Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606

Volume 05 Issue 02
2023

Review Article
https://doi.org/10.56979/502/2023

Initial Prediction of Skin Cancer Using Deep Learning Techniques: A Systematic Review

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Received: March 12, 2023 **Accepted:** July 19, 2023 **Published:** September 17, 2023

Abstract: Skin disease is a common medical condition that affects the outer layer of our body and requires early intervention to prevent it from becoming life-threatening. The techniques of deep learning have been developed as a necessary tool for identifying skin diseases, attracting the attention of researchers. In this review, we examine the efforts of researchers who have utilized deep learning technology for skin disease identification. We provide an overview of skin diseases, including their types, datasets, and data pre-processing techniques. Furthermore, we explore deep learning approaches and popular methods used by researchers in diagnosing skin diseases. The primary aim of this study is to present acomprehensive review of recent research on skin disease detection using deep learning methodologies. Our observations demonstrate that these methods, known for their accuracy, outperform dermatologists, machine-based therapies, and other classification methods in recognizing skin disease images.
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Keywords: Skin disease; Deep learning; CNN; KNN; Skin disorder.

1. Introduction

Being healthy depends on a person's genes, lifestyle, and surroundings. There are two main factors that affect a person's health: determinants and actions (things done to improve health). Diseases are abnormalities in the body's structure or function that cause physical or mental problems. Many factors, like genetic mutations, can contribute to the development of these illnesses. Illnesses like cancer can be caused by things like harmful substances in the environment, viruses, bacteria, or personal choices. Cancer occurs when abnormal cells grow excessively and form a mass in the body. It can affect different organs and tissues, such as the lungs, breast, intestines, prostate, and blood, and can develop anywhere in the body. Skin cancer is a significant global health concern[1]. It's the most common cancer, with over 5 million cases identified each year in the United States[2]. Skin cancer varies with age group and the individuals with age higher or equal to seventy years are most likely to effect with skin cancer. Melanoma skin cancer occurrence by age shown in the figure 1.

The epidermis, the largest tissue in the body, makes up more than 15% of total body weight and is important for communication with the outside world[3]. Damage to the epidermis can cause changes in a specific area of the skin[4]. Skin infections can affect the color and structure of the epidermis. Bacteria, viruses, fungi, and allergies can impact the skin[5].

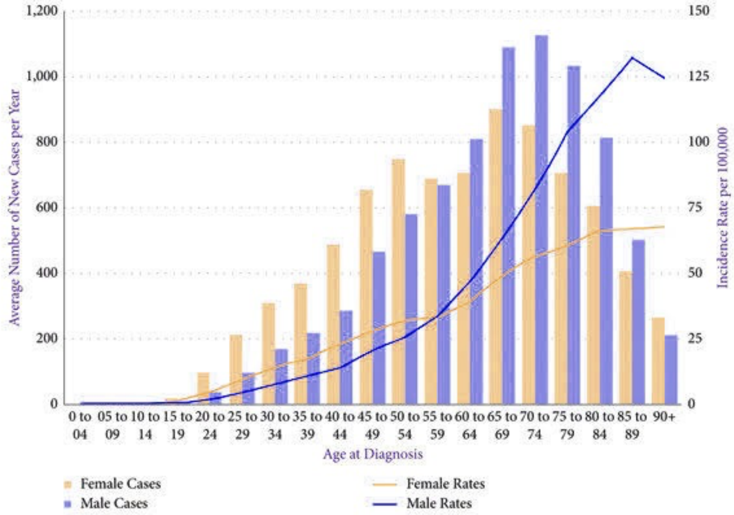


Figure 1. The age group likely to effect with Skin Cancer

Exposure to sunlight, especially ultraviolet (UV) rays from the sun or tanning booths, is a major contributor to a type of skin cancer called cutaneous melanoma. UV rays can harm skin cells, causing them to grow and divide abnormally, leading to cancer spread. Melanoma is a crucial form of skin cancer caused by melano-cytes. It quickly spreads to other part of the body, so early detection and treatment are crucial. If not detected early, it can travel to remaining body parts and have severe consequences[6]. Non-melanoma skin cancers are a group of tumors that originate from the top layer of the skin.

