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Review Article

A Review on Skin Cancer Detection and Classification using Infrared images

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Abstract *- Skin cancer is considered one of the most complex forms of cancer. If the skin cancer is not treated early, there is a high possibility that cancer could spread to different parts of the body. Melanoma skin cancer count has been increasing day by day. Early detection plays a very vital role in the treatment of cancer. However, present-day technological developments can detect skin cancer as early as possible. This review focuses on the characteristic features such as texture, shape, color, and structure, the essential paradigm for detecting skin cancer. In medical image processing, skin cancer detection at its initial stage can be done through computer-aided detection, artificial intelligence, swarm technique, etc. In the case of an automatic diagnosis system, there are, most importantly, two major steps, namely skin anomaly detection, and classification. We present a thorough review of skin cancer detection and classification using infrared imaging, artificial neural networks, Gaussian classifiers, etc. This review also delivers obligatory information on numerous techniques and primary steps for the automatic detection and classification of skin cancer.*

Keywords *- Artificial intelligence, Classification, Computer-aided detection, Infrared imaging, Melanoma skin cancer.*

I. Introduction

There are many more cases of cancer in today's world than earlier. Out of these globally, skin cancer covers an overall 40%. Squamous Cell Carcinoma (SCC), Basal Cell carcinoma (BCC), and melanoma are the crucial types of cancer. Among these, BCC and SCC are labeled as Non-Melanoma Skin Cancer (NMSC) which have a lesser impact than melanoma skin cancer. Since 2008, 53% of melanoma patients have recovered from this disease [42]. Digital dermoscopy, dermoscopy, and pathological analysis of skin biopsy are some of the diagnosis methods used for melanoma. The risk of false-positive detections and low accuracy are major drawbacks of dermoscopy. The risk of false-positive detection results in the variation of melanoma over time and causes observation error. By photographing and recording dermoscopic images, the map of moles in the human body can be attained with digital dermoscopy. This is used in detecting point localization. Hence, handling high-risk skin cancer patients are possible [26]. The pathological analysis of skin biopsy is an effective way to treat skin cancer, and it provides accurate results.

As the biopsy practice results in undesirable scars, the pathological analysis is not appropriate for patients with multiple moles [71]. The classification of skin cancer cells is based on the presence of grey-scale features that are widely used in biological image processing. The feature reduction is executed using discrete wavelength transform accompanied by principal component analysis (PCA) [1]. Artificial Neural Network (ANN) and the K-nearest neighbor (KNN) methods are employed for classification. Feature extraction can be performed by the Grey Level Co-occurrence Matrix (GLCM) [2]. The resolution of the appropriate image should be enriched to retrieve the finer particle of the image. A modified Laplacian filter with intensity correction is being exploited [3].

A classification method is described in [4] based on irregular streaks and the detection of essential patterns of striped lines. Graphically, the modeling of these streaks is performed. The features of the valid streaks are measured as the crucial factors for classification, and the color and texture. The color, symmetry, and multi-scale texture analysis have been determined [6]. The multi-class AdaBoost algorithm is a widely used technique in classifying cancerous and benign melanoma [7]. Benign is said to be non-cancerous, whereas melanoma is a cancerous one. In this multi-stage illumination modeling, an illumination-correction-based method has been presented. In this method, a three-stage progression is accomplished with parametric modeling to evaluate final illumination and deduction of variations in illumination. The advanced hierarchical k-NN classifier is strongly recommended for classifying non-melanoma-melanoma skin lesions [8]. For classifying non-melanoma-melanoma skin lesions, an advanced hierarchical k-NN classifier has been recommended [8]. An image processing method is presented in [9]. The challenge is to improve the accuracy rate, for which few of the melanoma features are considered. The features considered are asymmetry, border, color, and diameter. The infrared camera is being used for capturing images. This camera utilizes several thermal coordinates such as thermal diffusion, metabolic heat generation, and tissue-specific heat [10].

The most important of skin cancer is classification. Skin cancer is broadly classified into two sectors - one is melanoma, and the other is non-melanoma or benign cells.

Figure 1 represents a dermoscopic image. Melanoma is nothing but the malignant part of the cells, which are cancerous, and the benign cells are normal or can be called the cells without cancer.

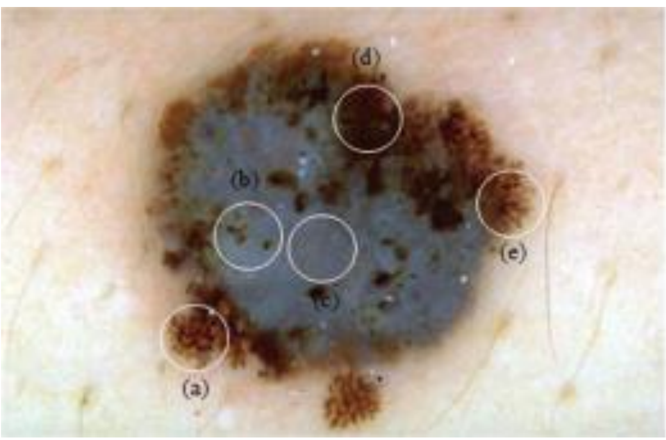

Fig. 1 Dermoscopic image

Skin cancer is very common among the people of the United States. The people who have higher chances of getting skin cancer include the following characteristics: a white-colored person has more chances than a dark-skinned person. Skin covers the entire body, so it's comparatively challenging to detect cancer as the skin is throughout the entire body. Even a mole that changes in size, shape, etc., must be monitored thoroughly. A person needs to be careful in checking out for the changes.

