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

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Abstract— The most prevalent type of cancer that can be seen in people is skin cancer. Early identification of this cancer has become a primary priority as a result of the illness's ongoing global increase, high cost of therapy, and high mortality rate. The majority of skin cancer cases are curable when detected early. Therefore, detecting skin cancer in its earliest stages can save patients' lives; if this could be done, the survival rate would be greatly increased. Skin cancer detection still has a lot of serious issues, despite the considerable amount of effort that has been done to improve it. Many people have been working on creating automated systems to find melanomas. Technology advancements have made it possible to detect skin cancer early more frequently. These investigations have enormous and unimaginable potential benefits. In addition, there are numerous difficulties, thus the fresh contributions provided in this area are very valued. On the other hand, it is generally acknowledged that more accurate detection systems require a higher level of confidence and reliability. One of the many parts of an automated diagnosis of skin cancer is the construction of an autonomous skin cancer categorization system. Additionally, utilising various preprocessing techniques, the relationship of skin cancer photos across various neural network types is investigated. In order to enhance the image's quality, the system uses the acquired photos and puts them through a number of image processing steps. The cancer cell is then excised from the area of skin that is damaged and left in the image. Information that can be extracted from these images and then used to train and test the classification system can then be supplied into it. The neural networks that are used as classifiers are the back-propagation neural network (BNN), the auto-associative neural network (AANN), and the convolutional neural network (CNN). In an image database that contains both dermoscopy photographs and digital photos, 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 92.5%. The analysis of the prior work using MATLAB..

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

I. INTRODUCTION

In recent decades, everyone has been experiencing an increase in the prevalence of skin ailments (Barati et al. 2011). There are a number of factors that have a role in the start of various diseases, and typically each age group has distinct sets of symptoms. Conditions that are humid, moist, and heated are ideal for the growth of germs and moulds. Prolonged and prolonged exposure to abnormally high levels of UV radiation from the sun will make the skin more sensitive, will make it easier for infections to take hold, and may create skin problems. In in addition to the exterior infections, internal sebum glands, dead skin, and sweats are also factors. when combined with dust and other unwelcome secretions, it is possible for it to induce additional significant skin conditions, illnesses. The human skin is the largest organ in the body, and it is composed of three layers, each of which has a specific function the epidermis, the dermis, and the subcutis, which are revealed to have different functions and optical qualities in Figure 1.1. The epidermis is quite thin and is made up of keratinocytes, which are pigmented cells keratin, a protein that assists the skin in protecting the rest of the body, is produced by these cells body. In addition, the epidermis is home to melanocytes, which are the cells responsible for creating melanin is their end result. Melanin is a pigment that is responsible for the brown or tanned appearance of human skin colour. It has a powerful absorption of light in the ultraviolet and blue portions of the visible spectrum (UV) spectrum, so serving as a screen to shield the deeper layers of the skin from the effects of sun exposure the potentially dangerous consequences that UV radiation can have.

The basal layer, which is the deepest part of the epidermis, is made up of basal cells, which are constantly dividing to produce new keratinocytes to replace the older ones that are lost due to the surface of the skin wearing away. The dermis, which is located in the middle layer of the skin, is significantly thicker than the epidermis. It is also home to hair follicles, sweat glands, blood vessels, and nerve endings. The word "stratum corneum" refers to the most superficial layer of the epidermis, which functions as a protective barrier and is made up of keratinocytes that have died and are continually being replaced by fresh ones form. Melanoma 2016, Maglogiannis, and Doukas 2009 state that pigmented skin lesions can be classified as melanocytic or nonmelanocytic depending on whether or not they arise from melanocytes (Melanoma 2016).

