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IMAGE PROCESSING BASED EARLY DETECTION OF SKIN CANCER UTILIZING MODERN DEEP LEARNING APPROACH

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Abstract— Skin cancer is the most common sort of cancer that affects people. The continued global rise of this malignancy, the expensive expense of treatment, and the high fatality rate have made early detection of this disease a top priority. When found early, the majority of skin cancer cases are treatable. The survival rate would be significantly higher if skin cancer could be found in its earlier stages, saving patients' lives. Despite the significant amount of work that has been done to improve it, skin cancer detection still has many critical problems. To find melanomas, many people have been developing automated systems. The ability to identify skin cancer early has become more common because to technological breakthroughs. The potential benefits of these investigations are huge and unthinkable. Additionally, there are several issues, making the recent contributions made in this field particularly valuable. On the other hand, it is generally accepted that higher levels of confidence and dependability are needed for more precise detection systems. The creation of an autonomous skin cancer classification system is one of the many components of an automated diagnosis of skin cancer. Additionally, using a variety of preprocessing methods, the association between images of skin cancer and different kinds of neural networks is examined. The system takes the captured photographs and goes through various image processing procedures to improve the image's quality. The injured skin is removed from the area after the cancer cell has been removed, leaving only the picture. The classification system can then be fed data that can be retrieved from these photos and used to train and test it. The back-propagation neural network (BNN), the auto-associative neural network (AANN), and the convolutional neural network (CNN) are the neural networks that are employed as classifiers. The recognition accuracy of a three-layer back-propagation neural network classifier is 91%, that of an auto-associative neural network is 82.6%, and that of a CNN is 94.5% in an image database that contains both dermoscopy photographs and digital photos. MATLAB examination of earlier research.

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

I. INTRODUCTION

Everyone has seen an upsurge in the frequency of skin conditions in recent decades (Barati et al. 2011). Numerous variables might contribute to the onset of different diseases, and normally, each age group experiences a unique set of symptoms. Mould and bacteria can thrive in warm, damp, and humidified environments. The skin will become more sensitive as a result of lengthy and sustained exposure to excessively high amounts of UV radiation from the sun, which will also make it easier for infections to spread and may result in skin issues. Internal sebum glands, dead skin, and sweats are additional contributors in addition to the external illnesses. It's possible for it to cause more serious skin diseases and illnesses when mixed with dust and other unpleasant secretions. The epidermis, dermis, and subcutis, which are each revealed to have distinct roles and optical properties in Figure 1, are the three layers that make up the human skin, the biggest organ in the body. Keratinocytes, which are pigmented cells, make up the epidermis, which is rather thin. These cells' bodies create keratin, a substance that helps the skin shield the rest of the body [1-2]. Melanocytes, which are the cells that produce melanin as their byproduct, also call the epidermis home. Melanin is a pigment that gives human skin the appearance of being brown or tanned. It serves as a screen to protect the deeper layers of skin from sun exposure and the potentially harmful effects that UV radiation can have since it has a strong absorption of light in the ultraviolet and blue regions of the visible spectrum (UV).

Basal cells, which make up the basal layer, the deepest layer of the epidermis, are constantly dividing to create new keratinocytes to replace the older ones that are lost as the skin's surface ages. The central layer of the skin, known as the dermis, is substantially thicker than the epidermis. Additionally, it has blood arteries, nerve endings, sweat glands, and hair follicles. The word "stratum corneum" refers to the epidermis' outermost layer, which serves as a barrier of protection and is made up of dead keratinocytes that are continuously being replaced by new ones. According to Melanoma 2016, Maglogiannis, and Doukas 2009, pigmented skin lesions can be categorized as either melanocytic or nonmelanocytic based on whether or not melanocytes are the source of the lesions [3].

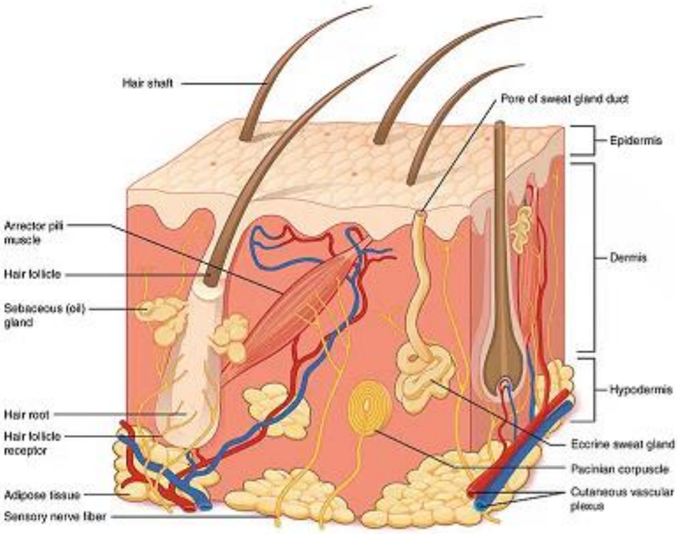

Figure 1: Structural representation of skin

The threat to people around the world from skin cancer, one of the top causes of mortality, is global. If this cancer is discovered in its early stages, it may be cured. The relevance of skin cancer early detection has been viewed as a crucial issue in light of the rise in statistical evidence for the disease, and computer-based diagnosis is an important tool for this goal. Concern from a variety of sectors has been raised about skin cancer early detection. The knowledge of human skin and the various methodologies for detection systems are required knowledge in this area because the work presented in this thesis focuses on the automatic detection system for skin cancer.

