

**How to Cite:**

Shaikh, J., Khan, R., Ingle, Y., & Shaikh, N. (2022). Improved skin cancer detection using CNN. *International Journal of Health Sciences*, 6(S2), 14347–14360.  
<https://doi.org/10.53730/ijhs.v6nS2.8762>

# Improved skin cancer detection using CNN

**Juveriya Shaikh**

Modern Education Society's College of Engineering, Pune  
Corresponding author email: [juveriyash05@gmail.com](mailto:juveriyash05@gmail.com)

**Rubeena Khan**

Modern Education Society's College of Engineering, Pune  
Email: [rubeena.khan@mescoepune.org](mailto:rubeena.khan@mescoepune.org)

**Yashwant Ingle**

Modern Education Society's College of Engineering, Pune  
Email: [yashwant.ingle@mescoepune.org](mailto:yashwant.ingle@mescoepune.org)

**Nuzhat Shaikh**

Modern Education Society's College of Engineering, Pune  
Email: [nfshaikh@mescoepune.org](mailto:nfshaikh@mescoepune.org)

**Abstract**---Pollution, an unhealthy lifestyle, UV radiation, and other factors can contribute to skin cancer. A variety of machine learning techniques have been developed in the past to detect such malignancies before they worsen. The goal of this article is to utilize a convolutional neural network to segment skin lesion images. The purpose of this study is to see how deep learning may be utilized to segment skin lesion photos. People may discover what skin diseases they may have, how to protect themselves from it, and what measures they can take early on to successfully treat the disease using Artificial Intelligence. Machine learning may be used to diagnose the problem and help us predict the result. The most widely used classification technology is the support vector machine. The discoveries might help doctors treat sickness early on and avoid further deterioration.

**Keywords**---image segmentation, convolutional neural network, skin cancer.

**Introduction**

Skin cancer is a rare and serious disease that should be detected as soon as possible. It can be present with a variety of symptoms and come in a variety of forms, all of which can be cured or, thankfully, terminated totally. It can strike anyone of any age group and, if not treated promptly, can be fatal. Skin cancer

affects one out of every six persons. It is a disease that affects the body in a variety of ways and causes some body cells to grow fast and uncontrollably, spreading to other parts of the body. Cancer can arise from any of the billions of cells that make up the human body. Overexposure to sunshine has been linked to an increase in sickness, according to medical authorities. Artificial intelligence refers to a robot whose ability to accomplish tasks is controlled by a computer commonly associated with intelligent intelligence and judgement. Artificial Intelligence (AI) for skin cancer detection is a cost-effective and technologically advanced method that can save lives. This paper's work focuses on a review of skin cancer detection that aids in our understanding of the disease and its detection using Machine Intelligence. Python and AI are important parts of the study because they assist us understand how it works and other strategies. The task is divided into three tiers, each of which aids us in comprehending the technique in a clear and accurate manner.

Machine intelligence systems, deep learning algorithms, in particular, are quickly penetrating the medical business. A task to be executed, such as pattern recognition which is automatic, large datasets are analyzed using layered mathematical models (1). One of the areas is image analysis where researchers are making the most development right now (2), such as in the qualitative and quantitative analysis of lung nodules on radiographic pictures (3), graphics detection of probable strokes (4), and breast mammograms (5). In the era of dermatology, artificial intelligence or machine learning - based technologies are designed to evaluate the severity of psoriasis or to discriminate among onychomycosis and abundant nails (6, 7). The sensitivities of machine intelligence-based algorithms in distinguishing melanomas from nevi in experimental circumstances were comparable or better than dermatologists' (9–11). Because early evaluation of melanomas improves prognosis and distinguishing melanomas from innocuous lesions is typically difficult, AI-based classification systems could be extremely beneficial to disease struck with worrisome skin lesions. Anyhow, still there is some debate about whether AI can be used for diagnosis in "real-world" healthcare settings. Biases, a lack of transparency and ability to explain the growth, data aggregation and interoperability, stability, security, confidentiality, and ethics of consolidated electronic files are all issues that need to be addressed. (12, 13).