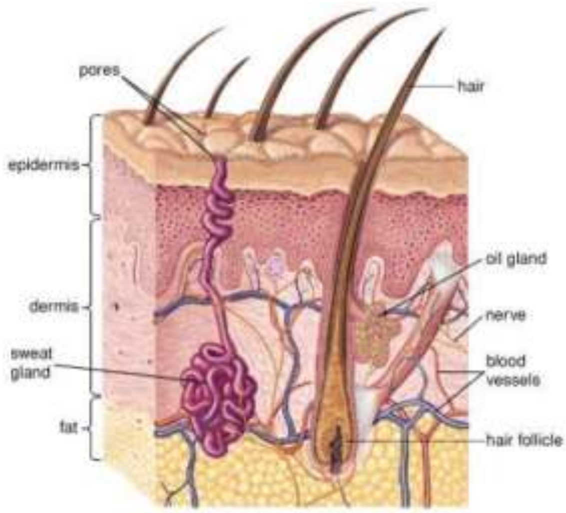


Figure 1: Structural representation of skin

Skin Cancer as one of the leading cause of death is the threat to human beings in entire world. This cancer can be cured if it is diagnoses in early stages .With respect to the raises in statistical foundation of skin cancer, the importance of its early detection has been considered as a vital issue and the computer based diagnosis is an important tool for this purpose. The early detection of skin cancer has attracted much concern from different fields. Since the work presented in this thesis lies on the automatic detection system for skin cancer, the knowledge about human skin along with the different available techniques for detection systems are the necessary information in this area.

Epidermis and Dermis are the two main layers in human skin which are described as follows [10]:

Epidermis: This layer as the top layer in human skin is built of squamous cells which are flat cells in skin. The round cells below the squamous cells are called basal cells. The cells in a deepest part of epidermis are called melanocytes which have been located between the basal cells. The pigment (color) in skin is appeared by Melanocytes.

Dermis: The second main layer of skin is dermis which is located below the epidermis. It includes different types of cells such as lymph vessels, blood vessels and glands. Some glands help the skin to dry out, some others help to cool the body and make sweetening. The figure 1.3 indicates the layers and cells of skin.

Trillions of living cells consists the human body. These cells grow, and divide into new cells in normal bodies and die orderly. In adults, the cells division is to substitute worn-out, damaged, and also dying cells. When the growing of abnormal cells in a part of body increase out of control causes to cancer [11]. The growth in cancer cells will make new cancer cells and able to invade other tissues as well [10].

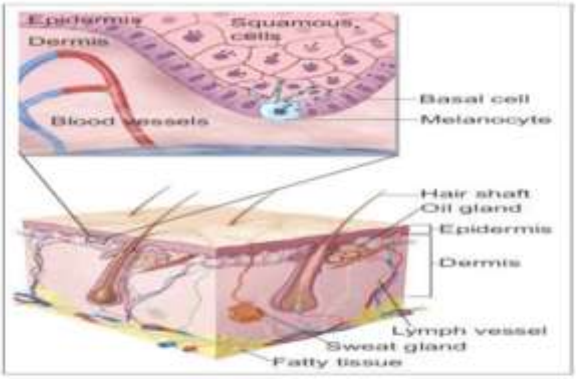


Figure 2: Structural representation of skin

Mostly cancer cells build a tumor, but in some cancers such as leukemia, the tumors are built rarely. The cells in these types of cancers are found in blood and bone marrow. Not all the tumors are cancers, those are called benign which can grow and make problems and pressure on healthy organs. They are not able to invade into other tissue [11].

Skin cancer as the most common cancer in human begins in the skin [12]. Some cancers also can start in other organs and spread on the skin, but these cancers are not considered as skin ones [13]. The different types of skin cancers commonly can be categorized as malignant melanoma and non-melanoma skin cancer (NMSC), the latter including Basal Cell Carcinoma and Squamous Cell Carcinoma as the major subtypes.

Melanoma, basal cell, and squamous cell skin cancers are all types of skin cancer that fall under the umbrella of skin cancer (Antkowiak 2006, De Sousa Lé 2015, Skin cancer 2015). Skin cancer is the most hazardous disease in the world among the many skin diseases. Melanoma is the most lethal form of skin cancer, and the fact that its prevalence has been steadily rising all over the world makes it a highly significant and concerning public health issue. There were an estimated 76,100 thousand newly diagnosed cases of malignant melanoma in 2014, and of those, 9,710,000 people succumbed to the disease. Melanoma accounts for fewer than 2% of all incidences of skin cancer, but it is responsible for the deaths of nearly all people who have skin cancer. In the white population, there is a 2.4% lifetime chance of developing the condition, which is far higher than the lifetime risk of developing the disease in African Americans, which is 0.1%. Since at least 30 years ago, the rates at which it has been occurring have been steadily climbing. Worldwide, there are around 2 million to 3 million cases of non-melanoma skin cancer and 132,000 cases of melanoma skin cancer diagnosed each year. The American Cancer Society reports that skin cancer accounts for one out of every three cases of cancer that are detected. According to the foundation's data, one out of every five Americans will develop skin cancer in the course of their lifetime (INTERSUN 2016).

