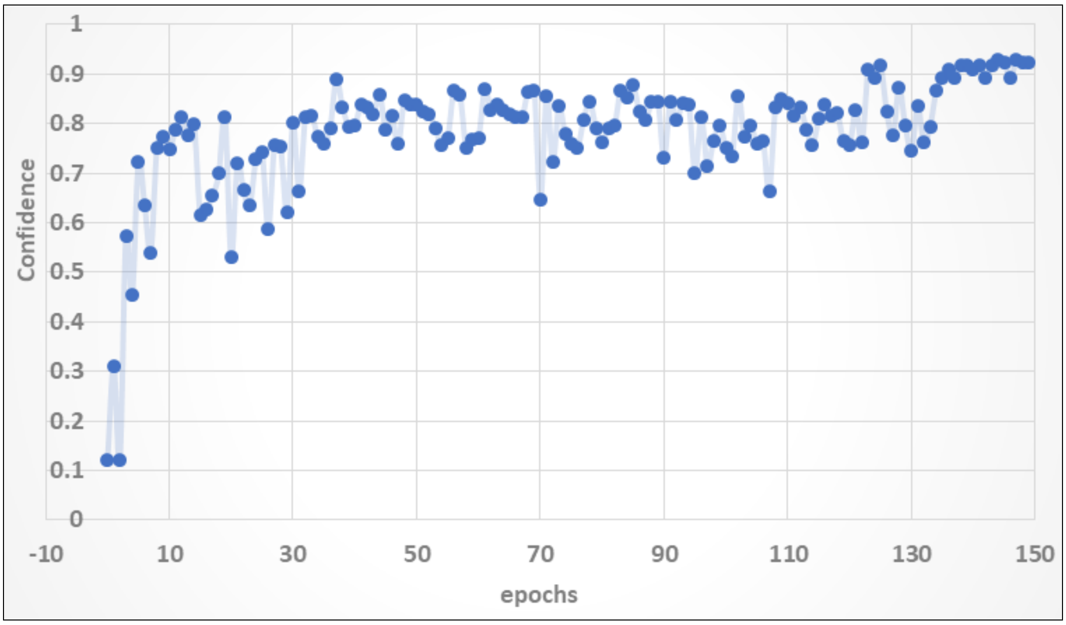

Fig 3: The Precision chart as shown after 120 epoch, the confidence becomes stable above 92%.

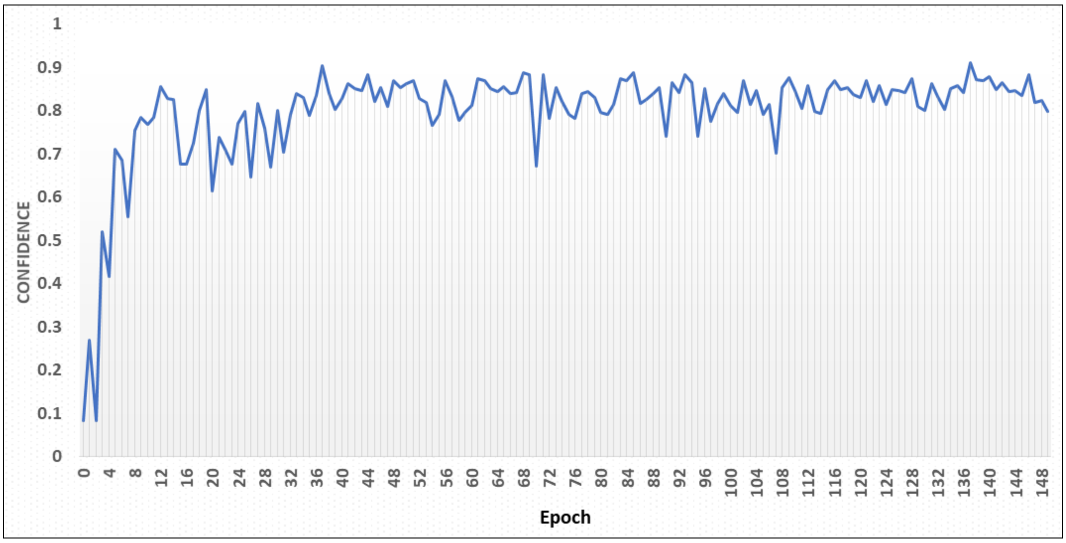

Fig 4: The F1-score chart as shown after 130 epoch, the confidence becomes stable

Conclusion

We have created a workable technique for detecting skin cancer using photographs of the afflicted individual as a result of our research. The outcomes of our work are quite precise because we created our own CNN model. To gauge the effectiveness of the suggested system, we compared it to earlier works. We carefully examined a range of research articles and methodology as part of our investigation. In this study, we sought to understand the critical function provided by neural networks in the identification, classification, and detection of skin cancer. We compared several designs and methods to learn about their advantages and objectives. We used dataset contains over 25,000 image with various kinds of censers for our experiment and we found that the accuracy of the application is around 92%.

By assessing the model's performance on enhanced photos that were created randomly, we furthered our investigation. Impressively, this enhancement experiment produced findings that were virtually as accurate and precise as the first ones. Key performance indicators including Accuracy, F-score, Precision, and Recall served as the foundation for our evaluation.

It can be said that using CNN to extract features may improve performance in diagnosing skin cancer, which helps doctors in the early detection of this lesion and helps in its treatment [29].

The definitive results showed that the application of the Standard CNN technique produced the best results for skin cancer diagnosis in light of our thorough investigation. This highlights the possibility of using convolutional neural networks to advance the diagnosis of skin cancer and supports their efficacy in providing precise and trustworthy diagnoses.

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