Melanoma as a type of skin cancer can be fatal. Early detection of melanoma enhances the likelihood of survival by 75 percent (14), whereas other kinds of skin cancer have survival rates as low as 4–5%. (15). If these skin lesions are caught early enough, they can be easily treated. Melanoma can swiftly progress to the final stage and cause metastases if discovered late. The patient's probability of surviving are dwindling. Through statistical data, a patient with melanoma in its latter stages can live for up to 5 years. For the early detection of melanoma, the encounter of the experienced dermatologist taking the clinical examinations is quite trivial. The utilisation of pictures produced by dermoscopy devices boosted the finding success rate of skin lesions in clinical examinations. Dermoscopy is a noninvasive technique for assessing the colours and epidermal, dermo epidermal interface, and papillary dermis micro - structural that are not visible to the naked eye in real time. These structures are linked to histological characteristics. Dermoscopy is utilized to magnify visual aspects of lesions that aren't or can't be

able to see through normal human eye. Regardless of the existence of such photographs, distinguishing skin lesions with extremely similar characteristics such as shape, texture, edge irregularity, and so on might be challenging. Several analysis techniques are utilised to determine if the lesion is benign or malignant depending on the observed features. To determine the type of lesion, experts employ the ABCD (16) rule, CASH algorithm (17), Menzies method (18), 7-point control list, and 3-point checklist techniques (2008, 2008). Despite the contrasts and advantages of these approaches when compared to one another, pathological exams are the gold standard for the differential diagnosis of skin lesions. It is unnecessary, time-consuming, and costly to request a pathology examination for each patient. It's also a stressful situation for the patient.

Various algorithms and methodologies are being created as a result of advances in artificial intelligence to improve clinical diagnosis success rates. In experiments using Machine learning algorithms have become increasingly popular in past few years, promising findings have been found. When artificial intelligence models and experienced dermatologists were compared in various research, it was discovered that deeper algorithms gave greater benefits in the identification of skin lesions. These techniques may be used to turn any device, substrate, or operating system into a splitting edge medical gadget (21). The idea of this article is to give an update on artificial intelligence algorithms for the visitor, the efficacy in detecting skin cancer as well as how to help reduce or minimize or even eradicate it.

### **Related Work**

Deep learning neural networks are widely used in the detection of skin cancer (40). It is comprised of a series of inter connected nodes. Its shape and structure is comparable to that of a normal human brain in comparison terms of neuronal connections. Its nodes collaborate to tackle specific issues. Machine learning neural networks are computer programmers that are programmed to do certain tasks. They function as pro in the areas for what they were programmed. In current research, neural networks were taught and trained and couched to categories images and differentiate of the different skin related cancer cells. International Skin has a variety of skin lesions. For skin cancer detection, we looked into various learning approaches such as ANN, CNN, and KNN. The next sections go over the research on each of these deep neural networks in depth.

### **Artificial Neural Network (ANN)**

An artificial neural network is a statistical and nonlinear prediction approach. Its structure is based on the human brain's basic structure. ANN is made up of three layers. The input layer is the initial layer of neurons which transmits information to the neurons in the new stage layer of neuron. The hidden layers are the layers in the middle. There may be multiple hidden or undiscovered layers in a traditional ANN. Data from intermediate neurons is received by the third layer of output neurons. Back propagation is a technique for discovering complex links between input and output layers. It functions similarly to a neural network. In computer science, the phrases neural network and artificial neural network appear to be synonymous.

In skin cancer detection systems, ANN is employed to differentiate retrieved features. After the training set has been identified as melanoma or non-melanoma, input photos are classified as melanoma as well as non-melanoma skin cancer. The quantity of hidden layers in an ANN is determined by the quantity of images put in the system. The input dataset connects the ANN process's input/first layer to the camouflaged layer. The dataset can be named or unnamed, and either observational or non-regulatory learning mechanisms can be used to handle it. . Back propagation or feed-forward architecture is used by a neural network to learn the weights present at each network connection/link. For the underlying dataset, both architectures use a distinct pattern. Neural networks with a feed-forward architecture only exchange data in a single direction. The data goes from the input to the output.

### **Convolutional Neural Network (CNN)**

Convolutional neural networks are one of the most popular types of deep neural networks in computer vision. It's used to classify images, group input images together, and recognize images. By integrating essential properties like curves and edges to build more complicated features like forms and corners, CNN is an excellent technique to obtain and comprehend global and local data (32). Convolution layers, nonlinear pooling layers, and fully connected layers are among CNN's hidden layers (33). Many convolution layers are followed by multiple fully connected layers in a CNN.