Getting treated early is one of the important things a person should consider in treating cancer. Small symptoms found. It is advised that the patients rush to the physician even if they are minors. The physician will advise based on the severity of the problem. Any cancer is crucial. Earlier detection can give a person a better solution. The basic four steps of detection and classification of skin cancer are - preprocessing, segmentation, feature extraction, and classification. Our paper will discuss all the possible methods using which the methods mentioned above can be implemented.

The skin color detection delivers a computational effect. Skin color is a complementary form of data to other constraints such as shape and texture. Also, it can be used to construct precise face recognition systems. Skin color detection is employed as the initial phase [15]. Innovative and modern camera developments and minimum equipment costs are the two major factors that sparked interest in the emerging medical field [3]. The surface temperature inclination is explained in [17].

The skin-colored pixel detection technique is found to be quite challenging. In any image, the presence of skin hardly hangs on the illumination condition at the instant of image capture. Because of color constancy, humans can recognize the color of an object in an extensive range of illuminations [100]. This color constancy is termed a mystery of observation. The main challenge is signifying a color in its invariant way or unresponsive to illumination changes. The selection of color space highly distresses the performance of any skin detector along with variation in illumination state. If the environment is not in a controlled state, wood, leather, and skin-colored clothing causes skin detector to predict false detections in the background [21]. While compared to Magnetic Resonance Imaging (MRI) and mammography, dynamic thermography is more costly.

Additionally, it is a non-ionizing diagnostic process where the patient does not undergo pain. The drawbacks of the mammography technique can be overwhelmed by infrared thermal imaging by optimizing the contrast in dense tissue areas [11]. Thermography is an advanced, quick diagnostic and economic method. It is a risk-free system that does not emit ionizing radiation [13].

In near-infrared (NIR), the human skin can be mentioned as six layers. It is made up of dermal tissue along with changing quantity of water and melanosomes [101]. Each layer transmits and reflects light depending on the absorption coefficient, decrease in scattering coefficient, and thickness. Subcutaneous fat is present below the six layers of skin with a huge reflectance in NIR. A skin reflectance model is defined based on thickness, optical coefficients knowledge, and subcutaneous fat reflectance [16].

Many researchers have focused on further advancements in detecting skin problems and their applications [46]. Several new technologies have been deployed in the medical field for skin detection. Mobile technology is another budding idea in the detection of skin cancer. Computer vision algorithms and their applications have gained more attention among researchers as it works in the mobile environment and is portable. Not only is skin cancer detection application, these smartphones have become a good accessible environment but also for several innovative applications that employ computer vision methods [12]. How any substance absorbs, transmits, and reflects light is termed spectroscopy. UV-Vis-NIR spectroscopy is mainly concentrated because a traditional camera sensor with a CCD could capture images in UV, Vis, and NIR regions. UV-Vis-NIR spectroscopy is used for optical absorbance and reflectance dimensions in 200 to 1500 nm wavelength series. A substance can be distinguished by examining its light reflectance, as each substance has its distinctive reflectance feature [14].

The wavelength dependence of the presence of skin is to be determined for proper understanding and assessing the significance of NIR in skin imaging. Since several features have to be considered, the modeling of skin is quite complex. Certainly, it is strictly inhomogeneous and transparent material, not just a planar reflectance. The reflection, absorption, and scattering effects are well measured [18 [25].

2. Steps involved

2.1. *Skin Cancer Detection*

The numerous layers of skin entail distinct functions with distinct optical properties. When white light reaches the skin, it penetrates superficial layers of skin. Some of the particles get absorbed, and some get remitted back. This can be registered by employing a digital camera [30]. The epidermis and dermis are the two major areas of imaging. Epidermis, also known as the" melanin layer," is the major component accountable for pigmented coloration of the skin [38]. Melanin pigment is the main reason behind the color difference in humans [55]. The epidermis layer is equitably thin, and scattering does not occur. The dermis layer is present underneath the epidermis layer. The hemoglobin absorption and essential scattering occur in the dermis layer [18]. Stratum corneum is known as a protective layer that entails keratin-impregnated cells. The stratum corneum differs according to thickness. It is optically neutral [58]. The epidermis includes connective tissues, melanin-producing cells, melanocytes, and melanin [47].

Fig. 2 represents a clear difference between normal skin area and tumor area.