Epidermis and Dermis are the two main layers in human skin which are described as follows [4]:

Epidermis: Squamous cells, which are flat skin cells, make up this layer, which is the top layer of the human skin. Basal cells are the rounded cells that lie beneath squamous cells. Melanocytes, which are situated between basal cells in the epidermis' deepest layer, are a type of cell. Skin's pigment (colour) is produced by melanocytes.

Dermis: Dermis, which is situated beneath the epidermis, is the second major layer of skin. It contains a variety of cells, including glands, lymphatic veins, and blood vessels. Some glands aid in skin drying, while others assist in cooling the body and producing sweetener. The skin's layers and cells are depicted in figure 1.

Each living cell in the human body numbers in the trillions. In healthy bodies, these cells develop, divide into new cells, and die in a controlled manner. Adults divide their cells to replace ageing, damaged, and also dead cells. Cancer develops when an area of the body experiences an uncontrolled growth of aberrant cells [5]. Invasion of other tissues is also possible as a result of the proliferation of cancer cells [6].

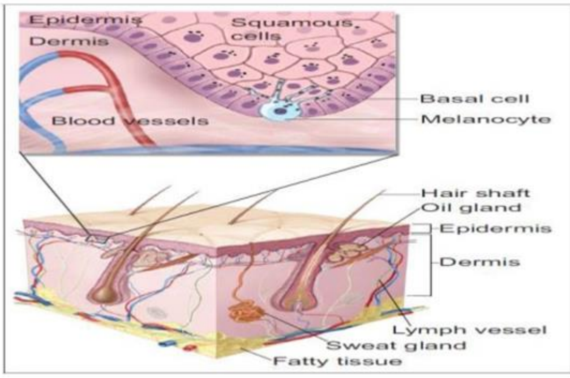

Figure 2: A squamous cell, basal cell, and melanocyte and epidermis and dermis layers in Human skin

Cancer cells typically form tumours, although in some malignancies, including leukaemia, tumour formation is sporadic. These malignancies' cells can be discovered in the bone marrow and blood. Not all tumours are cancerous; some are benign and can enlarge, cause issues, and put strain on healthy organs. They cannot infiltrate other tissue [7].

The most prevalent kind of cancer in humans, skin cancer, starts there [8]. Although some cancers can begin in other organs before spreading to the skin, these malignancies are not thought of as skin cancers [9]. Malignant melanoma and non-melanoma skin cancer (NMSC), the latter of which includes Basal Cell Carcinoma and Squamous Cell Carcinoma as the principal subtypes, are two of the most prevalent categories for the various types of skin cancer.

Skin cancer is the collective term for several different forms of skin cancer, including melanoma, basal cell, and squamous cell (Antkowiak 2006, De Sousa Lé 2015, Skin cancer 2015). The most dangerous skin condition worldwide among the numerous others is skin cancer. The fact that melanoma is the deadliest type of skin cancer and that its prevalence has been continuously increasing worldwide makes it a very important and worrisome public health issue. Malignant melanoma cases were predicted to have increased to 76,100,000 in 2014; 9,710,000 persons lost their lives to the illness. Less than 2% of cases of skin cancer are caused by melanoma, but it is the cause of death for almost all skin cancer patients. The lifetime risk of the ailment in the white population is 2.4%, which is far higher than the lifetime risk of the condition among African Americans, which is 0.1%. The rates at which it occurs have been gradually increasing for at least 30 years. Each year, 132,000 new instances of melanoma skin cancer are discovered worldwide, compared to 2 million to 3 million non-melanoma cases. One out of every three cancer cases that are discovered, according to the American Cancer Society, is skin cancer. Data from the foundation show that one in five Americans will have skin cancer at some point in their lives. 2016 (INTERSUN).

Malignant melanoma: One of the types of skin cancer that is on the rise globally and that kills 65% of its victims is malignant melanoma. In the UK, the number of melanoma patients increased between 1991 and 2000 by 59% in males and 41% in women, respectively. The anticipated incidence of skin cancer and melanoma in Australia in 2010 is 11,500 and 1500, respectively. The high incidence of both melanoma and non-melanoma skin cancer in Australia makes it a prime location for this field of study. [10, 11] It is derived from epidermal melanocytes and can develop in any tissue that has these cells. However, it most frequently appears on the lower limbs of females and the back of men. Since it happens on the skin's surface, ocular inspection can identify it. The nature and location of the tumour will affect the clinical presentation. Malignant melanoma sample image is shown in Figure 3 [12].