Convolution layers, the three main types of layers utilized in CNN are pooling layers, completely connected layers, and full-connected layers (34). CNN-based machine learning systems that are automated and have achieved milestone performance in medical imaging detection, classification operations and segmentation (35). A fully convolutional residual network (FCRN) with 16 residual blocks was utilized in the segmentation process to increase efficiency. The recommended approach for classification employs an average of SVM and other classifiers. It had an accuracy of 85.5% with segmentation and 82.8% without segmentation in melanoma classification (36). This suggested a CNN with many scales. The inception v3 framework was fine-tuned on two density ranges of input lesion pictures: fine-scale and coarse-scale. To capture the shape features of lesions as well as the entire contextual information, the coarse-scale was used. The finer scale, on the other hand, gathered textual information on the lesion in order to differentiate between numerous types of skin lesions.

### **Kohonen Self-Organizing Neural Network (KNN)**

The Kohonen organizing itself map is a well-known type of deep network machine learning. CNNs are taught utilizing unsupervised learning, which means they don't require any developer involvement during the acquisition process, as well as the required information about the qualities of the incoming data. A KNN typically consists of two layers. The input layer is also known as the first layer, while the competitive layer is the second layer. All connections between the first- and second-layer dimensions occur in any of these layers. A KNN may be used to cluster data without understanding the connections between the input data constituents. Another name for it is a self-organizing map. Instead of an output

layer, each and every node in the competitor layer plays the role of the output node in KNNs.

A KNN is most commonly used as a dimensionality reducer. It can take high-dimensional data and reduce it to a low-dimensional format, as a 2D plane. As a result, it offers discrete representations of the input dataset. In terms of learning technique, KNNs differ from other forms of NN because they use competitive learning rather than the error-correcting learning discovered in BPN or feed-forward acquiring system. During the mapping of dimensionality from top to bottom, the topological component of the input data space is preserved by KNN. Preservation refers to the conservation of different position among the data dimensions of space. Variables that are tighter in the input data space are localized closer together, whereas data points that are further away are mapped further apart in this technique, based on the relative distance between them. As a result, for high-dimensional data, a KNN is the optimal technique. Another important aspect of a KNN is its capacity to generalize. Unknown input data can be recognized and organized by the network. The ability of a KNN to map difficult relationships of data points, including nonlinear correlations, is its most important feature. KNNs are utilized to diagnose skin cancer because of these advantages.

### **Generative Adversarial Network (GAN)**

GANNs are a form of deep neural network (DNN) influenced by zero-sum game theory i.e., a mathematical understanding of a situation in which the benefit that is won by one of two sides is what is lost by the other side (38). GANs are based on the idea that two neural networks compete to assess and capture variation in a database. To fool the discriminator module, the generating module uses data dispensing to make fake data samples. The discriminator module, on the other hand, is responsible for distinguishing between legitimate and fraudulent data samples (39). Both of these neural networks repeat these stages even during the pre-execution or beta phases, and their performance improves with each competition. One of the most important advantages of a GAN network is its ability to build not genuine samples that are equivalent to actual samples utilizing the same data distribution, such as photorealistic photographs. GANs that can tackle a crucial deep learning difficulty include deep convolutional GANs (DCGANs), super-resolution GANs (SRGANs), Vanilla GANs, condition GANs (CGANs), and Laplacian Pyramid GANs (LPGAN). Scientific investigations are now utilizing GANs.

### **Methodology**

Deep-learning (VGG CNN) is used for segmentation in order to fetch the area of interest of the images hence dropping the parts that are of no use to us. Feature extraction is done using Max Pooling layer in the classification model. There are two phases in CNN i.e., encoding and decoding. After segmentation and feature extraction, image would be classified in the basic two types i.e., melanoma and benign cancer.

Architectural diagram is as follows:

