ADVANCED METHOD FOR MELANOMA AND NONMELANOMA SKIN CANCER DETECTION USING CONVOLUTIONAL NUERAL NETWORK: A SURVEY

Shikha Verma, M.Tech Scholar, Department of Computer Science & Engineering, Kanpur Institute of Technology, Kanpur, India.

Kanchan Gautam, Assistant Professor, Department of Computer Science & Engineering, Kanpur Institute of Technology, Kanpur, India.

Abstract— Cancer of the skin is one of the most common and potentially fatal types of the disease. Deoxyribonucleic acid (DNA) in skin cells that has not been repaired can lead to the development of genetic abnormalities or mutations on the skin, both of which can lead to skin cancer. Skin cancer has a propensity to progressively spread across other parts of the body, and because it is more treatable in its earlier stages, it is important to diagnose it when it is in its earlier stages. Because of the rising incidence of skin cancer, the high death rate, and the high cost of its treatment, it is imperative that its signs be recognized as early as possible. Researchers have created a variety of early detection methods for skin cancer in light of the gravity of the issues at hand. The utilization of lesion criteria such as symmetry, colour, size, shape, etc., allows for the detection of skin cancer as well as the differentiation of melanoma from less dangerous forms of skin cancer. This paper provides a comprehensive and methodical evaluation of deep learning approaches that can aid in the early diagnosis of skin cancer. Analyses were performed on research articles that had been published in respected publications and that were pertinent to the subject of diagnosing skin cancer. In order to facilitate a deeper level of comprehension, the results of the research are given in the form of tools, graphs, tables, strategies, and frameworks.

Keywords— Skin Cancer, Melanoma, Non-Melanoma, Image Processing, ANN, CNN, KNN, GAN.

I. INTRODUCTION

Skin cancer has emerged as one of the most common and aggressive forms of the disease in the last ten years [1]. It is easy to see why people believe that skin cancer is the most common form of cancer in humans [2], given that the skin is the body's largest organ. Melanoma and non-melanoma skin cancer are the two primary subtypes that are typically distinguished from one another [3]. Melanoma is a dangerous kind of skin cancer that is extremely uncommon and almost always fatal. Melanoma skin cancer accounts for only 1% of all instances of the disease, but it has a significantly higher mortality rate [4]. These findings come from research conducted by the American Cancer Society. Melanoma occurs in cells called melanocytes. It begins when normally healthy melanocytes begin to develop uncontrollably, which results in the formation of a tumour that is malignant. It is possible for it to affect any part of the human body. It most frequently manifests itself on the parts of the body that are subjected to the sun's rays, such as the hands, face, neck, lips, and other locations. Cancers of the melanoma type can only be healed if they are discovered at an early stage; otherwise, they spread to other regions of the body and result in a painful death for the victim [5]. Melanoma is a form of skin cancer that can take many different forms, including nodular melanoma, superficial spreading melanoma, acral lentiginous, and lentigo maligna [3]. The vast majority of cancer diagnoses fall into the nonmelanoma category, which includes subtypes including basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC) (SGC). In the middle and higher layers of the epidermis, respectively, basal cell carcinoma, sebaceous gland carcinoma, and squamous cell carcinoma can develop. These cancer cells have a relatively low risk of metastasizing, or spreading, to other areas of the body. Malignancies that are not caused by melanoma are easier to treat than cancers caused by melanoma.

Therefore, getting an early diagnosis is the most important component in the therapy of skin cancer [6]. The biopsy technique is the standard approach that medical professionals take when looking for signs of skin cancer. During this operation, a biopsy is taken from a suspicious lesion on the skin so that it can be analyzed by a doctor to identify whether or not the lesion is malignant. This procedure is unpleasant, drawn-out, and time-consuming all at once. Skin cancer signs can be diagnosed more quickly, with less side effects, and at a lower cost thanks to advancements in computer technology. Multiple methods that are not invasive in any way are recommended in order to investigate the symptoms of skin cancer and determine whether or not they point to melanoma or another type of skin cancer. Acquiring the image, performing preprocessing, segmenting the acquired preprocessed image, extracting the desired feature, and finally classifying the image are the general steps involved in the process of detecting skin cancer. These steps are illustrated in Figure 1.