Figure 3: Malignant melanoma [15]

Phenotypic characteristics include sun exposure patterns, infrequent exposure to the sun, and UV radiation can all lead to malignant melanoma. Other risk factors include having fair skin and a first-degree cousin or close friend who has had malignant melanoma [13]. Malignant melanoma varieties include [14]:

Superficial spreading and nodular melanomas: The lesions are commonly asymmetrical with irregular border. It has more than one colour and the diameter is more than 0.6 cm. It may be swollen and ulcerate.

Lentigo maligna and lentigo maligna melanoma: It usually occurs on the face in elderly patients. It looks like a large and irregular mole which tends to grow slowly.

Acral lentiginous melanoma: It usually occurs on the skin of palms and soles which doesn't have any hair. It almost diagnosed late, thus have a poorest prognosis among other types of malignant melanoma.

Amelanotic melanoma: It usually prognosis false. The correct diagnosis is determined after biopsy.

Non-melanoma skin cancer: The main two types of non-melanoma skin cancer are [14, 15]:

Basal Cell Carcinoma: It is the most common malignancy in different countries. It occurs in different parts of shoulders, ears, face, back, and scalp. Its clinical appearance is different according to the type and site of tumour.

Nodulocystic basal cell carcinoma: It is small, pearly nodule, translucent and often with surface telangiectasia. As the lesion is magnified, it usually ulcerates to make a rolled edge and adherent crust. Figure 1.5 is a sample of nodulocystic basal cell carcinoma.

Figure 4: Nodulocystic basal cell carcinoma

Superficial basal cell carcinoma: It is scaly, plaque and pink which grows slowly. It is usually appear on the trunk. The telangiectasia and rolled edge are usually observable by good light. Figure 1.6 is a sample of superficial basal cell carcinoma.

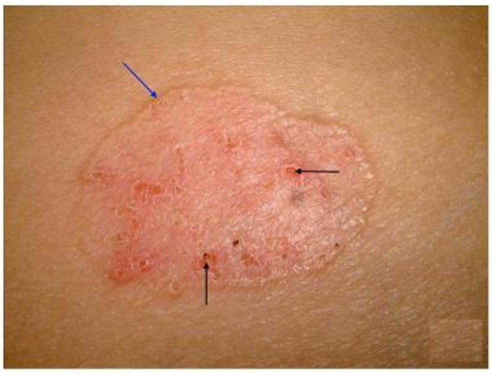

Figure 5: Superficial basal cell carcinoma

Sclerosing (morphoeic) basal cell carcinoma: It is scar-like plaque which the edge is poorly specified. It is a white lesion with a slowly expanding. Figure 1.7 is a sample of sclerosing (morphoeic) basal cell carcinoma.

Figure 6: Sclerosing (morphoeic) basal cell carcinoma

Squamous Cell Carcinoma: It is usually appeared in chronic solar damage include scalp, dorsum of hand, lower lip, forearm and ear. It starts from small and crusted plaque and becomes indurated and nodular. It is almost with ulceration. Figure 1.8 is a sample of Squamous Cell Carcinoma.

Figure 7: Squamous Cell Carcinoma

II. LITERATURE REVIEW

By identifying the clusters together with the neutrosophic c-means clustering (NCM) for the input dermoscopy pictures, Amira Ashour et al. (2018) suggest a method histogram-based on the data for effective skin lesion diagnosis. This improves the effectiveness of skin lesion detection. To group the pixels, first convert the dermoscopic images to neutrosophic-based features. Both the h-v and v-h approaches are employed in the HBCE algorithm's calculations. The implementation is done with the aid of the ISIC 2016 public data set, which uses 379 images for testing and 900 images for training. The ISIC 2016 data sets must be considered when doing the evaluation since they demand efficient training and testing based on the availability of ground truth photos. The work that has been proposed has produced results that are better than those of the traditional approach NCM without HBCE. In a two-stage method that includes pre-processing and segmentation, Seetharani Murugaiyan Jaisakthi et al. (2018) describe a semisupervised learning strategy for autonomously segmenting lesions in line with the provided photos produced from dermoscopy. The bi-linear interpolation method is used for image scaling during the pre-processing stage; the CLACHE algorithm can be used to improve the image's uneven illumination. After then, a Frangivesselness filter was used in an inpainting process. To get the required result, FMM are used in place of the hair pixels. The segmentation approach is described as being used to identify the lesion zones based on the uniformity of pixels, such as colour and texture properties. In order to segment the foreground image and identify the approximate lesion sites, the GrabCut approach makes use of the border and region information. The accuracy of these regions is then increased by using k-means clustering, which groups pixels based on the RGB colour space and aims to forecast the precise lesion regions. Deep learning techniques can be used to improve the dice co-efficient values in order to increase accuracy, and this is something that is currently being researched for future research.

Simplifying the goal of the analysis and making use of some kind of hypothetical information about the imaged structures is one of the greatest ways to get around the difficulties that were described earlier in the context of automating the diagnosis of medical imaging conditions. The information that has to be analysed can be anatomical knowledge about the structures' typical look (such as shape and grey levels) and position, or it can be statistical knowledge about the structures' attributes (such as the grey level of the tissues that are contained in those structures). After that, the pictures can be sorted according to their morphological, colour, fractal, and texture characteristics respectively. In his work, Laws, 1980 processed digital images to identify regions of interest and provided an input dataset for segmentation and features detection operation. This was done in digital images.