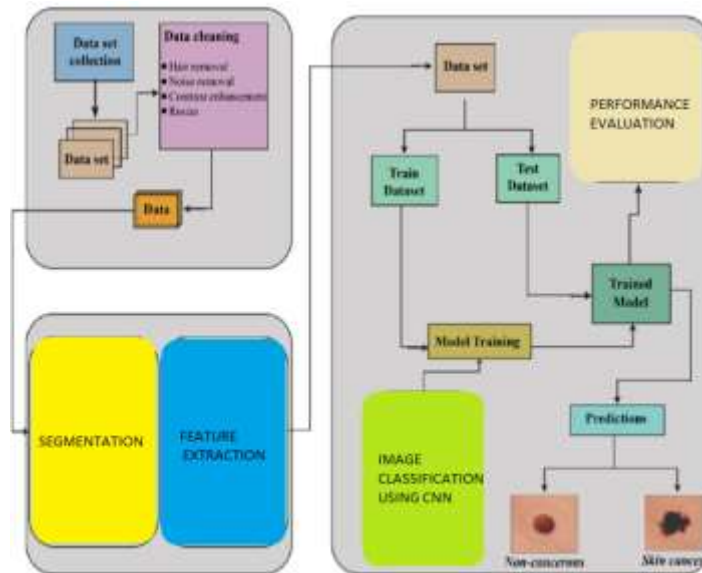


Fig. 1: Architectural Diagram

### Evaluation Metrics

Each object is assigned a class by a classifier. This assignment isn't flawless, and objects could end up in the wrong class. As a result, in order to assess a classifier, the real class of the objects must be known. In this assessment, the classifier's assigned class is compared to the actual class. As a result, the objects may be classified into the four groups listed below.

- True positive (TP): correct prediction of the positive class.
- True negative (TN): correct prediction of the negative class.
- False positive (FP): incorrect prediction of the positive class.
- False negative (FN): incorrect prediction of the negative class.

### Accuracy

Statistical values for the classifier are derived based on the cardinality of these subgroups. Accuracy is a commonly used metric that is only useful if the different classes in the dataset are spread about evenly. Accuracy is determined by

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (3)$$

It indicates the percentage of items that have been categorised properly.

### Sensitivity

Sensitivity and specificity are two more crucial measures. Despite the uneven distribution of classes, these can be used. Sensitivity is defined as the proportion

of correctly categorized positive objects in a dataset divided by the total number of positive objects.

$$\text{Sensitivity} = \frac{(TP)}{(TP+FN)} \quad (4)$$

### Specificity

Specificity is determined as the percentage of negative items accurately categorized as negative out of the total number of negative objects in the supplied dataset.

$$\text{Specificity} = \frac{(TN)}{(TN+FP)} \quad (4)$$

A probability distribution over the classes is interpreted as the output of a binary classifier. In a binary classifier, items with an output value larger than 0.5 are usually allocated to the positive class, while objects with an output value less than 0.5 are usually assigned to the negative class. Based on the receiver operating characteristic, an alternate strategy is adopted (ROC). The classification threshold ranges from 0 to 1, and the sensitivity and specificity of each threshold are established. The area under the curve is a good overall metric for the curve (AUC). The ROC curve is generated by graphing sensitivity against 1-specificity and may be used to assess the classifier. The better the classifier, the more the ROC curve deviates from the diagonal (41).

### Results and Discussion

A dataset of 200 images has been used with a training and testing percentage of 70% and 30% respectively. Size of dataset can be increased further by image augmentation techniques and also by adding more images to it.

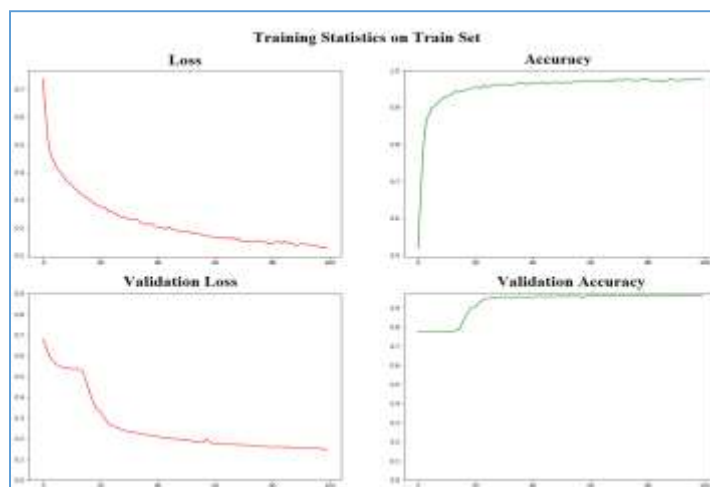


Fig.2: Training Analysis

```

reshape_2 (Reshape) (None, 192, 256) 0
-----
Total params: 11,303,469
Trainable params: 11,177,795
Non-trainable params: 15,674

Epoch 1/100
16/16 [-----] - 545s 34s/step - loss: 0.7581 - iou: 0.6617 -
dice_coef: 0.3774 - precision: 0.3225 - recall: 0.5471 - accuracy: 0.5578 - val_loss:
0.6715 - val_iou: 0.6689 - val_dice_coef: 0.3817 - val_precision: 0.0000e+00 -
val_recall: 0.0000e+00 - val_accuracy: 0.7782
Epoch 2/100
15/16 [-----] - ETA: 33s - loss: 0.5580 - iou: 0.7441 -
dice_coef: 0.4793 - precision: 0.5168 - recall: 0.0079 - accuracy: 0.7001
    
```