The melanin pigment absorbs light in the UV and visible spectrum blue part. In this approach, melanin pigment acts as a filter [65]. This filter safeguards the inner layer of skin from the hazardous effect of UV radiation. There is a little amount of scattering surrounded by the epidermal layer. As a result, the light particles that are not absorbed by the melanin pigment can be considered dermis [70]. In contrast to the epidermis, the dermis consists of sensors, blood vessels, receptors, and nerve ends. The dermis includes collagen fibers [30]. In accordance with skin health, diagnosis is the basic procedure of recognizing a skin texture by its specifications and signs [52]. The resultant outcome of this process is known as the diagnosis. Diagnosis examines any problem by answering the corresponding questions. Skin cancer is a malignant tumor that develops in the skin cells [50]. Skin cancer accounts for almost more than 50% of all cancers. According to the American Cancer Society, more than one million Americans were well-diagnosed with non-melanoma-melanoma skin cancer in 2007. Also, 59,940 people have been diagnosed with melanoma. Providentially, these skin cancers are very rarely observed among children.[51].

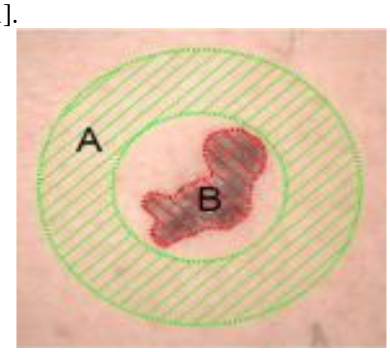

Fig. 2 (A) Normal skin area, (B) Tumor area

In several stages of skin cancer, itching and bleeding occur. If a person has undergone a radiation diagnosis, the radiated area is more likely to become tumorous. The skin cancer recognition system is chiefly positioned to spot and identify the symptoms of skin cancer at its earliest stage [61]. The patients also could take early measures to get out of cancer. The early detection of this cancer becomes less risky for doctors to diagnose. Also, it helps evaluate the further advancements in skin dialysis and advises the best solution [73]. The major steps to be incorporated in diagnosing skin cancer are image preprocessing, segmentation, feature extraction, and classification.

Figure 3 represents the skin cancer image processing [89].

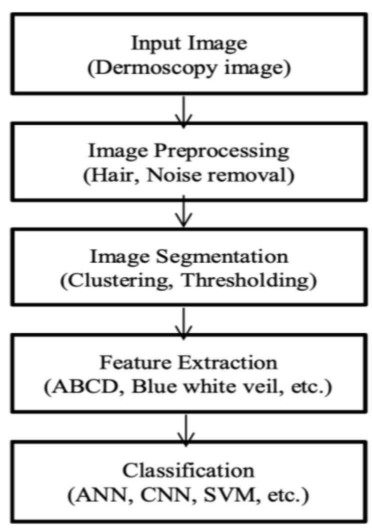

Fig. 3 Steps involved in skin cancer diagnosis

2.1.1 Preprocessing

This technique is the most important. It checks if there exists any noise or disturbances in the image and that it has any necessary information to be removed by means of any techniques like noise removal filtering etc. Other means could be used to remove the disturbances that occur in the images. There are two different preprocessing stages - hair removal and noise removal. The skin has hairs all over, and the images can proceed through two stages - noise and hair removal. Noise removal is the disturbance that occurs in one's image through the wind. Hair removal helps to improve strength by removing the hair and other disturbances.

2.1.2 Segmentation

This deals with the splitting of a region into multiple parts. Segmentation plays a crucial role in detecting and classifying skin cancer techniques. The segmentation helps us to find the region of interest (ROI). It helps us focus on the regions already split into many regions. Segmentation is one of the crucial parts of detecting and classifying skin cancer. The parts of the interest are then identified and checked whether these parts match with the region of interest.

Segmentation deals at the heart of the detection and classification of skin cancer. Segmentation is the second step of classifying a cancerous image. The region of interest is identified and then allowed to check if they match or not. The values are subsequently found, and the corresponding response is the value of the extracted image used to check the various features. The features are observed, identified, and collected for further processing.

2.2 Classification of Skin Cancer

An essential learning algorithm is required for classifying any image. Supervised and Unsupervised algorithms are the two major categories of machine learning approaches [19]. The classified input data is deliberated as input data in supervised learning. In case when the classified data is not available, the unsupervised training data is being employed [99]. Artificial Neural Network (ANN) is one such supervised machine learning approach inspired by the neurons in the human brain. ANN is being fruitfully used in skin cancer image classification [20]. By the process of approximation of the non-linear relationship between the input layer and output layer, backpropagation works. The three layers used in ANN are the input, output, and hidden layers [22]. During the training phase, a learning rule is deployed in ANN that allows tuning of the adaptive weights. In the event of the classification phase, the feature vector extracted is attained, and the training manner begins for adjusting the weight values [77]. Three hidden layers are being used for training [23]. Sigmoid is the commonly used activation function for feed-forward and backpropagation neural networks [68].