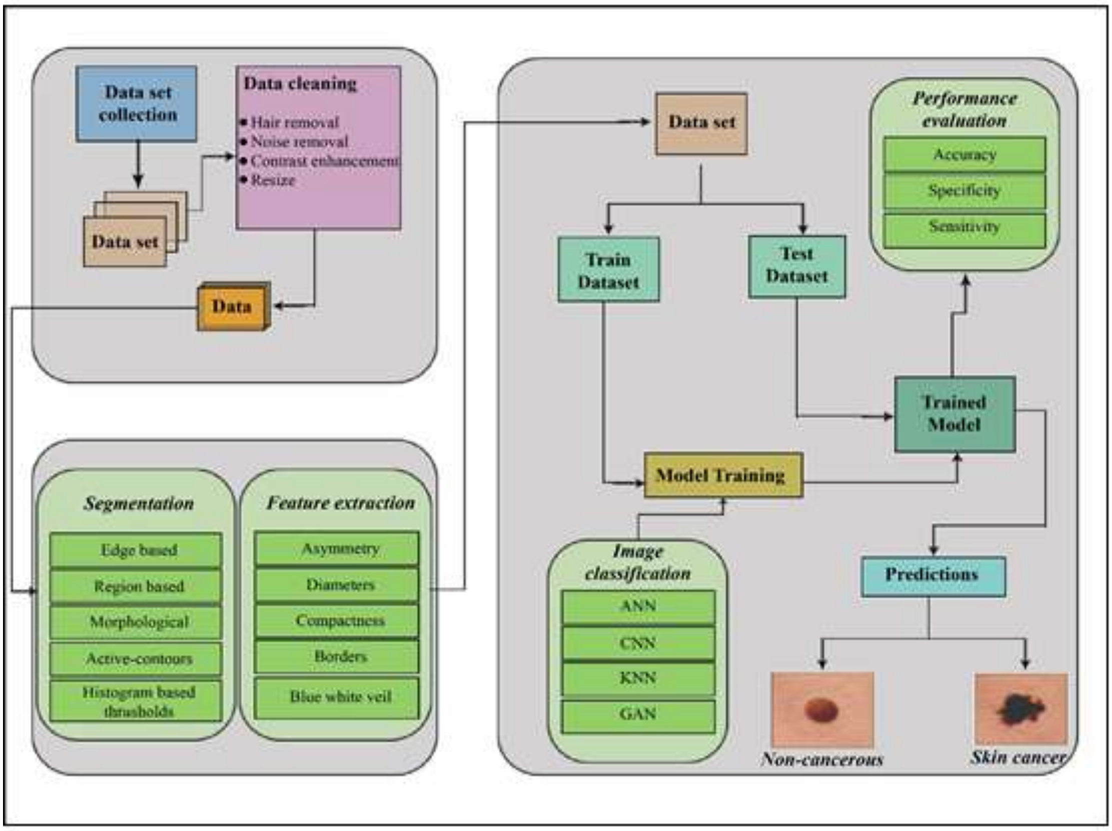

Figure 1: The process of skin cancer detection

During the last few decades, deep learning has brought about a sea change throughout the entire landscape of machine learning. It is the area of machine learning that deals with the most complex algorithms for artificial neural networks and is regarded the most advanced of its subfields. The operation and make-up of the human brain served as a model for the development of these algorithms. There is a wide variety of applications for deep learning techniques, including speech recognition [7], pattern recognition [8], and bioinformatics [9]. Deep learning systems have been shown to yield outstanding outcomes in a variety of applications, particularly when contrasted with more traditional techniques to machine learning. In recent years, various approaches from the field of deep learning have been utilized for the computer-based identification of skin cancer. In this study, we examine and analyse in great detail various methods for the identification of skin cancer that are based on deep learning. This paper is primarily concerned with the presentation of a comprehensive and systematic literature review of traditional approaches to deep learning, such as artificial neural networks (ANN), convolutional neural networks (CNN), Kohonen self-organizing neural networks (KNN), and generative adversarial neural networks (GAN), for the purpose of identifying skin cancer.

On this subject, there has been a substantial amount of investigation carried out thus far. As a result, it is of the utmost importance to compile and evaluate the studies, organize them, and compile a summary of the available study findings. We constructed search strings in order to collect material that was pertinent to the valuable systematic review of skin cancer detection methods that we conducted using deep neural network-based categorization. We limited our search to articles that were published in conferences and journals with a solid reputation. On the basis of the search that we devised, we picked 51 relevant research publications using multi-stage selection criteria and an evaluation technique that we developed. These papers have undergone meticulous evaluation and analysis from a variety of perspectives. The current advances in skin cancer detection systems provide a great deal of cause for optimism; yet, there is still room for future development in diagnostic methods that are now in use.

This article is broken up into four major sections for your convenience. In Section 2, the research approach that was utilized to effectively execute an analysis of deep learning techniques for the identification of skin cancer (SC) is outlined. In it, you'll find a description of the review domain, as well as search strings, search criteria, the sources of information, the information extraction framework, and selection criteria. Selected research publications will be appraised, and Section 3 will give a comprehensive assessment of SC detection strategies. The overall findings of the study are outlined in Section 4, along with a concise conclusion.