Fig.3: Results after First Epoch

Table I  
results after each 10 epoch

		<b>IOU</b>	<b>DI</b>	<b>Precision</b>	<b>Recall</b>	<b>Accuracy</b>
After 1 Epoch	Training	65.81	37.28	31.37	49.28	53.81
	Validation	66.96	30.12	0	0	77.82
After 10Epoch	Training	84.59	58.67	85.80	88.40	92.38
	Validation	74.13	25.25	0	0	77.82
After 20Epoch	Training	89.43	65.31	90.67	92.90	94.60
	Validation	87.56	54.34	93.69	73.92	93.19
After 30Epoch	Training	91.54	69.02	92.63	92.91	95.77
	Validation	91.08	63.22	92.21	87.04	95.48
After 40Epoch	Training	92.96	72.45	93.74	92.88	95.96
	Validation	92.62	66.86	92.60	88.39	95.90
After 50Epoch	Training	94.19	74.37	93.71	94.92	96.88
	Validation	93.50	69.57	91.62	90.61	96.08
After 60Epoch	Training	95.06	76.78	94.81	95.23	97.25
	Validation	94.10	71.62	91.02	91.98	96.25
After 70Epoch	Training	94.58	75.69	91.36	91.55	97.28
	Validation	94.50	73.48	90.49	93.23	96.37
After 80Epoch	Training	95.48	78.55	93.82	95.59	97.07
	Validation	94.80	74.49	92.51	90.98	96.39
After 90Epoch	Training	96.26	80.71	95.64	95.87	97.65
	Validation	95.08	75.82	91.39	92.86	96.48
After 100Epoch	Training	96.28	80.98	94.57	95.97	97.42
	Validation	95.22	76.41	91.79	92.18	96.47

1. IMD390



(a) Input Image      (b) GT image      (c) Predicted output

2. IMD392



(a) Input Image (b) GT image (c) Predicted output  
Fig.4: Testing Analysis

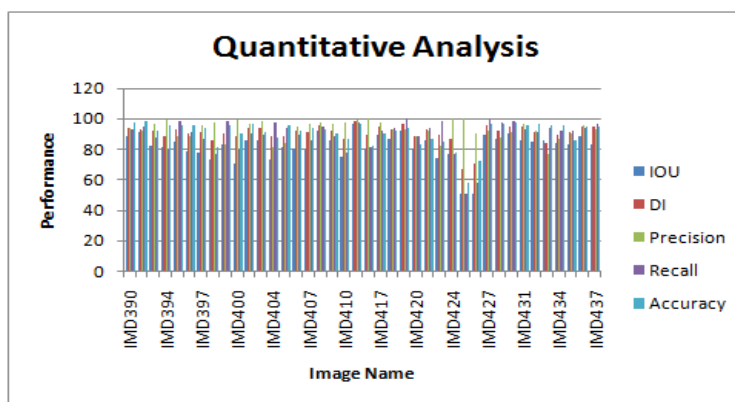
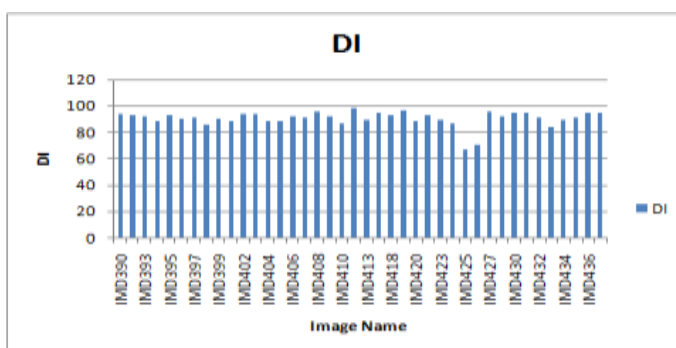
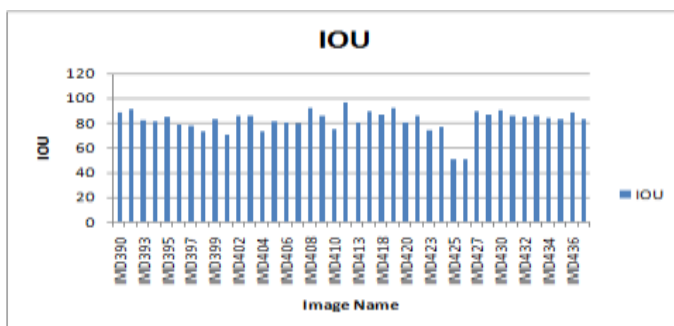