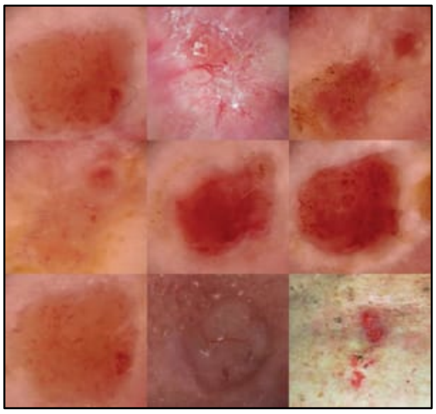


Figure 2. Skin Disorder Pictures from the ISIC dataset [13]

Early detection is crucial for valuable treatment and improved results in skin diseases. The diagnosis of skin diseases has indeed posed a significant scientific challenge. To address these challenges, people have employed machine-based methods, like computers, to detect skin disorders earlier using skin pictures[7]. Artificial intelligence (AI) approaches can help classify different skin diseases, which can benefit patients[8].The use of image processing techniques in diagnostic imaging has experienced a notable rise in recent years. Due to an uneven distribution of dermatologists, there is a high demand for quick and accurate diagnoses based on data. Deep learning models excel in categorizing data and images compared to older models. These models can adapt to changing environments and identify features in data that can aid in problem-solving. Deep learning models can also uncover trends in data that may not be explicitly evident, even in simpler computer models, making them highly effective. Supervised techniques like fuzzy systems and artificial neural networks (ANN) can be utilized to detect skin-related illnesses from dermatological pictures. Additionally, the k-nearest neighbors algorithm (KNN) can categorize pixels in each image based on their similarity, allowing for distinction between normal and abnormal images{9].

To tackle these challenges, we have created deep learning algorithms that continually gather data and automatically extract features using feature extraction techniques. These techniques help overcome common problems in feature extraction and produce accurate diagnosis results. Currently, the main approach for identifying skin diseases from images is through convolutional neural networks (CNNs) in deep learning. CNNs excel at representing features effectively. The mentioned papers discuss the utilization of deep learning techniques for identifying integumentary diseases [10-12].

The primary goal of this paper is to present a comprehensive and structured review of the existing literature on the application of conventional deep learning methods such as Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) in combination with the K-nearest neighbors algorithm (KNN) for skin cancer detection. It provides valuable insights into the strengths and limitations of using deep learning in diagnosing skin conditions. By examining this research, readers can gain a comprehensive understanding of the pros and cons associated with applying deep learning techniques to skin-related conditions.

2. Materials and Methods

2.1 Resources of Search

In order to obtain information on NN techniques for cancer detection, we conducted our study utilising search engines with a solid reputation, includes IEEE Xplore, ACM, Springer, and Google Scholar. In initial search, root research materials pertinent to the main subject were excluded. Further analysis was done on the chosen research articles and conference proceedings in accordance with the assessment criteria.

2.2 Initial Selection Criteria

Research publications and conference papers were first chosen based on a variety of specified criteria, including the paper's language, publication year, and topic's applicability to the chosen field. This study only considered academic works that were authored in English. Our review article concentrated on studies released between 2013 and 2023. The chosen articles required to be pertinent to the keywords included in a search hierarchy.

2.3 Selection and Evaluation Procedure

In accordance with the basic search parameters, 1150 research articles and conference reports were found. We chose 95 publications with titles that we thought appropriate for our investigation from the papers that were found. Then, 64 research articles were selected from those publications. After carefully evaluating the significance of those research' abstracts. In-depth studies were conducted on the research articles that passed the screening strategy based on abstract criteria. 48 research articles were chosen for the final assessment after the calibre of those papers was thoroughly checked. In the final selection, 25% of articles from Science Direct and 21% of papers from Springer were chosen, while 12% of papers from ACM DL and 29% of papers from IEEE were. Google Scholar's selection rate was 13%.As shown in table 1.