Several methods have been discussed over previous years for skin cancer classification and segmentation. Various techniques have been initiated and tested for skin cancer segmentation, classification, and feature extraction tasks at the International Skin Imaging Challenge (ISIC)in 2016 [88]. A comprehensive study consistently exhibited advanced segmentation and classification precisions of 95.3% and 91.6%. Classification outcome was entirely based on identifying two kinds of cancer such as benign and malignant [24]. On ISIC 2016 dataset, the concert of Inception-v3 and VGG-16 were examined for skin segmentation. This method regained nearly 61.3% and 69.3% testing precision at maximum performance [31].

An innovative and improved architecture, "U-Net," was introduced for medical image segmentation. This U-Net gained high accuracy in the outcome, and it was used in several modalities of computational pathology and medical imaging. Recurrent Residual Convolutional (RRN) U-Net was presented in 2018. The RRN is also termed as R2U-Net. Prominent qualitative and quantitative advancements were noticed in the results of SegNet and ResU-Net models. In 2018, one such model was developed, LadderNet. This enriched structural design of the U-Net model enclosed a chain network of several encoding and decoding units. This model is projected to be multiple FCNs, employed in retinal blood vessel segmentation [56].

A skin classifier is a system that signifies the decision margin of the skin color class in the feature space. The selection of color space is the feature space in the perspective of the skin detection process [35]. The skin classifier is directly prompted by the shape of the skin class in the color space. The color space is dominated by a skin detector system [62]. The simplicity or complexity of the function of the classifier depends on the compactness and regular shape of the skin color class. A pixel in which color penetrates the skin color class boundary is considered skin. Defining the boundary level is the simplest way of defining whether a pixel is skin color or not [76]. The features of the elliptical boundary can be evaluated from the skin database during the training phase [21].

2.2.1 Gaussian Classifier

Gaussian mixture-based classifier is the foremost skin-color distribution modeling broadly used. The chief advantage of this classifier is that they use only a few training data [90].

Single Gaussian Models (SGM)

The skin colors of different entities cluster together in a minor area under controlled illuminating circumstances in a single Gaussian model. Thus, the skin color dispersal of several characters can be exhibited [11] and is used to model a skin color distribution.

Gaussian mixture models (GMM)

It has been presented that more than a few modes co-exist within this cluster, even though human skin color samples for diverse race individuals cluster in a particular region. It is difficult to model this effectively using Gaussian distribution [12]. As illumination conditions change rapidly, assuming a single model does not work. Several researchers have focused on the Gaussian mixture model for describing complex forms of distributions in such cases.

Multi-layer perceptron (MLP) classifier

MLP is one popular Artificial Neural network (ANN) [86]. It is a feed-forward network consisting of simpler neurons or processing elements. The ability to learn composite non-linear input-output connections and simplify any complex data is the major advantage of the MLP classifier. MLP has been widely used in several kinds of pattern recognition concerns. In a gradient descent approach, the backpropagation algorithm is predominantly used to upgrade weights in the network iteratively. All inputs are processed in a feed-forward way, and it compares the attained results and expected results. The total number of hidden layers and hidden nodes denotes the performance of the MLP classifier [15].

Maximum entropy (MaxEnt) classifier

MaxEnt modeling is a statistical tool engaged in estimating the data's probability distribution. When the data distribution is found to be minimum, it must be as constant as possible. This is the basic principle of the MaxEnt classifier. The maximum entropy will be achieved. A labeled training data is being used to develop a set of constrictions for the typical model that defines the class-specific prospect of the distribution. The corresponding constraints are defined as predicted values of the features. By using ML means, the factors of the model are projected. Beth Tree approximation is being used for apprising MaxEnt model factors [15].

Bayesian Network (BN) Classifier

BN classifier is a paradigm of directed acyclic graphs. Effective depiction of the joint probability density functions is established using a BN classifier. The vertex present in the graph denotes the random variable. The edges of the graph specify the straight correlation among the variables. Tree Augmented Naïve Bayes (TAN) and the Naïve Bayes (NB) classifier are the two major examples of Bayesian networks. TAN classifier is being employed to progress the function of the NB classifier [15].

Bayes theorem is well exploited in this classification technique. The independence assumption between the predictors is achieved. Since there are no iterative factors for evaluation, it is modest to form a Naive Bayesian model. For solving high computational problems, a Naive Bayesian classifier has been used. The subsequent probability function can be evaluated using the Bayes theorem.

Artificial Neural Network (ANN)

The artificial neural network is a well-known mathematical model. This model is stimulated by the function of neurons in the human brain. An interconnected group of artificial neurons is entailed in a neural network. Based on internal or external data curving all over the network through the learning phase, ANN varies its structure and function [21]. Feedforward neural network is the simplest form of ANN. The data source diverges in a single direction [33].