The method that Sahar Sabbaghi and her colleagues (2018) suggest is referred to as the Quad-Tree method. The melanoma detection method is an expert colour evaluation model that is accurate. This model produces colour observations, which make it possible to readily categorise the lesion as one that is either non-cancerous or cancerous. In this post, the terminology that were utilised in the investigation were explained. During the pre-processing phase, there is an increase in the contrast between the lesion and the background areas phase. This is because the contrast between the melanomas and the concentric quartiles and the Euclidean distance is at its highest during this phase. The utilisation of has a good effect on the lesions that have a lower colour contrast procedures in morphology, such as the top-hat operation and the bottom-hat operation. This is due to the fact that it improves the colour contrast of the lesions. The hybrid thresholding approach is a strategy that is helpful in the detection of lesion borders after they have been exploited; the procedure of segmentation may be split down into two different parts. In the earlier step, a modified form of the Otsu test was employed to determine the threshold for the core lesions, and in the latter stage, which makes use of an adaptive histogram function, the core lesion region ends up becoming enlarged along the radii. The regulation is analysed in relation to a number of different classifiers, and the results demonstrate that the SVM classifier has the highest overall performance when measured using the characteristics of the ROC curve.

Amira Soudani et al. (2019) advocate for the use of a segmentation recommender in order to minimise the training period based on the information gathered from the public and the transference of one's knowledge. Two examples of models that have already been pre-trained are the VGG16 and VGG19 architectures. The ResNet50 convolutional layers have been developed, and they are currently being utilised in the process of feature extraction. The CNN is a classifier that consists of five nodes, and each of them reflects a different part of the data segmentation methodologies that are evaluated, and then an output layer is produced according to the results of those considerations. The By utilising both, it is possible to recognise local characteristics from a wide variety of locations by analysing the three-dimensional structure of images acquired by dermoscopy. As a result of the outcome, I have arrived at the conclusion that the methodology that was presented accurately predicts the segmentation method for finding skin abnormalities and lesions.

Walker et al. (2019) examines the CNN architecture and shares their findings. It expands even further and deeper into the convolution layers in order to accommodate inception v2 network to determine whether the dermoscopic images are benign or malignant. An iterative approach is utilized for the training of the inception v2 parameters. Within the scope of deep learning, there is a method that is called stochastic decent gradient. The process of evaluation results in a variety of distinct kinds of outcomes from pictures obtained by dermoscopy, including sonification and visual characteristics. As shown by the study, findings suggest that teledermoscopy, a form of imaging, is capable of achieving enhanced precision and a highly sensitive cancer detection for both pigmented and nonpigmented skin. The outcome of the sonification process results in the formation of non-pigmented lesions.

Particle Swarm Optimization (PSO), which is utilized by Teck Yan Tan et al. (2018), is utilized for feature optimization, which is necessary for skin cancer diagnosis using dermoscopy images. The proposed approach specifies several stages, including pre-processing, skin lesion segmentation, feature extraction, PSO-based feature optimization, and classification, among others. The initial population is split into two sub swarms, and the leader of each sub swarm then directs the search for the optimal solution for the entire population by focusing on avoiding less desirable options. This technique incorporates local as well as global food and adversary signals, attraction, mutation-based exploitation, and is also capable of attenuating premature convergence of the PSO model. Three different types of random walks, including the Gaussian, Cauchy, and Levy distributions, are used to improve the sub-swarm leaders. Utilizing the dynamic matrix representation and probability distribution allows for an extremely broad range of search possibilities to be explored. The proposed method demonstrates higher improvement in the classification of melanomas in addition to the resolution of uni-modal and multi-modal benchmark issues. The Wilcoxon rank sum test is used because it allows the proposed algorithm to be even better.

Anuj Kumar et al. (2018) conduct a comparative investigation of various methods of image segmentation. The analysis and classification that go into segmentation are processes that the process of identifying significant elements or things that are displayed inside the image. The discontinuities of the edges are represented by edge based segmentation, which is a crucial characteristic for image analysis and reflects the discontinuities in terms of intensity. Calculating the threshold value for an image and then comparing that with the value of a pixel are the two steps that make up the canny edge detector's process for getting rid of broken edges in an image. The greater pixel value leads one to the conclusion that an edge must be present; otherwise, the hypothesis cannot be supported. It is necessary to enclose the region that was chosen for the region-based segmentation. Preprocessing is the first phase of the watershed transform. This step helps generate a well-segmented image by lowering the amount of noise in the image and adjusting the intensity of it while still maintaining the information contained in the image. Therefore, we can draw the conclusion that the edge detector is accurate offers the highest possible performance through the use of regional growth, which When opposed to separating and merging regions, the segmentation procedure is significantly faster.