Table 1. Search outcomes

No.	Source	Early Search	Selection based on time	Selection based on Abstract	Final Paper for study
1	IEEE	142	31	17	14
2	Google Scholar	93	28	13	8
3	ACM DL	56	18	10	5
4	SPRINGER	73	24	12	10
5	SCIENCE DIRECT	128	17	16	11
	TOTAL	492	118	68	48

After a in-depth examination of whole texts of selected research publications, answered several quality control question. In the current systematic investigation, the following questions regarding quality evaluation were posed.

• Did the selected research cover every facet of the topic under review?
• Was the selected article's quality justified?
• Does the chosen study effectively address the problems identified by the study?

The comprehensive explanation of skin cancer deep learning approaches screening was the focus of the first quality evaluation question. To verify the calibre of the work, We checked the reputation of the journal where the chosen paper was published and looked at how many times it has been cited. Only the studies that were most pertinent to our field of study were selected. To be eligible for selection, these publications required to address the aforementioned research issues. Research articles containing material unrelated to our study subject and those that did not sufficiently address the research or quality control concerns were eliminated.

Each question in the quality control assessment had a binary response, either "yes" or "no." A score of 1 was assigned for each "yes" response and a score of 0 for each "no" response.The 51 studies that were chosen for the first quality control question were assessed for their topic coverage articles and yielded an excellent score of 77%. The second research question further enhanced the overall grade by confirming the calibre of the chosen publications. It produced a result of 82%, which was good.In order to respond to the primary research questions for the review, the third question was crucial. It produced a 79% outcome, which served as a gauge of how well the papers addressed the review's research questions. Responses to these high-quality questions appeared to have generally positive effects.

3. Deep Learning Methods for Detecting Skin Cancer

Deep neural networks play a significant role in aiding the diagnosis of skin cancer. These networks consist of interconnected nodes, which contribute to their effectiveness in identifying and classifying skin cancer, similar to the network of neurons in the human brain. These networks work together to solve specific problems by collaborating and sharing information. With training, NNs become specialized in specific tasks they was trained for, allowing them to excel in their respective fields.In our study, neural networks were trained to classify and distinguish various forms of skin cancer by analyzing photos sourced from the International Skin Imaging Collaboration (ISIC) dataset. Figure 2 shows various skin lesions. We explored several learning strategies for skin cancer detection systems, including artificial neural networks (ANN), convolutional neural networks (CNN), and k-nearest neighbors (KNN). This section offers a comprehensive summary of the research conducted a deep neural network on each of these networks.

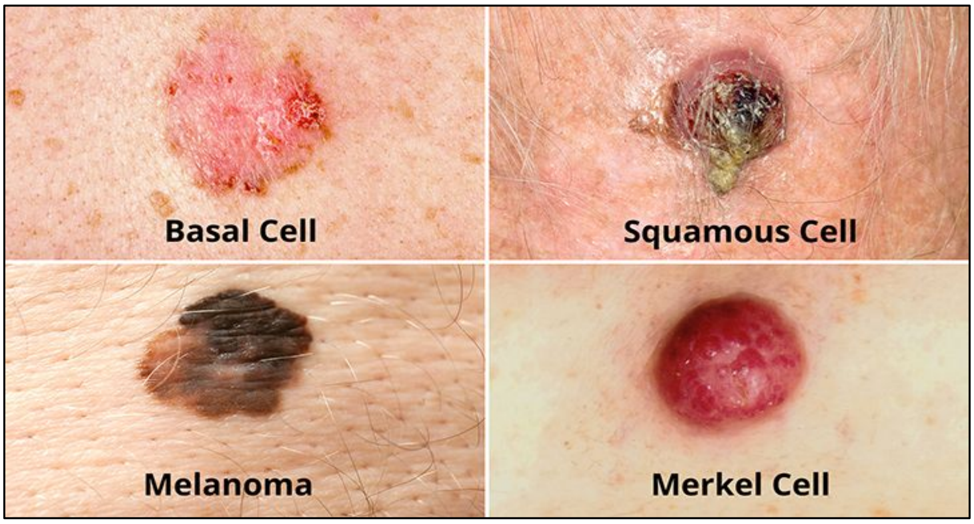


Figure 3. Skin illness classifications based on data from the (ISIC)[14]