II. DEEP LEARNING STRATIGIES FOR SKIN CANCER DETECTION

The early identification of skin cancer is significantly aided by the use of deep neural networks. They are made up of a collection of nodes that are linked together. In terms of the interconnection of their neurons, their structure is comparable to that of the human brain. Their nodes collaborate with one another to find solutions to specific issues. After receiving training in a particular field, neural networks go on to perform as competent specialists in the fields for which they were initially developed [9]. In the course of our research, neural networks were educated to identify photos and to differentiate between a numbers of distinct forms of skin cancer. Figure 2 displays a variety of skin lesions taken from the dataset of the International Skin Imaging Collaboration (ISIC). For the purpose of developing skin cancer detection systems, we looked into a wide variety of learning methods, including ANN, CNN, KNN, and GAN. In this section, a comprehensive discussion is had on the research that pertains to each of these deep neural networks.

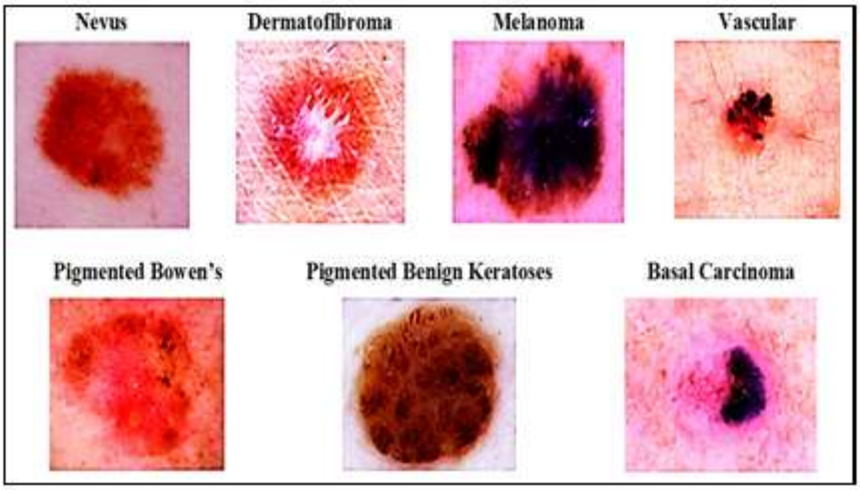

Figure 2: Skin disease categories from ISIC dataset

Skin Cancer Detection Techniques by Artificial Neural Network

A nonlinear and statistical approach of prediction, an artificial neural network is also known as an ANN. Its structure is based on the organic structure of the human brain, which serves as its inspiration. An ANN has three layers of neurons to make up its structure. Input neurons are located in the first layer, which is referred to as the input layer. These neurons send data to the intermediate layer of neurons, which is the second layer. The terms "hidden layers" and "intermediate layers" are used interchangeably. The conventional artificial neural network (ANN) may conceal multiple levels of complexity. The data collected by the input neurons is transmitted to the third layer of output neurons by the intermediate neurons. Backpropagation is utilised for the purpose of learning the intricate associations and linkages that exist between the input and output layers. This allows for the computations to be learned at each layer. It resembles a neural network in several ways. At the present time, the terms "neural network" and "artificial neural network" are being used interchangeably in the field of computer science. Figure 3 provides an illustration of the fundamental architecture of an ANN network.

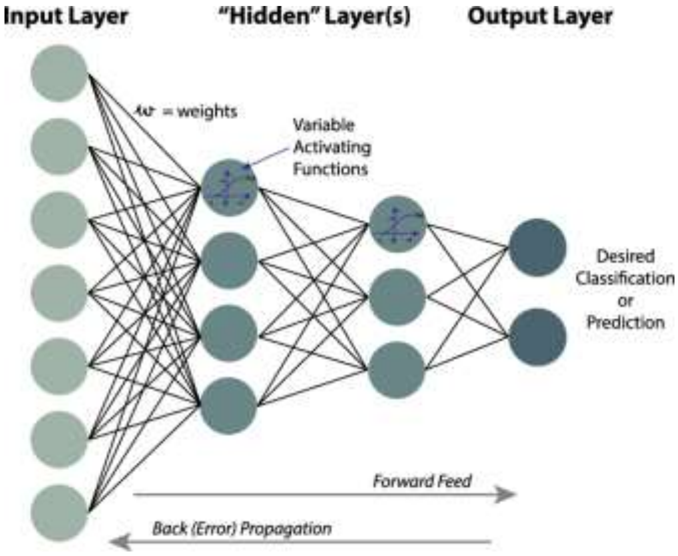

Figure 3: Basic ANN structure

In skin cancer detection systems, ANN is utilized for the classification of extracted features in order to make accurate diagnoses. After the successful training and classification of the training set, the input photos are labelled as either having melanoma or not having melanoma. An ANN has a variable number of hidden layers, the exact amount of which is determined by the number of input images. The input dataset is what establishes the connection between the first input layer of the ANN process and the hidden layer. The dataset may be labelled or unlabeled, and it may be processed using a supervised or unsupervised learning mechanism, depending on the type of labelling it contains. Backpropagation or feed-forward architecture can be used by a neural network to learn the weights that are associated with each connection or link in the network. Each architecture implements a distinctive pattern for the dataset that lies behind it. Neural networks that are built on feed-forward design can only transfer data in one way. The only direction data can flow in is from the input layer to the output layer.