Andre esteva1et al. (2017) discusses automatic classification of due to the fine-grained primary diagnosis of melanoma that can be done through initial screening and followed by dermoscopic analysis such as biopsy and histopathological examination, analyzing lesion images is considered to be a challenging task. This is because the primary diagnosis of melanoma can be done. The classification of skin lesions is accomplished through the use of a single CNN that learns the images from beginning to end by taking into consideration disease labels and pixel values. Therefore, the method CNN obtains higher performance in the identification of the most prevalent malignancies as well as the skin cancer that kills the most people. This leads researchers to the conclusion that AI is capable of classifying skin cancer with improvement when compared with dermatologists.

The most crucial part of an automated computer-aided diagnosis system is presented by Euijoon Ahn et al. (2017) and involves the detection of melanoma using segmentation of the body's lesions. Common phrases and some segmentation techniques have various technical shortcomings that lead to poor segmentation performance of the skin lesion. Uncertain lesion margins, little contrast between the lesion and the surrounding skin, and lesions that contact the imaging edges are some of these defects. To correct the mistakes, saliency-based segmentation techniques that are derived from sparse representation models are combined with unique background detection techniques. These techniques allow for a more precise classification of the lesion from the surrounding skin regions. To more clearly distinguish the lesion from the surrounding skin areas, this is done. The suggested Bayesian framework allows for a clearer definition of the lesion's structure and boundaries. On two publicly available datasets, the validation procedure is carried out by comparing it to other contemporary and cutting-edge lesion segmentation techniques as well as contemporary unsupervised saliency detection techniques. This is carried out in order to evaluate the method's efficacy. As a result, we can infer that the suggested strategy is preferable to the other options. The saliency optimisation algorithm for the lesion segmentation work that has been done has room for improvement.

III. METHODOLOGY

The purpose of this research is to propose contributions in different stages of this system. The algorithms try to speed up the detection with less error than other traditional ones. It is intended that the proposed algorithms have contribute in public health systems and help medical experts to screen skin cancer detected in early stages.

In summary, the topic of discussion can be categorized in stages as illustrated in figure 8:

- Pre-processing (Image algorithm)
- Segmentation process
- Feature extraction and Selection
- Classification

Generally, the results are analyzed by comparing the proposed algorithm with the existing ones to prove the accuracy of results and reducing the computational cost.

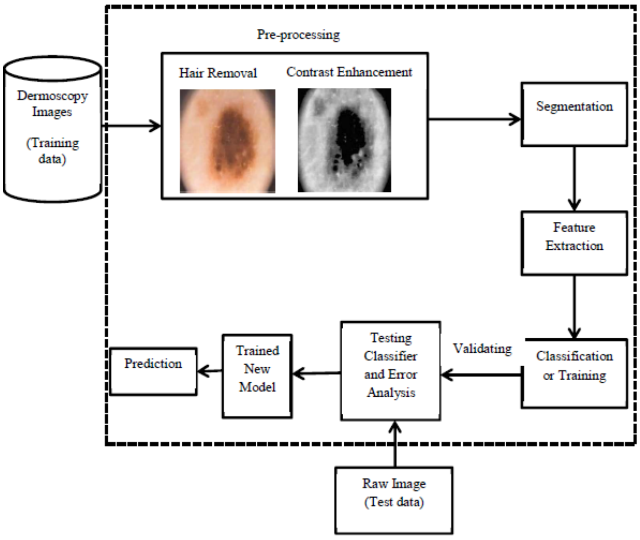

Figure 8: Skin Cancer detection system methodology

An intelligent decision procedure using a modified version of the CNN approach was proposed for the classification of normal, benign, and malignant on the basis of this body of data. The accumulation of numerous types of damage leads to melanoma, a serious and occasionally fatal form of skin disease. Figure 9 gives a graphic depiction of these integrated methods in the form of a block diagram for the detection of melanoma skin cancer. The integrated methods are included in the suggested model. The majority of the space in the next section will be devoted to a discussion of the crucial procedures involved in the identification of melanoma [12-14].