Neural Network Classifier

A neural network classifier is being used to categorize the cancerous image. Two types of classes, s1, and s2 are utilized for classifying any image using PNN. Class s1 possesses a cancer-affected image, and class s2 possesses a normal image [32]. The input image will be categorized as to whether it belongs to class 1 or 2. The retrieved approximation coefficient is deliberated to be input to the neural network classifier. A probabilistic neural network entails interconnected input and output along with a weight factor. By adjusting this weight factor, the PNN will be trained, predicting the correct class. The expected outcome was 0 for the abnormal case and 1 for normal ones. The training and testing phase is involved in the classification procedure. The identified data is provided and trained using the appropriate datasets in the training phase. The unknown data is given in the testing phase, and the classification is executed. Classifier capacity of allocating unrecognized body to the correct class is based on mined features. Effective means of the training phase yield precise and accurate classification [34].

Random Forest (RF) Classifier

A random forest classifier is incorporated with a number of decision trees. With dissimilar classification, all the trees procure its locus arrangement effect. By organizing the random sampling method, the assessment of the sampling allocation will be recognized.

Convolutional Neural Network (CNN)

A convolutional neural network is a form of a multi-layer neural network. In CNN processing, reduced preprocessing is executed. The CNN is employed to directly detect visual patterns from the pixel images [59]. Multiple convolutions and pooling layers are present in CNN. The last layer of CNN is fully connected. Using a filter kernel, the input image is filtered in the convolution layer. The pooling layer in CNN selects the maximum values in each window. This, in turn, minimizes the feature map size. The general outlines of the image are more noticeable in the resized image, so the decrease in the size of the feature map has gained more importance [63]. Identifying images using the brain's visual cortex evolved in CNN. In image classification for accomplishing improved outcomes, feature extraction has been used per the machine learning tasks. In the previous era of CNN, handcrafted feature extraction tools were used for digital image processing by several scholars [53].

By dropping the aspect of the input image and downsampling the adjacent pixel into a single pixel, the pooling layer extracts the size and shape of the invariant features [41]. In the CNN design model, various convolution layers are conveyed by a stack of pooling layers [45]. CNN exhibits reduced computational cost [57].

Deep Neural Network (DNN)

The deep neural network includes single input, single output, and interconnected multiple layers across them. DNN has been applied in several applications, and among them, the technology-related concerns are mostly solved [66]. This is due to evolving innovative learning algorithms and improved computing power. The main issues of multi-layer networks are over-fitting, vanishing gradient, and the computational load [18]. Increasing both width and depth size is the easiest approach to enhancing advancements in DNN [60]. By doing this, two major limitations might occur. An increase in volume could make the networks to be more effective. Conversely, this imposes a crowning increase in computer power [64].

AlexNet CNN Model

AlexNet CNN model was developed for ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). The specific parameter specifications are being considered, such as width (W) of 227, height (H) of 227, and depth (D) 3. D=3 denotes red, green, and blue [69].

3. Existing skin cancer detection and Classification Techniques

Skin Cancer detection and classification study all the stages involved in skin cancer techniques like Preprocessing, Segmentation, Feature Extraction, and Classification. Preprocessing helps remove the noise, segmentation splits the region into many parts, Feature extraction helps extract the necessary features, and classification helps classify if it is cancer or not.

The feature extraction techniques use discrete wavelet transforms to extract features. The classification uses Probabilistic Neural Networks. The detection and classification of skin cancer screening have fetched better results with proper segmentation [103], which involves adaptive thresholding and morphological analysis. Early detection helps in by using the neural network classification, which includes the backpropagation algorithm [104].

One of the traditional works of ABCD feature extraction. The classification can be done by the artificial neural network [105]. The ANN helps in the efficient classification process. This is about how the rural network is managed by using the feature extraction methods of ABCD extractions when possible [106]. The preprocessing work of median filtering and the segmentation by Otsu's thresholding[107] and that the classification proves to be a healthy one. The support vector machine uses the linear kernel and works as a better classification [108].

The segmentation gives maximum entropy methodology, Feature extraction using GLCM, and classification using the artificial neural network [109]. Thus, trying to improve the accuracy of the defined problem for detection and classification. The unique concept of pigment Network extraction [110] and the major feature extraction, the ABCD feature extraction, deal with a better accuracy [111].

The concept of multiple segmentation is very useful to get the region of interest [112]. The feature selection methodology of selecting the feature employs principal component analysis, the ABCD feature extraction [114] [115], and the classification using neural networks on various methods of neural network classifier [116]. Thus, the various algorithms are discussed to detect and classify the skin cancer technique.

3.1 Infrared Hyper-spectral Imaging

In infrared hyper-spectral imaging, the halogen lamps illuminate the part of the stomach. The radiations of the tissues are collected from the camera objective lens [72]. The radiations obtained from the slit will be anticipated to the prism grating prism components. Thus, the direction of propagation of the radiation varies following wavelength. A matrix detector measures each tissue point with monochromatic points [74]. This provides a continuous spectrum level along the direction of the spectral axis. A push broom scanner is used as the imaging technique [80].

3.2 Dynamic Infrared Imaging

Several noninvasive methods are taken as a research area for reducing the additional biopsies being performed. As these biopsies are found to be intrusive, they are painful. Digital dermatoscopy, video dermatoscopy, and Multispectral Imaging (MS) are some of the noninvasive techniques.[79][82].