Xie et al. [10] proposed a system for classifying skin lesions that divided lesions into two primary categories: benign and malignant. The mechanism that was proposed operated in three stages. In the beginning of the process, a neural network that generates itself was utilized to extract lesions from digital photographs. During the second step, characteristics such as the border of the tumour, its texture, and its colour details were retrieved. The computer system was able to extract a total of 57 features, including 7 novel features connected to the descriptions of lesion borders. The dimensionality of the features was reduced by using a technique known as principal component analysis (PCA), which ultimately led to the selection of the best possible collection of features. At long last, in the final phase of the process, lesions were categorized by employing a NN ensemble model. By merging backpropagation (BP) neural networks with fuzzy neural networks, Ensemble NN is able to increase the performance of classification. In addition, the results of the suggested system's classification were evaluated alongside those obtained from various classifiers, including SVM, KNN, random forest, Adaboot, and others. The suggested model achieved a sensitivity that was at least 7.5% higher than that attained by the other classifiers, while still maintaining an accuracy of 91.11%.

An artificial neural network (ANN)-based automated skin cancer diagnostic system was proposed by Masood et al. [10]. This paper looked at the effectiveness of three different learning methods for ANNs, including Levenberg–Marquardt (LM) [16], robust backpropagation (RP) [11], and scaled conjugate gradient (SCG) [18]. The LM algorithm obtained the highest specificity score (95.1%), and it continued to be effective at the classification of benign lesions. On the other hand, the SCG learning algorithm produced better results if the number of epochs was increased, scoring a sensitivity value of 92.6%. The comparison of performance showed that the LM algorithm achieved the highest specificity score (95.1%). It was postulated [19] that a mole classification system may be used for the early detection of melanoma, which is a form of skin cancer. The proposed approach gathered identifying characteristics by adhering to the ABCD rule of cutaneous lesions. The letters ABCD stand for the asymmetry of a mole's form, the borders of the mole, the colour of the mole, and its diameter. Both the asymmetry of a mole and its borders were extracted with the use of two different algorithms: the Mumford–Shah algorithm and the Harris–Stephen method, respectively. Moles that were neither black, cinnamon, or brown in colour were thought to be melanoma according to the suggested classification system because normal moles have one of these three colours as their primary component. Because melanomas typically have a diameter that is greater than 6 millimetres, a value of 6 millimetres was chosen as the minimum acceptable diameter for melanoma detection purposes. With an accuracy of 97.51%, the suggested system used a backpropagation feed-forward ANN to classify moles into three categories, such as common mole, unusual mole, or melanoma mole. These categories included common mole, uncommon mole, and melanoma mole.

Figure 4 is a representation of the automated skin cancer detection system that was proposed [12] and is based on backpropagation artificial neural networks. In order to extract features, this system made use of a technique called the 2D wavelet transform. The artificial neural network (ANN) model that was suggested assigned the input photos to one of two categories, such as cancerous or non-cancerous. Choudhari and Biday [13] came up with a proposal for an additional ANN-based skin cancer diagnosis method. A maximum entropy thresholding method was utilized in order to perform the segmentation of the images. In order to isolate distinguishing characteristics of skin lesions, a gray-level co-occurrence matrix (GLCM) was applied. In the end, a feed-forward ANN achieved an accuracy level of 86.66% by classifying the input photos as either being in a malignant or benign stage of skin cancer.