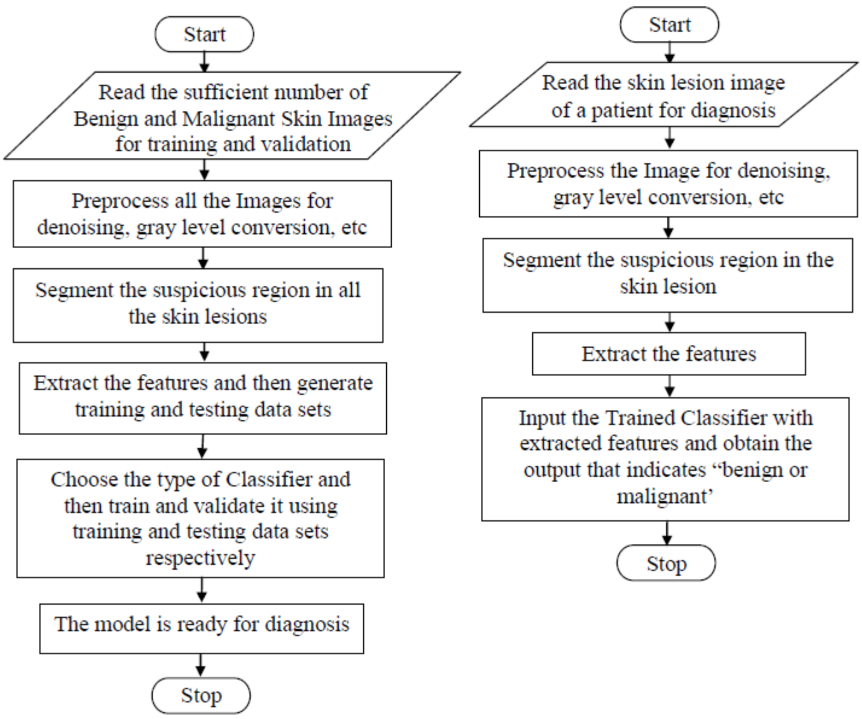

Figure 9: Computer Aided Diagnostic System (CADS)

The model is initially created by leveraging an existing set of image data to train and validate a classifier. The model will be prepared to be utilised for diagnosis once it has been trained and confirmed. The flow of processes that take place during the development of the CADS as well as its use for diagnosis are explained by the flow charts in Figures 9(a) and 9(b), respectively. These procedures involve image preprocessing, segmentation of the suspicious area, feature extraction, and classification.

Pre-processing

The capture of the tissue digital image for skin cancer detection is the initial stage in expert systems used for skin inspection. Typically, air bubbles, noise, and small hairs can be seen in skin cancer photos. These characteristics, which are not a part of cancer cells, would lower the precision of border identification or segmentation. Applying image processing techniques to the photos is the first thing to perform. Therefore, pre-processing used to refer to removing the undesirable skin features, and post-processing used to refer to improving the contour of the image.

To accomplish these objectives, various techniques are utilized, including the Karhunen-Loève (KL) transform histogram equalization and various filter types. Additionally, contrast enhancement can brighten the edge of the image and increase segmentation accuracy. since both digital photos and dersmocopies are included in the picture database. These photos have non-standard sizes and were gathered from various sources. The image must first be resized to have a fixed width of 360 pixels but a variable height. The second stage is to clean up the images' background noise. Here, wavelet de-noise via two-dimensional bior3.3 wavelet is the technique employed. An improved linear wavelet used in image reconstruction and decomposition is called biorthogonal (bior).

Segmentation Process

The improved skin image is split at this step to distinguish the tumour from the surrounding skin. Segmentation discovers the region of interest while removing the image's healthy skin. After segmentation, the cancer cells typically remain in the image. Threshold segmentation is the type of segmentation utilised here. Thresholding offers a simple and practical method for segmenting an image based on the various intensities or colours in the foreground and background areas. An image in grayscale or colour is often used as the input to a thresholding process. The result of segmentation is a binary image. The process of segmentation involves scanning the entire image pixel by pixel and categorising each pixel as either an item or a background based on its binarized grey level.

The two fundamental features of intensity values discontinuity and similarity are the foundations of segmentation algorithms. The first category is to divide an image based on sharp contrast changes, such as image edges. The second category is based on dividing an image into regions based on shared characteristics determined by predetermined criteria. This group includes the Histogram Threshold method.

Since the majority of cancer cells have a nodular shape, the intriguing characteristics of melanoma are incorporated inside the border. For a precise diagnosis, the boundary structure provides crucial information. The border is used to determine a number of clinical characteristics, including asymmetry and border irregularity. In this thesis, statistical region merging (SRM) and threshold are implemented, and their accuracy is compared to that of a neural network classifier.

Feature extraction and Selection

At this stage, the important features of image data are extracted from the segmented image. By extracting features, the image data is narrow down to a set of features which can distinguish between Malignant and Benign melanoma. The extracted features should be both representatives of samples and detailed enough to be classified. 2D wavelet transform is used for the feature extraction. In this system, 2-D wavelet packet is used and the enhanced image in gray scaled as an input.

Assume a digital image sized M x N pixels is transformed by the discrete wavelet, produced by the level decomposition, The result of the decomposition L and H stand for low and high frequency components. FL and FH represent low-pass and high-pass filters. Perform discrete wavelet transform to the image. LL(0) is the original image. LH(1), HL(1) and HH(1) are the output of high-pass filter that's represent the horizontal details, vertical details and diagnosing details. LL(1) represents the approximation with the same size of LH(1), HL(1) and HH(1) that's use to perform the second-level decomposition.

Classification

An artificial neural network, or ANN, is a statistical and nonlinear method of prediction. It draws influence from the organic structure of the human brain for its design. Three layers of neurons make up the structure of an ANN. The first layer, often known as the input layer, contains input neurons. These neurons transmit information to the second layer of intermediate neurons. There is no distinction between "hidden layers" and "intermediate layers." Multiple levels of complexity may be hidden by a traditional artificial neural network (ANN). The intermediate neurons send the information gathered by the input neurons to the third layer of output neurons. In order to understand the complex relationships and linkages between the input and output layers, backpropagation is used. This makes it possible for each layer to learn the computations. In numerous ways, it is similar to a neural network. In the field of computer science, the phrases neural network and artificial neural network are often used interchangeably.