Malignant melanoma: Malignant melanoma, as one of the types of skin cancer, is increasing worldwide and leads to death of 65% of its victims. Between 1991 and 2000 in UK, the patients of melanoma grew by 59% and 41% in men and women, respectively. In 2010, Australia, the mortality of Skin cancer and melanoma with projected incidence being 11,500 and 1500 respectively. The high occurrence of both melanoma and non-melanoma skin cancer in Australia provide this country as a place of research in the area [14, 15] It is derivative from epidermal melanocytes and can arise in any tissue which contains these cells, but commonly it is appeared on the lower limbs in females and on the back in males. As it occurs on the skin surface; therefore it is detectable by visual inspection. The clinical appearance is different according to the type and site of the tumour. Figure 3 shows the sample image of malignant melanoma [15].

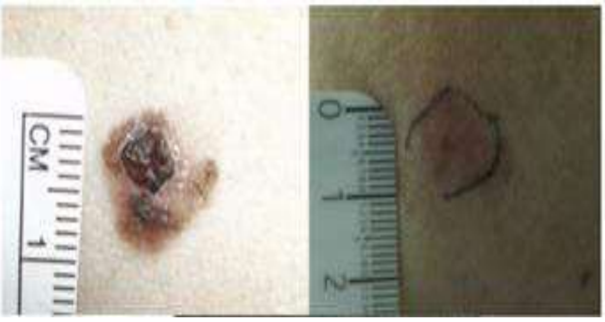


Figure 3: Malignant melanoma [15]

Malignant melanoma can occur by the phenotypic factors such as sun exposure habits, intermittent and ultraviolet radiation. The other risk factors are the fair skin type, having the history of malignant melanoma in personal or first-degree relative [14, 15]. The different types of malignant melanomas are [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

A technique histogram-based on the data is proposed by Amira Ashour et al. (2018) clustering estimate for efficient skin lesion identification is feasible by determining the clusters along with the neutrosophic c-means clustering (NCM) for the input dermoscopy images. This makes it possible to detect skin lesions more effectively. First, translate the dermoscopic images to the neutrosophic-based characteristics so that the pixels can be grouped. The HBCE algorithm uses both h-v and v-h methods in its computations. The implementation is carried out with the use of the public data set of ISIC 2016, which employs 900 photos for training and 379 images for testing respectively. When doing the evaluation, it is necessary to take into account the ISIC 2016 data sets, which call for effective training and testing based on the availability of ground truth photographs. The results obtained by the work that has been proposed are superior to those obtained by the conventional method NCM without HBCE. Seetharani Murugaiyan Jaisakthi et al. (2018) present a semisupervised learning strategy for automatically segmenting lesions in accordance with the provided pictures obtained from dermoscopy using a two-stage method consisting of pre-processing and segmentation. During the pre-processing step, the bi-linear interpolation approach is utilized for the purpose of image scaling; uneven illumination in the image can be improved by using CLACHE algorithm. After that, an inpainting technique with a Frangivesselness filter was utilized FMM are employed in place of the hair pixels to get the desired effect. The method of segmentation is referred as carried out to separate the lesion regions based on the homogeneity of pixels such as colour and texture attributes, carried out to isolate the lesion regions based on the homogeneity of pixels. The GrabCut method utilizes the boundary and region information for the purpose of segmenting the foreground image, from which the approximate lesion regions are identified. These regions are then further improved through the utilization of k-means clustering, in which the grouping of pixels is accomplished based on RGB colour space, with the goal of predicting the exact lesion regions. The dice co-efficient values can be enhanced for the purpose of increasing the accuracy by utilizing techniques from deep learning, and this is something that is being studied for future study.

One of the best approaches to overcome aforementioned challenges in automating medical imaging diagnosis is to simplify the objective of the analysis and to exploit some kind of hypothetical information about the imaged structures. The information about the structures to be analyzed can be anatomical knowledge about their typical appearance (such as shape and grey levels) and position; or statistical knowledge of their properties (such as gray level of the tissues included in those structures). The images can then be classified using their morphological, color, fractal, and texture properties. Laws, 1980 in his work transformed digital images to identify regions of interest and provided an input dataset for segmentation and features detection operation.