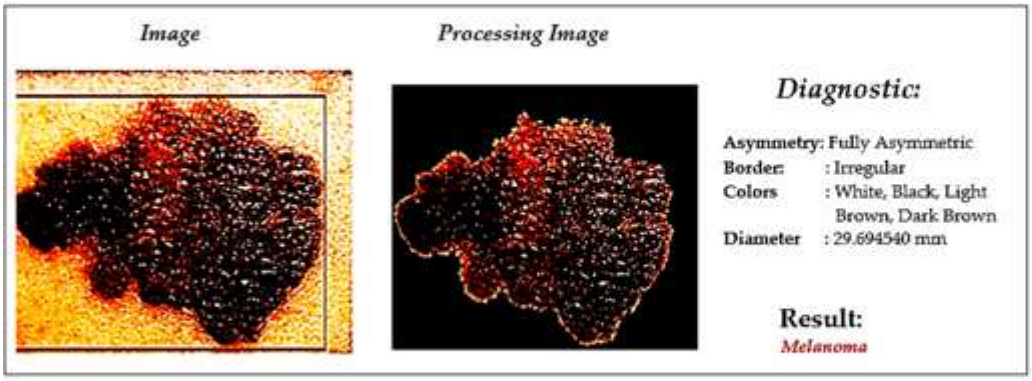

Figure 4: Skin cancer detection using Artificial Neural Network

Skin Cancer Detection Techniques by Convolutional Neural Network

One of the most important subcategories of deep neural networks is known as a convolution neural network, and it finds widespread application in computer vision. Image recognition, the assembly of a collection of input photographs, and image classification are the three primary uses for this tool. CNN is a terrific tool for collecting and learning global data as well as local data by accumulating more straight-forward characteristics such as curves and edges to produce more complicated features such as shapes and corners [13]. CNN is also a fantastic tool for learning global data. Convolution layers, nonlinear pooling layers, and fully linked layers are the components that make up CNN's hidden layers [9]. CNN is capable of having numerous layers of convolution, which are then followed by several layers of completely connected data. Convolution layers, pooling layers, and full-connected layers are the three primary types of layers that are utilized in the creation of CNN [30]. Figure 5 provides an overview of the fundamental construction of a CNN.

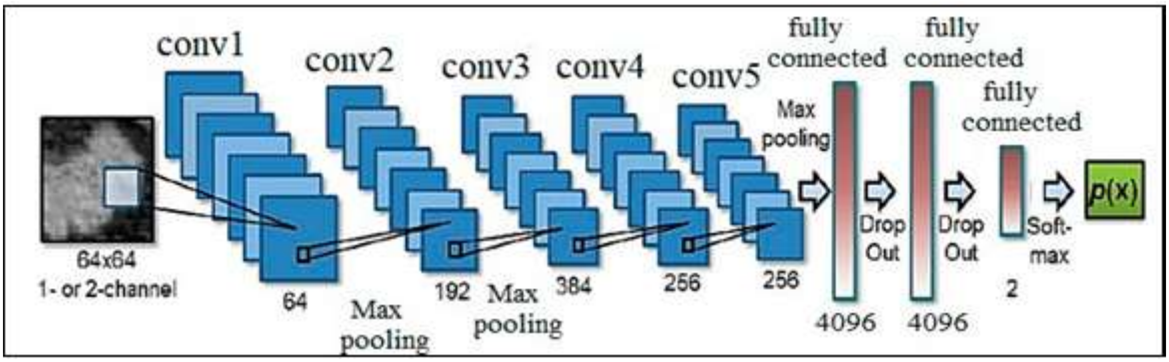

Figure 5: Basic CNN Architecture

In the detection, segmentation, and classification processes of medical imaging, CNN-based automated deep learning algorithms have achieved exceptional levels of performance [13]. Lequan et al. [32] presented a very deep CNN for melanoma detection. In order to achieve better results from the segmentation process, a fully convolutional residual network (FCRN) consisting of 16 residual blocks was utilised. The proposed method for classification used the average of the results obtained from the SVM and the softmax classifier. With segmentation, it demonstrated an accuracy of 85.5% in melanoma classification, while without segmentation, it showed an accuracy of 82.8%. A multi-scale convolutional neural network (CNN) was proposed by DeVries and Ramachandram [33], who used an inception v3 deep neural network that was trained on an ImageNet dataset. In order to classify skin cancer, the pre-trained version of inception v3 was further fine-tuned and adjusted on two resolution scales of input lesion images: coarse-scale and finer-scale. The coarse scale was utilized for the purpose of capturing the shape properties of lesions in addition to general contextual information. On the other hand, the finer scale was able to collect textual detail of the lesion, which enabled distinction between the many forms of skin lesions.

In their study [8], Mahbod et al. presented a method for the categorization of skin lesions that would involve the extraction of deep features from a variety of well-established and pre-trained deep CNNs. As deep-feature generators, we employed pertained versions of AlexNet, ResNet-18, and VGG16. We then trained a multi-class SVM classifier on the features that were generated by these neural networks. In the end, the findings of the classifiers were combined in order to accomplish classification. The suggested system was tested on the ISIC 2017 dataset, and its performance for seborrheic keratosis (SK) and melanoma classification respectively showed an area under the curve (AUC) of 97.55% and 83.83%, respectively. A deep CNN architecture that was pre-trained using ResNet-152 was suggested in [10] as a means of classifying a total of 12 distinct types of skin lesions. It was first trained using 3797 lesion photos; however, later on, a 29-times augmentation was applied based on illumination positions and scale transformations. Initially, it was trained on 3797 lesion images. The proposed method achieved an area under the curve (AUC) value of 0.99 when used to the classification of hemangioma lesions, pyogenic granulomas (PG), and intraepithelial carcinomas (IC) that were found on the skin.