3.1.Methods employed in the detection of skin cancer using Artificial Neural Networks (ANN)

The discovery of biological neural networks in animal brains led to the development of artificial neural network computer systems. They are also referred to as neural nets or neural networks. ANNs generally consist of 3 layers of neurons. The first layer is termed the input layer, where input neurons receive signals. The second layer, sometimes referred to as the intermediate or buried layer, receives information from these input neurons. A conventional ANN may have a number of hidden levels. The third layer, which is made up of output neurons, receives the signals from the intermediate neurons. Back-propagation is used to comprehend the calculations and computations learned and processed at each layer, enabling the ANN to generate predictions or classifications based on the input data. Back-propagation is employed to understand the complex relationships and interactions between the input and output layers, showcasing the characteristics of a neural network. In computer science, the terms artificial neural network and neural network are often used interchangeably. Figure 3 provides a visual representation of the basic structure of an ANN network.

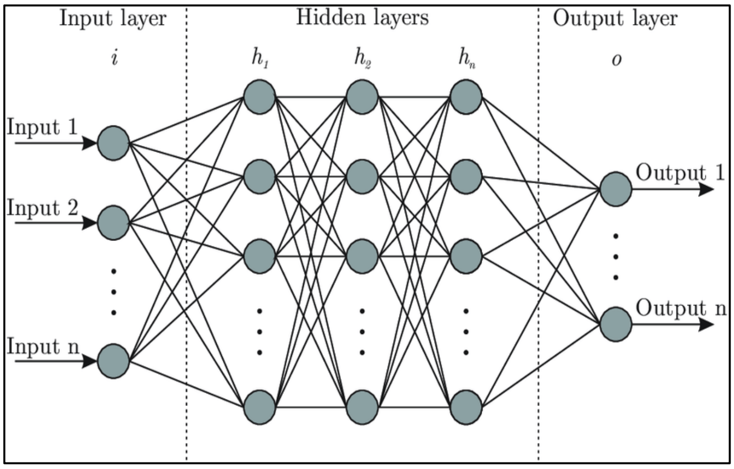


Figure 4. Core ANN structure

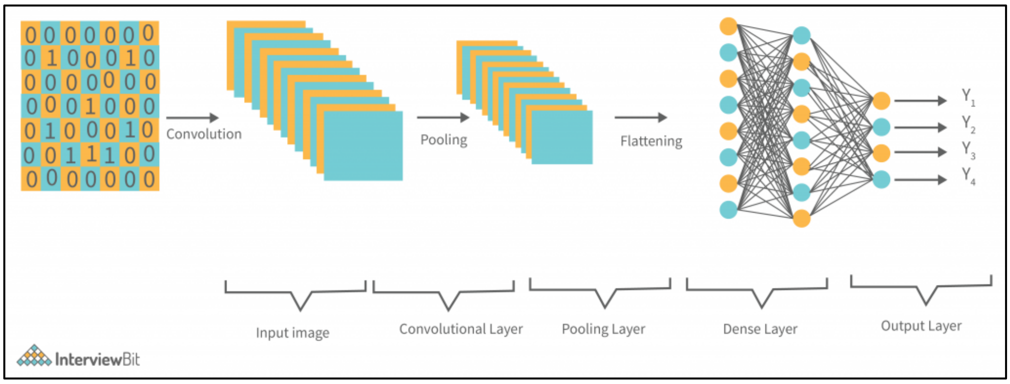
ANNs are used in systems that detect skin cancer to classify retrieved characteristics. Upon successfully training and categorizing a training set, The input images are classified as either melanoma or non-melanoma. An Artificial Neural Network (ANN)'s (hidden layer count) depends on the volume of input pictures. Input dataset connect the input/first layer to the hidden layer in the ANN process. Both supervised learning systems and unsupervised learning systems can be used for this purpose and the dataset is correctly handled. A neural network has the capability to learn and assign weights to each connection within the network using either a backpropagation architecture or a feed-forward design. The underlying data is collected using both methods. employ a certain pattern. In feed forward neural networks, there is only one way to transmit data. Only between the input and output layers can data flow.