3.3 Spectroscopic Methods

The study of how substances absorb, transmit, or reflect light is termed spectroscopy. Here, UV-Vis-NIR spectroscopy and a camera sensor with a CCD could provide images in UV, Vis, and NIR regions. It is also used in optical absorbance and reflectance measurements in 200-1500 nm wavelength. A substance can be distinguished by analyzing the light reflectance, as each substance has its unique reflectance [14].

The scattering and absorption properties of the skin tissue are replicated by the diffuse reflectance spectrum [28]. For examining non-melanoma-melanoma, diffuse reflectance-based approaches have been introduced. The DR spectroscopic device has the chief advantage of binary diagnosis of whether the cancer cells are present or not. The DR spectroscopic device is an effective monitoring technique that could be functioned with the minimal prerequisite of additional training [83].

Table 1 represents the comparison of various techniques for detecting skin cancer along with their advantages.

Table 1. Comparison of various techniques for skin cancer detection

Author	Techniques	Advantages
Jain.et.al (2012)	Feature Extraction Discrete Wavelet Transform Classification Probabilistic Neural Network	Statistically significant increase in radiologist screening efficacy.
Blackledge et al. (2008)	Segmentation Adaptive thresholding Morphological analysis	Effective result
Lau et.al (2010)	Classification Back Propagation Neural Network	Back Propagation Neural Network for auto-associative neural networks.
Angurana et.al (2019)	Feature Extraction ABCD Rule Classification Artificial Neural Network	This algorithm works fast.
Jain et al (2015)	Feature Extraction is done with features like ABCD features.	Mainly used for rural areas.
Victor et al (2017)	Preprocessing Median Filter Segmentation Otsu's Thresholding Feature Extraction Area, Mean, Variance, and Standard Deviation	As different classifiers are used, it gives a better result.
Suganya. et al (2016)	Classification Support Vector Machine (SVM)	Classification using SVM has provided better accuracy.
Jaleel, et.al (2014)	Segmentation Maximum Entropy Thresholding Feature Extraction GLCM Classification Artificial Neural Network	Improves accuracy
Alfred et al (2015)	Pigment Network Extraction	Helps to extract better features.
Jaworek-Korjakowska et al (2014)	Feature Extraction ABCD	The algorithm shows a better result.
Codella et.al (2018)	Segmentation Multiple segmentation	Better Result.
Alquran (2017)	Principal component analysis (PCA)	The accuracy obtained with low computational competency

Dubal, et.al (2017)	Feature extraction ABCD Classification Neural Network	Better Accuracy
Angurana et al (2019)	Feature Extraction ABCD Classifier Neural Network	Accuracy is better
Jain et.al (2015)	Neural network classification	The better result on neural network Increases the speed

3.4 Infrared Thermo-Graphic Images

The scattering and absorption properties of the skin tissue are replicated by the diffuse reflectance spectrum [28]. For examining infrared thermographic images, both thermal and perceptible images are being utilized to classify any lesion as malignant. Primarily a cooling unit has been used to minimize the temperature of the lesion and neighbor skin tissue [85][87]. So, the registration must be executed for each frame of infrared video with the aid of employing a projective transformation [84].

Figure 4 represents the camera setup, and Figure 5 depicts the visual representation of an RGB image and a thermal image.

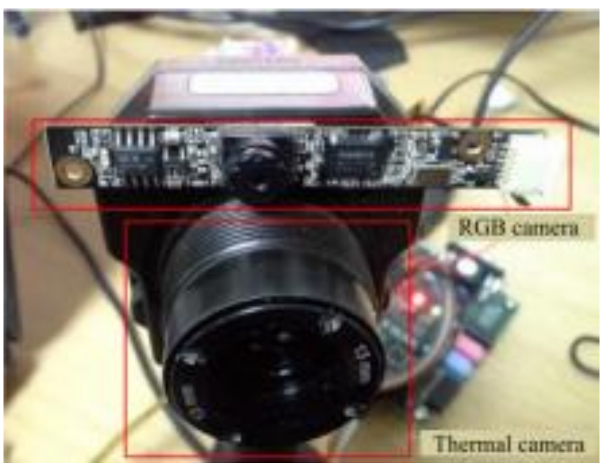

Fig. 4 Camera Setup

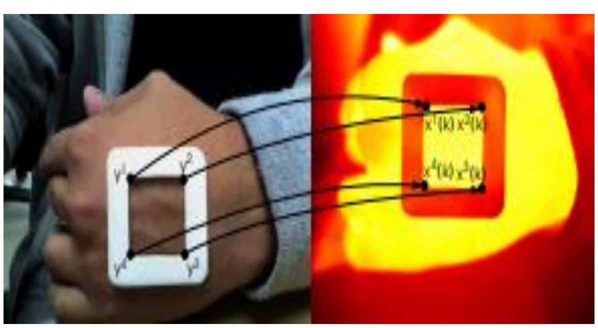

Fig. 5 RGB image and a thermal image visual representation

3.5 Gray level co-occurrence matrix (GLCM)

Each different class of skin cancer can be distinguished with the aid of several distinguishing features. A distinguishing feature from the skin cancer-affected image can be extracted using feature extraction. Once feature extraction is done, the necessary features for processing will be obtained [67]. In the GLCM technique, the RGB image initially gets converted to a gray-scale image. It will be fed as an input image to GLCM[39].