Dorj et al. [11] presented a method for the classification of skin lesion images that may be broken down into four distinct categories. After the features were extracted with the use of a deep CNN that had been pertained and given the name AlexNet, an error-correcting output coding SVM was employed as the classifier. The suggested system produced the greatest scores possible for the average sensitivity, specificity, and accuracy for basal cell carcinoma (BCC), solar cell carcinoma (SCC), and actinic keratosis (AK), with 95.1%, 98.9%, and 94.17%, respectively. The pre-trained deep CNN architecture VGG-16 that was proposed by Kalouche includes a final three finely tuned layers in addition to five convolutional blocks. Figure 6 is an illustration of the VCG-16 model that has been proposed. The VCG-16 models demonstrated an accuracy of 78% when it came to the classification of lesion photographs as melanoma skin cancer. A deep convolutional neural network (CNN)-based system has been proposed as a method for identifying the borders of skin lesions in photographs. In order to train the deep learning model, 1200 images of normal skin as well as 400 photographs of skin lesions were used. The incoming images were separated into their two primary categories—normal skin image and lesion image by the technique that was proposed, which achieved an accuracy of 86.67%.

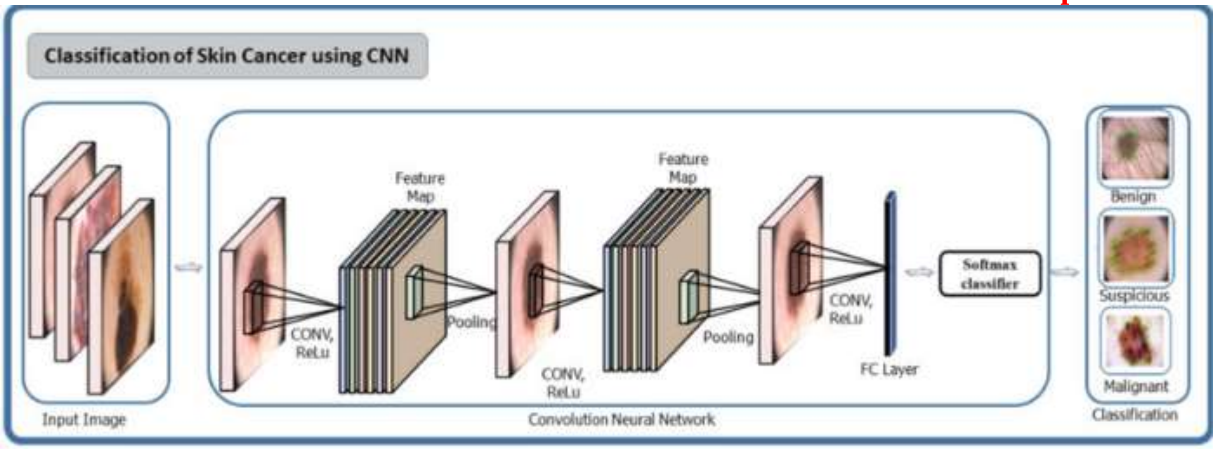

Figure 6: Skin cancer diagnosis using CNN

Skin Cancer Detection by KNN

One of the most well-known kinds of deep neural networks is called the Kohonen self-organizing map. CNNs are trained on the basis of unsupervised learning, which means that a KNN does not require any intervention from a developer in the learning process and also requires very little information about the characteristics of the input data. This is in contrast to the training of CNNs, which is based on supervised learning. In most cases, a KNN will have two distinct layers. One of the layers in the two-dimensional plane is referred to as the input layer, while the other is called the competitive layer. Each connection between these two layers goes from the first layer dimension to the second layer dimension. Both of these layers are interconnected in their entirety. It is possible to cluster data using a KNN even when one is unaware of the connections between the members of the input data. A self-organizing map is another name for this type of diagram. In KNNs, there is no such thing as an output layer because each and every node in the competitive layer also functions as its own output node.