Skin lesions can be classified into two categories: benign and malignant using a technique developed by Xie et al. [15]. The planned system ran in three stages. Initially, a self-generating NN was employed to remove lesions from pictures. In the second step, characteristics such the tumour borders, information on texture, and colour were retrieved. Seven different indicators that indicate lesion boundaries were among the system's total of 57 characteristics that were retrieved. In order to choose the most useful collection of characteristics, the dimensionality of the data was reduced using principal-component analysis (PCA). In the last stage, lesions were categorized using an ensemble artificial neural network (ANN) model. This ensemble approach enhances the classification performance by combining fuzzy neural networks and the backpropagation (BP) NN algorithm.The proposed system's classification results were compared to other classifiers such as SVM, KNN, random forest, and Adaboot. With a narrow margin of 7.5%, the suggested model outperformed the other classifiers in terms of sensitivity and achieved an accuracy rate of 91.11%.

Aswin et al. [16]proposed a novel genetic algorithm (GA) and ANN-based approach to skin cancer diagnosis.Images were preprocessed to remove hair using the area of interest (ROI) extraction approach using the medical imaging application Dull-Rozar. In addition, To separate out unique features from the segmented pictures, the GLCM approach was used. Then, lesion pictures were divided into classifications for carcinogenic and non-cancerous lesions using a hybrid ANN and GA classifier. The given strategy has a total accuracy score of 88%.

3.2.Methods for detecting skin cancer using Convolutional Neural Networks (CNNs)

The CNN often used in computer vision, is the foundational deep learning network. It's used for image recognition, image categorization, and assembling a collection of input photographs. CNN is an effective tool for capturing and understanding both local and global information because it combines basic characteristics like To create more intricate elements like forms and corners, use curves and edges [17].Convolution layers, non-linear pooling layers, and fully linked layers are some of the hidden layers in CNNs[18]. A CNN may have several convolutional layers, which may be followed by a number of fully connected layers. CNNs use three primary types of layers: convolution layers, pooling layers, and fully chained layer [19].Figure 5 depicts a CNN's basic architecture.



Figuer 5. Basic CNN structure [20].

Mahbod et al.created a method to classify skin lesions by extracting deep features from several well-known and pre-trained deep Convolutional Neural Networks (CNNs)[21].In their study, the researchers employed pre-trained versions of AlexNet, ResNet-18, and VGG16 as deep-feature generators. These deep networks were used to extract meaningful characteristics from the skin lesion images. Subsequently, Using these extracted characteristics, a multi-class Support Vector Machine (SVM) classifier was trained to categorise the skin lesions into different categories. The outturns from the classifier were ultimately merged to achieve categorization. Results for the proposed system's classification of seborrheic keratosis (SK) and melanoma using the ISIC 2017 dataset revealed 98.65% and 83.93% area under the curve (AUC) performance, respectively. Using pre-trained ResNet-152, a deep CNN architecture was proposed to classify twelve different types of skin lesions. [22]. In order to adjust for variations in size and illumination, 29 instances of augmentation were carried out after the system had originally been taught with 3797 pictures of lesions.The recommended approach for identifying hemangioma lesions, pyogenic granuloma (PG) lesions, and intraepithelial carcinoma (IC) skin lesions achieved an exceptional AUC (Area Under the Curve) value of 0.99.