3.6 Extreme Learning Machine

An extreme learning machine is a type of feed-forward network which includes three-layer functions. The hidden elements are independent of the training data and target functions [102]. This is the main difference while related to some of the other networks. Progressive generalization performance is presented in this method as the hidden elements are found to be independent. The extreme learning machine learns quicker when compared to that the other learning algorithms. Also, simple math calculation is well adopted for this technique. This method is appropriate for resolving common disputes concerning traditional classic algorithms such as local minima and over-fitting. The process, execution procedure, and required time are lower in extreme learning machines than in BP and SVM. This method has no tuning of parameters except an insensitive parameter, L. This method has the advantage that several non-linear functions can be used. This technique necessitates additional hidden nodes than the BP technique and fewer nodes than SVM. Hence, the BP and extreme learning machine take only reduced time to classify unknown data than SVM [36].

3.7 Internet of Health Things-Driven Deep Learning

Internet of health things-driven deep learning is a good classification area in which cancer images can be processed. Two types of modules are deployed here. One model is known as the front end utilized .NET framework. MongoDB is used for storing algorithm extractor and classifier data. SOAP protocol served as a communication medium for transmitting messages from one device to another. The second model is the Python model, the chief factor concerning processing, detecting, and classifying any image. The first and the second model perform together with each other. While the .NET module executes the call, preprocessing will be accomplished in the input image of the skin. By means of histogram equalization, the outliers from the skin are eliminated. The segmented image features might be used as inputs to the various classifiers implored by the .NET module. The system stores the RGB or gray-scale image for preprocessing. In preprocessing, they observe images on a trained or pre-trained model to give an effective outcome [75].

3.8 Computer-Aided Diagnosis (CAD) System

Computer-aided decision support systems are well utilized [5]. For accomplishing diagnostic and predictive tasks, prediction models are employed. Based on the knowledge that institutes data acquired from various cases, these predictive models are assembled. As with the knowledge-based expert systems, the data can be preprocessed and conveyed in a set of rules. Therefore, this possibly will assist as training data for machine learning and statistical models [78]. Finding the position of a lesion and defining an appropriate estimation of the possibility of the occurrence of the disease are the major functions exhibited by a CAD system. The digital images retrieved from the ELM are the input image fed to the CAD system. They possess the probability of adding other acquisition systems such as confocal microscopy. The initial process to be performed is preprocessing. In this, the negative effects are minimized and other artifacts like hair. Then the detection of the lesion by the image segmentation process is carried out. Various morphological and chromatic features are measured and used for classification once the lesion is localized [36].

3.9 Fluorescence Detection System

Tetracycline (TCN) and Demeclocycline (DMN) fluorescence were mainly used in defining and perceiving non-melanoma-melanoma skin cancer. TCN and DMN have achieved 13% and 20% success rates. In cases when the cancerous area appears brighter than the normal skin, Fluorescence Polarization Image (FPI) was found to be 94% effective. When motivated by a polarized monochromatic light centered at 390 nm, the cancerous area becomes bright. FPI relates well with histopathology in terms of size, shape, and position of tumor existence. While a comparison was made between cancerous tissue and normal tissue, the typical value of polarization of tetracycline derivatives was principally higher in cancerous tissue [29]. Optical sectioning of the thicker tissue is empowered by imaging of tetracycline fluorescence polarization. This helps in permitting only superficial tissue layers. Fluorescence at diverse depths can be monitored with polarized light for skin [83].

The fluorescence measurements were accomplished using a special design of the DyaDerm 1 fluorescence detection system. This extremely sensitive digital fluorescence imaging system anticipates bulky skin area analysis. A 10-bit CCD camera is being used to record the resulting fluorescence signal. This camera will be mounted on an amendable stand, and it will be fixed to a system in which the DyaDerm 1 controls image acquisition and processing. Photobleaching of PpIX is minimized due to short, pulsed excitation [25].

3.10 Raman Micro-Spectroscopy

[37] Completely 42 spectra were tested. Before the research study, informed consent was accomplished from every patient respectively. Before surgical excision, appropriate measurements were taken from patients with well-known non-melanoma-melanoma skin cancers. The Raman spectrum was accomplished from the internal part of the tumor margin. This Raman spectrum was retrieved from the neighbor's non-affected skin once both sites had been dressed well using an alcohol swab. The non-affected dimensions were made at a minimal distance of 1 cm from the presumed tumor margin. At a depth of 40 mm beneath the skin surface using 30-second integration and 40M laser power, all the spectra were dignified for evaluation. The spectral measurement location was recognized by a spot of inedible link within the margin. For histopathologic correlation, this location was punch-biopsied [27].