A KNN can be thought of as a dimensionality reducer in its fundamental form. It is able to transform high-dimensional data into low-dimensional representations, like a two-dimensional plane, for example. Therefore, it offers several distinct sorts of representation for the dataset that was input. When it comes to learning strategy, KNNs are distinct from other forms of NN since they make use of competitive learning rather than the learning that is based on error correction, as is the case with BPNs and feed-forward learning. During the process of mapping high dimensionality to low dimensionality, a KNN will keep the topological structure of the input data space intact. The term "preservation" refers to the maintenance of the same relative distance between data points as they are moved through space. In this mapping scheme, data points that are physically closer to one another in the input data space are mapped closer to one another. On the other hand, data points that are physically further apart in the input data space are mapped further apart from one another. As a consequence of this, a KNN is the most effective technique for dealing with high-dimensional data. A Key-Nested Neural Network (KNN) is a type of neural network that has the ability to recognize and arrange unfamiliar input data. This generalization ability is an additional essential characteristic that a KNN provides. Figure 7 presents a diagrammatic representation of the architecture of a KNN. The ability of a KKN to map complicated interactions of data points, including even nonlinear associations between data points, is the defining characteristic of this type of network. KNNs are currently being utilized in skin cancer detection systems as a result of the benefits described above.

Skin Cancer Detection by GAN

The idea behind the powerful class of DNN known as generative adversarial neural networks [12] comes from the concept of zero-sum game theory. GANs are founded on the concept that two neural networks, such as a generator and a discriminator, compete with each other to assess and capture the variation in a database. This principle forms the foundation of the GAN. The generator module takes advantage of the data distribution to generate bogus data samples, which it then utilizes to attempt to trick the discriminator module. On the other hand, the discriminator module's objective is to differentiate between authentic data samples and fabricated ones [13]. During the training phase, both of these neural networks will conduct these steps repeatedly, and after each competition, their overall performance will get better. The most important advantage that a GAN network can offer is the capability to create false samples that are analogous to actual samples by making use of the same data distribution. One example of this would be photorealistic photos. Additionally, it can tackle one of the most significant issues that arises in deep learning, which is the issue of insufficient training instances. GANs, or generative adversarial networks, have been put into practice by researchers in many different forms, including the Vanilla GAN, the condition GAN (CGAN), the deep convolutional GAN (DCGAN), the super-resolution GAN (SRGAN), and the Laplacian Pyramid GAN (LPGAN). GANs are currently being utilized in skin cancer diagnostic systems with a high degree of success. Figure 7 presents a diagrammatic representation of the architecture of a GAN.

Many researchers have been work over the Computer imaginative and prescient strategy for pores and skin most cancers detection. For segmentation over pores and skin lesion within the enter image, present systems either use manual, semi-automatic and completely automated answer detection methods. The functions in accordance with operate skin coup segmentation chronic among a variety of papers are: shape, colour, texture, or luminance. Many answer detection strategies are mentioned within the writing Some about the techniques include histogram thresholding, global thresholding regarding optimized color channels observed by means of morphological operations, Hybrid thresholding. In that study, we have applied Automatic thresholding then answer discovery method. Different photograph processing strategies bear been old after extract certain features. In [7], writer has added an computerized Global border-detection technique within dermoscopy images based totally concerning colour-space analysis or international histogram thresholding as reveals high performance among detecting the borders about melanoma lesions. In [2] the authors bear ancient the approach concerning sharing the input photograph into quite a number clinically significant areas the use of the Euclidean association seriously change for the extraction regarding coloration or ground features. The ABCD governance about dermoscopy, endorse as asymmetry is attached the nearly outstanding amongst the IV functions of asymmetry, answer irregularity, color then diameter. A variety concerning research have been carried outdoors about quantifying asymmetry of skin lesions. In Some techniques, the agreement function is considered primarily based on geometrical measurements over the total lesion, e.g. symmetric range or circularity9 Other studies, recommend the circularity index, as much a measure on irregularity regarding borders among dermoscopy images, The order [3] offers the overview about the close essential implementations of the composition yet compares the performance about various classifiers of the particular pores and skin coup diagnostic problem.