3.3 Skin cancer detection methods based on Kohonen Self Organizing Neural Networks (KNN)

The Kohonen self-organizing map is widely recognized and acknowledged as a prominent technique and widely used design for deep neural networks. Unlike CNNs that require supervised learning, a KNN can learn on its own without much guidance. Typically, KNNs have two layers. The input layer is at the top, representing the input data, and the competitive layer is at the bottom. These layers are connected through the first-to-second layer dimension. Key structure of KNN is given in Figure 6.

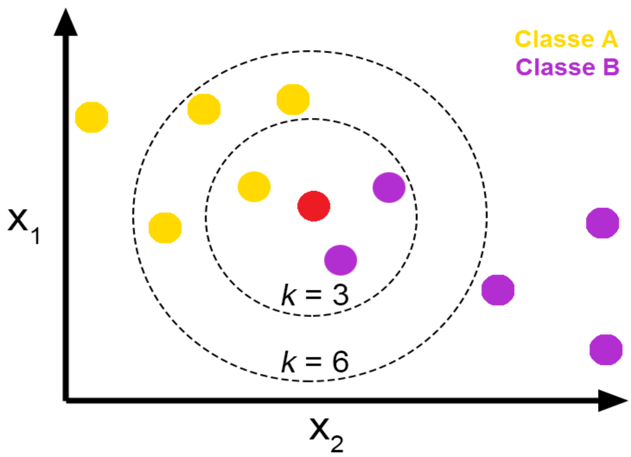


Figure 6 .Key Strcture of KNN

KNNs can be utilised to group data without fully understanding the relationships among the elements in the input dataset. Another term for KNN is a self-organizing map. Unlike other neural networks, KNNs do not have an output layer. According to Sajid et al.'s recommendation [23], the research evaluated the performance of various classifiers for skin cancer detection, including SVM, BPN, and a 3-layer NN. The accuracy achieved was 90.5% for the 3-layer NN, 91.1% for SVM, and 90.4% for BPN. However, The proposed method exhibited superior performance, surpassing all others, with an accuracy rate of 98.3% in detecting skin cancer. The proposed method incorporates a median filter to reduce visual noise, and the filtered images are then segmented using a statistical region growth and merging technique. This approach combines both linguistic and statistical elements. Textual characteristics are extracted using the curvelet domain, while statistical information is gathered from lesion images.

Table 2. Evaluation of the accuracy attained through comparison by different algorithms

Ref.	Techniques	Method	Accuracy
[39]	ANN	Computer vision	94%
[40]	ANN	Computer vision	90%
[41]	CNN	Google-Net inspection V-3	80.3%
[42]	KNN	Computer vision	96%-98%
[43]	CNN	AlexNet	98.6%
[44]	ANN(R-CNN)	Computer vision	95%
[45]	KNN	GCM morphology	93.15%
[46]	KNN	Otsu method for thresholding in segmentation is an automated technique.	98.3%
[47]	CNN	VGG-16	83.5%
[48]	CNN	Computer vision	95.93%

4. Methodology

This review paper's goal is to find and classify the most efficient techniques for utilizing neural networks (NNs) in the identification skin cancer. Systematic reviews involve collecting and evaluating previously published research using predetermined criteria. These analyses help establish the existing knowledge in the relevant research field[10].

In this systematic literature review, every piece of data obtained from reliable sources is carefully organized and examined. By conducting this thorough analysis, the main research question is answered in a clearer, more logical, and more conclusive manner[11].

These papers were selected based on their relevance to the topic of skin cancer identification using DNNs.