Convolution neural networks, one of the most significant subgroups of deep neural networks, are widely used in computer vision. The three main applications of this tool are picture categorization, image recognition, and the construction of a set of input images. By adding up simpler characteristics like curves and edges to build more complex features like forms and corners, CNN is a useful tool for gathering and learning both local and global data [15]. CNN is an excellent resource for gathering and studying both local and international statistics. The elements that make up CNN's hidden layers are convolution layers, nonlinear pooling layers, and fully linked layers [29]. With CNN, there might be a lot of convolutional layers followed by a lot of fully linked layers of data. The three main types of layers that are used to create CNN are convolution layers, pooling layers, and full-connected layers [16].

A CNN is a part of the neural network we previously mentioned. As in a standard neural network, the system consists of one or more fully connected layers that are followed by one or more convolutional layers, occasionally with a sub sample layer. The discovery of a visual brain process, the visual cortex, served as the impetus for the development of CNN. Numerous cells in the visual cortex, collectively known as the visual field, perceive light in condensed, overlapping areas of the visual field. The more advanced cells function as local filters throughout the input space and have larger receptive fields. The convolutional in a CNN performs the function of the brain system's cells [17]. A typical CNN for recognising traffic signs is shown in Figure 4. Each layer's feature receives information from a set of traits arranged in a small area known as the local receptive field in the layer above. Using local receptive fields, characteristics can extract fundamental visual properties such oriented edges, end-points, corners, and so on, which are then integrated by the protocol stack. In the traditional idea of pattern/image recognition, a hand-designed feature extractor collects significant data from the input and eliminates unnecessary variations. A trainable classifier, a common neural network that categorises feature maps, is employed after the extractor.

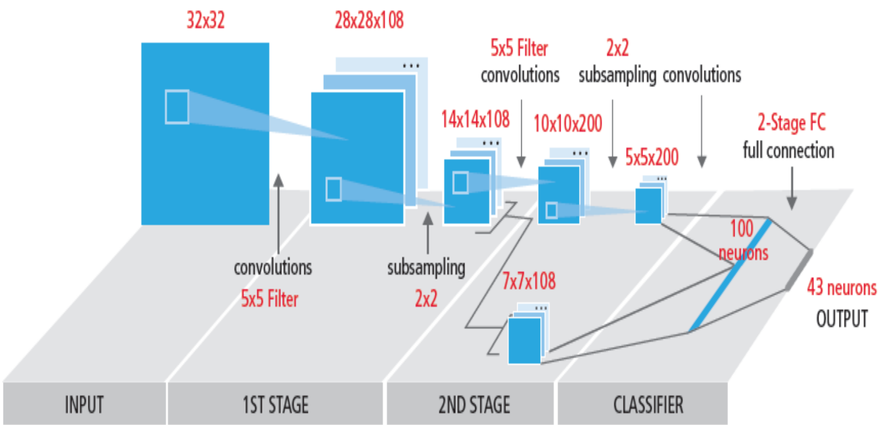

Figure 10: Typical block diagram of a CNN

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. RESULTS & DISCUSSION

Results of Pre-Processing

In this section, the different filters on different noises have been experimented to get the better filter for improving the images quality. This process obtained to true identification of skin cancer. Figure 5.1 and figure 5.2 show as true difference of skin cancer. Figure 5.1 show a true detected image of skin cancer. It is clear and real image of skin cancer.

Figure 5.2 show a false image of skin cancer. It is clear image but not observed a real symptom of skin cancer.

Figure 11: True Identification with/without skin cancer

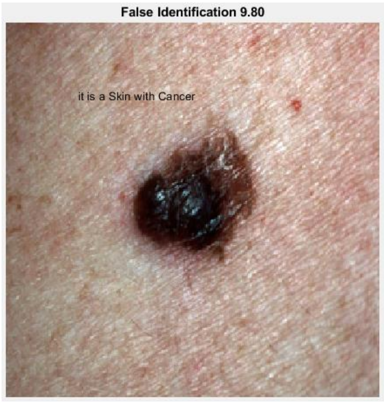

Figure 12: False Identification of skin cancer

Results of Segmentation process

Segmentation is accomplished by scanning the whole image pixel by pixel and labeling each pixel as object or background according to its gray level. This thesis computes segmentation by SRM.

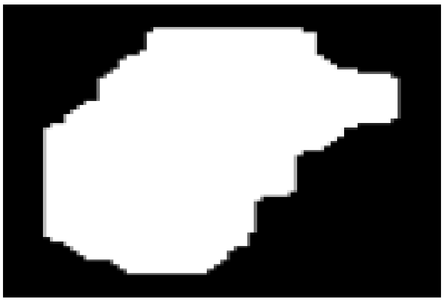

Figure 13: Segmentation from SRM

Results of Feature extraction and Selection

This step of thesis intends to rank the available extracted features by attention to their impact on skin cancer detection.

Figure 14: Gray image and BW image composition

Figure 15: DWT Gray image and DWT BW image composition

Result of classification

Two neural networks are used as classifier, Back-propagation neural network (BNN), Auto-associative neural network (AANN) and CNN. We obtained training image with simulation of MATLAB. These obtained training images to compare at different layer.