Fig.5: Qualitative Analysis



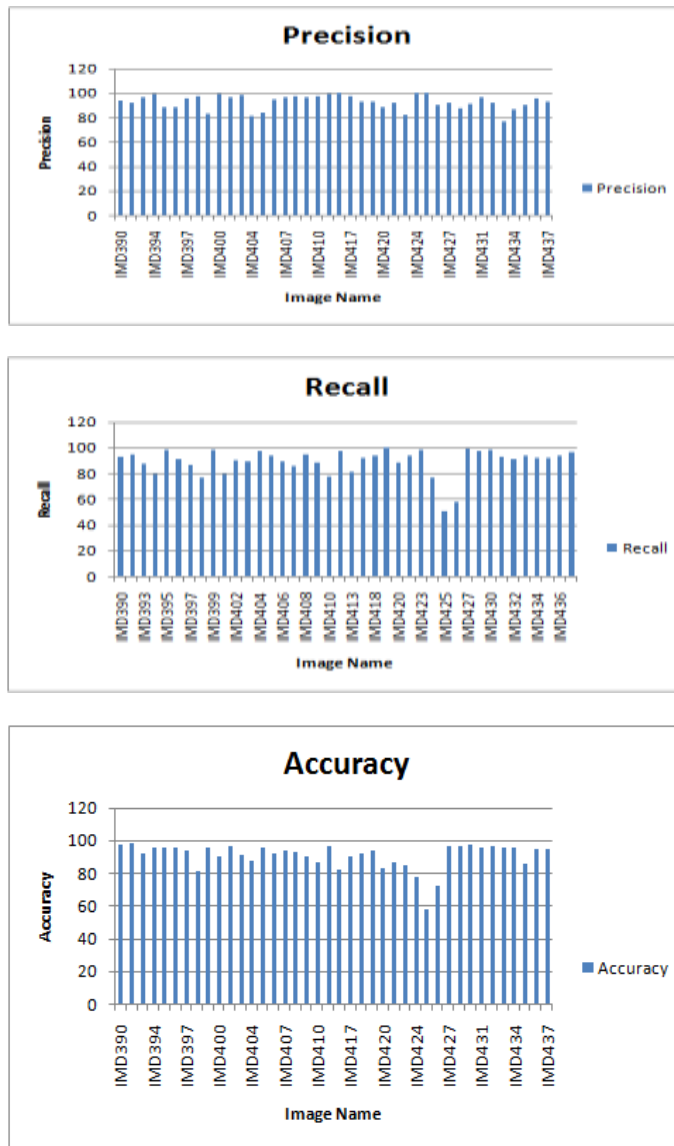


Fig.6: Graphical Analysis of Evaluation metrics

## Conclusion and Future Work

In the diagnosis of skin cancer, preparation and image fragmentation are preceded by careful extraction and categorization. This paper concentrates on deep-learning (VGG CNN) for lesion image segmentation and categorization. Choosing the correct categorization approach is the most crucial component in attaining the best results. However, when it comes to recognizing image data, CNN beats other types of neural networks since it is more closely linked to computer vision than the others. The majority of skin cancer identification and detection research focuses on identifying if a certain lesion picture is cancerous or not. Existing research, on the other hand, is unable to offer a response when an

affected person inquiries about a specific skin cancer symptom that is visible on any part of their body.

So far, the research has been confined to signal picture categorization. Future studies might employ full-body images to discover an answer to a commonly asked question. With autonomous full-body photography, the picture acquisition step will be automated and accelerated. Auto-organization is a notion that was developed specifically for deep learning technology. Auto-organization is an unsupervised learning technique for recognizing characteristics and establishing links or patterns in a dataset of image samples.

Convolutional machine learning, which include auto-organization techniques, improve the degree of features representation provided by pro systems. Auto-organization is a paradigm that is still under investigation and succession. But in any case, its discoveries may one day aid in improving the accuracy of image processing systems, particularly in the realm of medical imaging, in which the finest details of characteristics are very crucial for correct sickness detection.

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