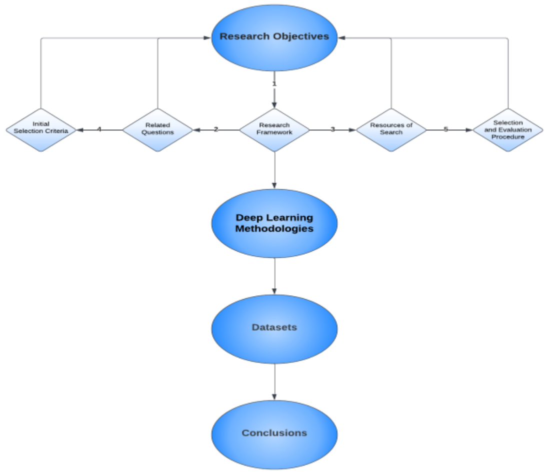


Figure 7. Systematic methodological process.

4.1 Research Objectives

This article's objective is to evaluate the progress and improvements in detection of epidermis cancer by using DL models and machine learning approaches. Every methodology got advanced and improved over time. This study presents the improvements of these methods as well as current research on skin disease detection and benefits of deep learning methodologies over other algorithms. This review demonstrates the critical analysis of deep learning algorithms applied practically for skin disease detection.

4.2 Research Framework

In the initial `step of the systematic review, The framework for the review was created. This framework consisted of a thorough strategy implemented during the systematic literature review. The plan included a preparation stage, a stage for selecting and analyzing data, and a stage for generating findings and drawing conclusions.

4.3 Related Questions

To conduct an effective evaluation on a topic, research questions must be prepared. The following were research questions developed for the current systematic study:

Q1:What are some popular and efficient deep-learning techniques for detecting skin tumor?

Q2:What are the most notable features of the currently available datasets on skin cancer?

Data Availability Statement: There have been several suggested computer origined approaches for diagnosing skin cancer. A strong and trustworthy For evaluating their diagnostic performance and verifying expected results, dermo-scopic image gathering is required. With the exception of pictures of Different skin cancer datasets have been sparse and uninteresting, whether they were melanoma lesions or nevi. It's hard To train artificial neural networks in classifying skin lesions, certain methods are employed because the datasets are small and don't have enough variety. Although a range of non-melanocytic lesions are frequently present in patients, previous research for automated skin cancer detection has mostly concentrated on recognizing astrocyte lesions, leaving the datasets with a very small number of diagnoses[24]. Therefore, having access to a consistent, trustworthy dataset of dermo-scopic pictures is essential. This section discusses real-world datasets for assessing suggested methods for detecting skin cancer. The key information about these datasets is included in Table 3.

Table 3. Datasets of skin cancer

Ref.	Name Of Dataset	Place of origin	Year of publication	Image formate	No. Of images
25,26	DermIS	Germany	Not Reported	.jpg	6588

27	HAM10000	Australia, Austria	2018	.jpg	10015
25,28	Dermnet	New Hampshire	1998	JPEG	23000
25,26,29	DermQuest	Not Reported	1999	JPEG	22082
30,31,32,33,34,35,36,37,38	ISIC archive	Spain, Australia, Austria, USA, Greece	2020	DICOM or .jpg	25331
27	PH^2	Portugal	2013	.bmp	200

5. Conclusions

In this systematic review, various neural network methods were explored for finding and categorizing skin cancer. These methods aim for accurate results without causing harm.The steps involved in detecting skin cancer contain several stages such as pre-processing, segmenting images, extracting features, and performing classification. The study focused on the use of artificial-neural networks (ANNs), convolutional-neural networks (CNNs), and k-nearest neighbors (KNNs) for classifying lesion images.Every algorithm possesses its unique plus and minus points. It is crucial to select the appropriate categorization technique to obtain the best outcomes. Among these neural network types, CNNs have shown superior performance in categorizing image data due to their strong connection with computer vision.

Most studies on identifying skin cancer primarily concentrate on determining whether a specific image of a skin lesion is cancerous. However, recent research lacks the ability to address a patient's inquiry about the presence of a certain skin cancer scar on other parts of body. Currently, the investigation is confined to the specific task of classifying the image that represents the signal.

In future studies, researchers may utilize full-body photography to assist in finding a solution. The use of Full-body photography taken autonomously can automate and simplify the process of capturing images of the entire body for medical purposes expedite the process of capturing images.

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