3.11 Support Vector Machine (SVM)

The process of detection of cancer-affected cells in any image is performed with the aid of SVM. The feature extraction from the image is performed by using Gray Level Co-occurrence Matrix (GLCM). SVM also supports classification and regression analysis [40].

SVM includes a combination of supervised learning methods. The classification error is reduced, and the classification accuracy is enhanced in this technique [43]. Every data is plotted at its corresponding coordinates in an N-dimensional feature space. The testing samples are estimated as soon as the hyper-plane is determined [44].

A different decision boundary occurs as two classes are defined, such as melanoma and nevus. SVM specifies the decision boundary by having the most extreme separation from the two defined classes [49].

3.12 Clustering Classifier

A clustering classifier is widely used to detect whether the input image generated is cancerous or not. Clusters are made used in classifying and identifying a cancerous image. The function of the cluster is to group the objects in which the objects in the same clusters are more similar to those found in other clusters. In skin cancer classification, Centroid based Clustering algorithm is being used. In this method, the clusters are recognized by a central vector. This may not be adequately a member of the same dataset. There are two types of classifications made, such as cancerous and non-cancerous, so only two numbers of clusters are fixed. The value of feature_vect is extracted from discrete wavelet transform in the centroid-based clustering technique. Then it computes the mean value, finds out the cluster centers, and allocates the objects to the adjacent cluster centers. In this way, the squared distances from the clusters are curtailed. The known data are provided in the training phase. The classification process is executed in the testing phase with unknown datasets by employing a clustering classifier [34].

3.13 K-Nearest Neighbor (KNN)

KNN is a machine learning algorithm. It helps classify the new training values by having the existing ones centered on a parallel constraint. Euclidean distance is being deployed to estimate the space between the attributes of training and testing data points. As KNN consumes all its resources to compute the value of the features, this persists as a major drawback of KNN [48].

In KNN, they train the test and training samples and load them into the database. These samples are characterized by estimating the nearest diameter to the preparation case. Then it conducts the classification of the samples. By fascinating the k adjacent position and asserting the mainstream signal, the KNN classifier extends this idea. Selecting k values is unique. Greater k values help in reducing the noise level in pixels rate in the training dataset. The selection of a subset of training data is the major concern in this method [54].

Table 2 represents the comparison of various skin cancer classification techniques along with their advantages and disadvantages.

Table 2. Comparison table of skin cancer classification techniques

Technique Used	Advantages	Disadvantages
Backpropagation Neural Network [91]	Weight Adjustment	Slow convergence rate Trapping in local minima
Convolution Neural Network [92]	Reduces the necessity of segmentation process and feature extraction independently	Time-consuming in case of a big dataset
ABCD rule [93]	Simplicity	Diameter of lesion < 6mm, this ABCD rule is not used
Neuro-Fuzzy system [94]	Accurate outcome by incorporating fuzzy values	
Hybrid Artificial Neural Network [95]	Resolves concern of local minima found in backpropagation neural networks	Highly complex system
Hybrid of Genetic algorithm and Artificial Neural network [96]	Genetic algorithm used to avoid local minima position	
K-means algorithm [97]	Clusters are used in identifying patterns No additional data required	Less accurate while compared to SVM and neural networks
SVM [98]	Accuracy	While compared to a random forest classifier, SVM cannot handle categorical data.
Visible and Near-Infrared Imaging [14]	The six-band camera can acquire both three Vis spectrum images and three other NIR spectrum images.	Costly
Multi-class Support Vector Machine [81]	WLS filter performs preprocessing	Complexity

4. Conclusion and Future Work

The presented review work discusses several detection and classification techniques employed for skin cancer. Melanoma cancer detection includes different phases like image preprocessing, segmentation, feature extraction, and classification. Several strategies like Genetic algorithm, SVM, ANN, CNN, KNN, Fluorescence Detection System, Raman Micro-Spectroscopy, Computer-Aided Diagnosis (CAD) System, etc., are discussed.

As discussed in this review, each algorithm owns its specific advantage and limitations. Conversely, among the analyzed techniques, SVM possesses reduced limitations. Also, SVM outweighs other techniques. Classification based on neural networks is found to be efficient and advanced. Convolutional neural network models perform classification independently without image segmentation and feature extraction. Input images are given directly to the CNN model and continue the classification process robotically. Thus, the review techniques for detecting and classifying skin cancer explain the advantages and disadvantages of various components. It also deals with the various techniques and explains the techniques that deal with preprocessing segmentation, feature extraction, and classification. Thus, the comparison is made, and various techniques are discussed based on the skin cancer detection and classification methodologies.

This research paper tackles a comprehensive overview of the last update in this field. Many popular algorithms are investigated, and a comparative analysis of these techniques is presented. It can be useful for researchers in this field as it covers the most recent skin cancer detection and classification techniques in one research paper. Further research work on skin cancer focuses on improving classification outcomes and accuracy by incorporating hybrid approaches with respect to appropriate skin characteristics.

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