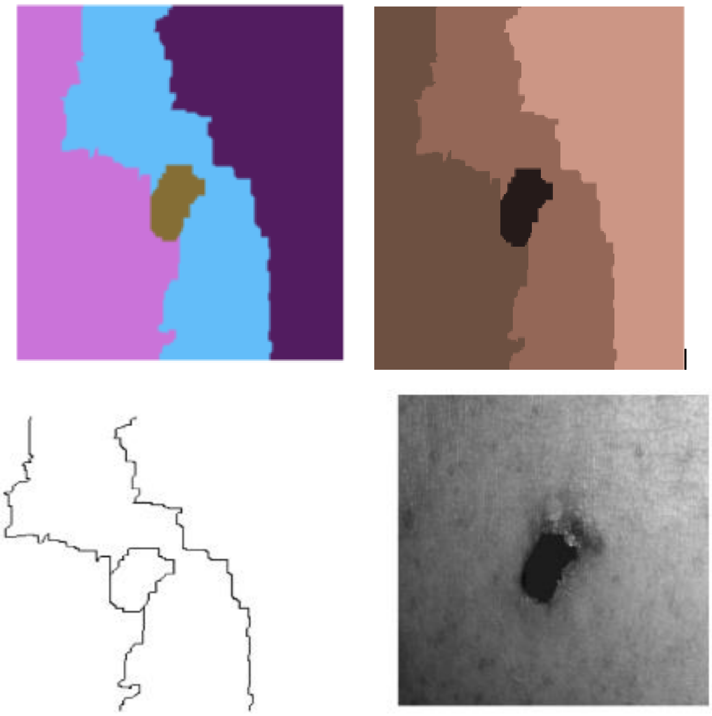

Figure 16 : Some training image results of detected skin cancer

Results of BNN classifier

Table 5.1 shows as a best result with highest overall accuracy is 90.2%. The best BNN is three hidden layer with 40, 25 and 10 neurons for each hidden layer. The accuracy is increase with number of neuron in hidden layer. However, number of hidden layer cannot improve the result but it could reduce the probability of over-fitting.

Results of AANN classifier

The best AANN testing result found is 20 neurons in the first and third layer with overall accuracy 81.5% as table 5.2 illustrated. Unlike BNN, ANN provides a stable classification result in different number of neuron. However, when the layer 1 and layer 3 have different size of neuron, the classifier result has a significant low accuracy diagnosing result.

Table 1: BPNN classification results with different layers

No of Layer	No of Neuron	Training (%)	Testing (%)	Validation (%)	Total (%)
1	10	82.5	55.6	63.7	74.5
1	20	98.3	60.6	61.5	88.7
1	30	100.1	52.3	77.2	90.4
1	40	98.7	51.6	75.7	87.5
2	10,5	80.5	47.8	54.8	67.6
2	20,10	97.6	52.4	73.5	88.7
2	30,20	98.2	55.8	72.9	85.4
2	40,20	98.6	51.5	75.2	86.6
3	10,8,6	95.4	60.6	67.4	88.4
3	20,12.8	97.6	62.4	76.5	89.7
3	30,20,10	97.5	61.2	71.8	87.3
3	40,25,10	98.8	63.4	78.9	92.3

Table 2: CNN classification results with size of neurons

Layer 1 to 4	Training	Validation	Testing	Total
10, 4 10, 4	88.9	59.6	72.3	78.7
10, 5 10, 4	84.5	57.8	68.6	74.6
20, 4 20, 4	89.8	59.9	71.4	77.4
20, 10 20, 10	91.4	64.4	70.8	83.6
30, 4 30, 4	91.6	59.5	73.3	78.2
30, 10 30, 4	88.8	57.7	65.4	79.4
40, 4 40, 4	90.5	66.3	69.8	82.6
40, 20 40, 4	88.3	58.6	64.9	79.8
40, 10 30, 4	46.8	39.7	41.1	44.5

V. CONCLUSION

In this systematic review research, a number of neural network techniques for diagnosing and classifying skin cancer have been studied. These treatments don't cause any disruption at all. For the purpose of identifying skin cancer, preprocessing is the first stage in a multi-step procedure that also involves picture segmentation, feature extraction, and classification. The classification of lesion pictures, with an emphasis on ANNs, CNNs, KNNs, and RBFNs, was the main objective of this review. Every algorithm has advantages and cons. For the best outcomes, choosing the classification approach to use must be done so with knowledge. But when it comes to categorising visual data, CNN performs better than other varieties of neural networks. The reason for this is that CNN has a closer relationship with computer vision than the other varieties. The majority of research in the field of skin cancer detection is focused on determining the malignancy of a particular lesion image. However, the information currently available cannot answer a patient's query about a particular skin cancer symptom and whether or not it appears on any particular portion of their body. The unique issue of classifying the signal picture has been the main focus of the investigation up to this point. Future study may involve taking photographs of the subject's full body in order to identify the remedy to the issue that regularly occurs. The image acquisition procedure will be more automated and swifter with the use of autonomous full-body photography.

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