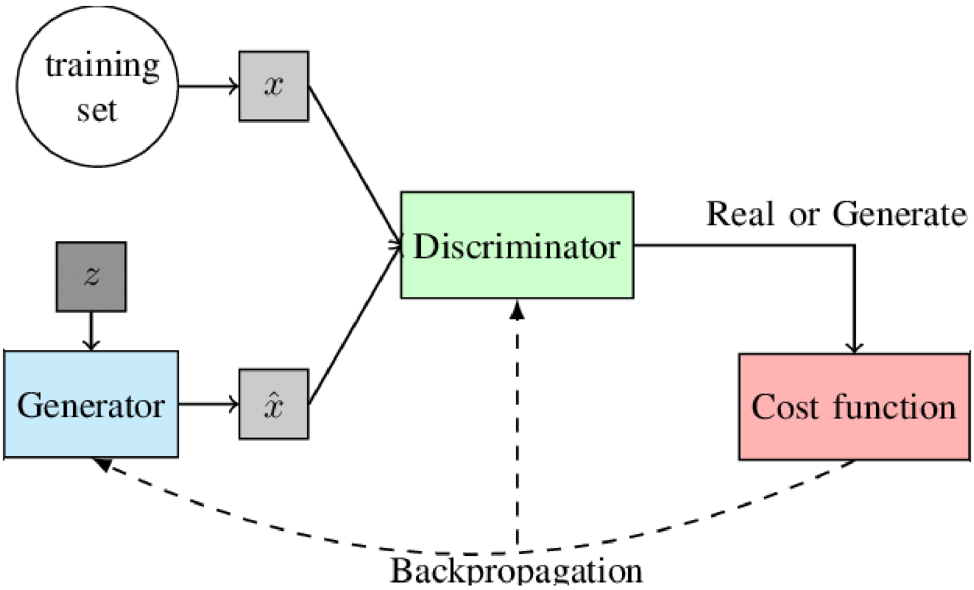

Figure 7: GAN architecture

III. DATASETS

There have been several different suggestions made for computerized methods of diagnosing skin cancer. A comprehensive and trustworthy collection of dermoscopic pictures is required in order to evaluate their diagnostic performance and validate the results that were expected. Other than photos of nevi or melanoma lesions, various skin cancer databases have been small and lacking in diversity, save for those that contain nevi. The limited quantity of the datasets and the absence of a wide variety of data both present challenges for the process of training artificial neural networks to classify skin lesions. Although patients commonly suffer from a variety of non-melanocytic lesions, previous research for automated skin cancer diagnosis primarily focused on diagnosing melanocytic lesions, which resulted in a limited number of diagnoses in the available datasets. Despite the fact that patients commonly suffer from a variety of non-melanocytic lesions, there has been significant progress made in this area.

PH^2 Datasets

The dermoscopic pictures that are included in the PH2 dataset were acquired in Portugal at the Dermatology Center of Pedro Hispano Hospital [68]. These photos were taken with the identical conditions utilizing a Tuebinger-Mole-Analyzer device. The magnification rate was set at 20. The PH2 dataset includes RGB colour images with a bit depth of 8 and a dimension of 768 * 560 pixels. The collection contains a total of 200 dermoscopic images, with 80 photos representing common nevi, 80 representing atypical nevi, and 40 representing melanoma skin tumours. This dataset includes medical annotation of the lesion images, such as medical segmentation of pigmented skin lesions, histological and clinical diagnosis, and evaluation of several dermoscopic criteria. Other medical annotations included in this dataset include: The evaluation was carried out using dermoscopic criteria, which included streaks, hues, regression areas, pigment network, and blue-white veil globules.

Derm Quest

The DermQuest dataset [14] that was made available to the general public included 22,082 dermoscopic images. Only the DermQuest dataset contains lesion tags for skin lesions; the other dermoscopic datasets did not include these tags. All of the photos in the dataset were tagged with a total of 134 lesions. In 2018, the DermQuest dataset was transferred over to the Derm101 platform. However, as of the 31st of December 2019, access to this dataset has been terminated.

DermIS

The dataset obtained by dermoscopy The acronym "DermIS" is the common name for the Dermatology Information System [15]. Both the Department of Dermatology at the University of Erlangen and the Department of Clinical Social Medicine at the University of Heidelberg worked together to compile the information contained in this dataset. It has a total of 6588 photos. Recent developments have resulted in the creation of two distinct subsets within this dataset: a dermatological online image atlas (DOIA) and a paediatric dermatology online image atlas (PeDOIA). The DOIA has 3,000 photos of different skin lesions and covers around 600 different dermatological diagnoses. It offers dermoscopic images, replete with differential and provisional diagnosis, case reports, and other information on practically all sorts of skin illnesses.

IV. CONCLUSION

In this systematic review research, multiple neural network algorithms for detecting and classifying skin cancer have been discussed. These methods are completely non-invasive in nature. The identification of skin cancer is a multi-step procedure that begins with preprocessing and continues with picture segmentation, feature extraction, and finally classification. The classification of lesion pictures was the primary topic of this review, with particular attention paid to ANNs, CNNs, KNNs, and RBFNs. Every algorithm has both positives and negatives associated with it. For optimal outcomes, it is essential to make an informed decision regarding the classification approach to use. However, when it comes to the classification of image data, CNN provides superior results compared to other forms of neural networks. This is due to the fact that CNN is more closely tied to computer vision than the other varieties.

The majority of research that is conducted in the field of skin cancer detection focuses on determining whether or not a particular lesion image is malignant. However, if a patient asks about a specific skin cancer symptom and whether or not it arises on any portion of their body, the research that is currently available cannot provide an answer. The research done up until this point has concentrated on the specific challenge of classification of the signal picture. In the future, study might include taking photographs of the subject's entire body in an effort to find the answer to the issue that frequently comes up. The image acquisition step will be made more automated and sped up by the use of autonomous full-body photography.

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