Quad-Tree is the name of the methodology that Sahar Sabbaghi et al. (2018) propose Melanoma detection method is an expert colour evaluation model that is accurate, which makes colour observations, which make it possible to easily categorise the lesion as one of either non-cancerous or cancerous. This article explained the terms that were used to investigate. The contrast between the melanomas and the concentric quartiles and Euclidean distance is during the pre-processing phase, there is an increase in the contrast between the lesion and the background areas phase. The utilization of has a beneficial effect on the lesions that have a lower colour contrast operations in morphology, such as the top-hat operation and the bottom-hat operation. For hybrid thresholding approach is a method that is helpful in the identification of lesion borders afterwards exploited; the procedure of segmentation can be broken down into two steps. The modified version of the Otsu test was used in the earlier stage to identify core lesions threshold, and the core lesion region ends up becoming extended along the radii later on stage that makes use of an adaptive histogram function. The legislation is reviewed with regard to various classifiers, and the results show that the SVM classifier obtains the best overall performance measured using the ROC curve's features.

Amira Soudani et al. (2019) advocate a segmentation recommender to shorten the training period based on information gathered from the crowd and transferring one's knowledge. The VGG16 and VGG19 architectures are two examples of pre-trained models. The convolutional layers of ResNet50 have been developed, and they are used to extract features. The CNN is a classifier that consists of five nodes, and each of them reflects a different aspect of the data segmentation approaches are considered, and then an output layer is constructed accordingly. The By the use of both, local characteristics can be acknowledged from a variety of locales dimensional structure of images obtained from dermoscopy. As a consequence of the outcome, I have come to the conclusion that the approach that was provided accurately predicts segmentation method for identifying skin lesions and abnormalities.

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.

Euijoon Ahn et al. (2017) present the most important component of an automated computer-aided diagnosis system, which is the identification of the presence of a disease melanoma by use of the segmentation of lesions in the body. The common place expressions, some of the ways to segmentation contain some of the technical flaws that result in poor segmentation performance of the skin lesion. These flaws include unclear lesion borders, low contrast between the lesion and the nearby skin, and lesions that touch the image boundaries. Saliency-based segmentation methods, which are derived from sparse representation models and united with novel background detection for more accurate categorization of the lesion from the surrounding skin regions, are used to renovate the errors. This is done in order to better differentiate the lesion from the surrounding skin regions. The shape of the lesion, as well as its borders, are more clearly delineated by the Bayesian framework that has been proposed. The validation procedure is performed on two public datasets by comparing it to other conventional and state-of-the-art lesion segmentation methods as well as the state-of-the-art unsupervised saliency detection methods. This is done in order to determine whether or not the method is effective. As a result, we can draw the conclusion that the proposed strategy is superior to the other approaches. There is room for improvement on the saliency optimization algorithm for the work that has been done lesion segmentation.

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.

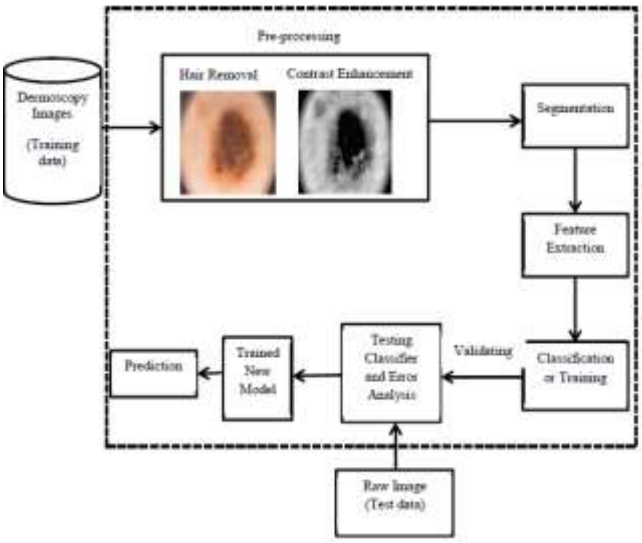


Figure 8: Skin Cancer detection system methodology

Based on this body of data, an intellectual decision method was presented for the classification of normal, benign, and malignant utilizing a modified version of the CNN approach. Melanoma is a significant and sometimes fatal form of skin disease that is caused by the accumulation of many different kinds of damage. The integrated methods are incorporated into the proposed model, and Figure 9 provides a graphical representation of these integrated methods in the form of a block diagram for the detection of melanoma skin cancer. The description of the important steps involved in the identification of melanoma will take up the most of the space in the following section.

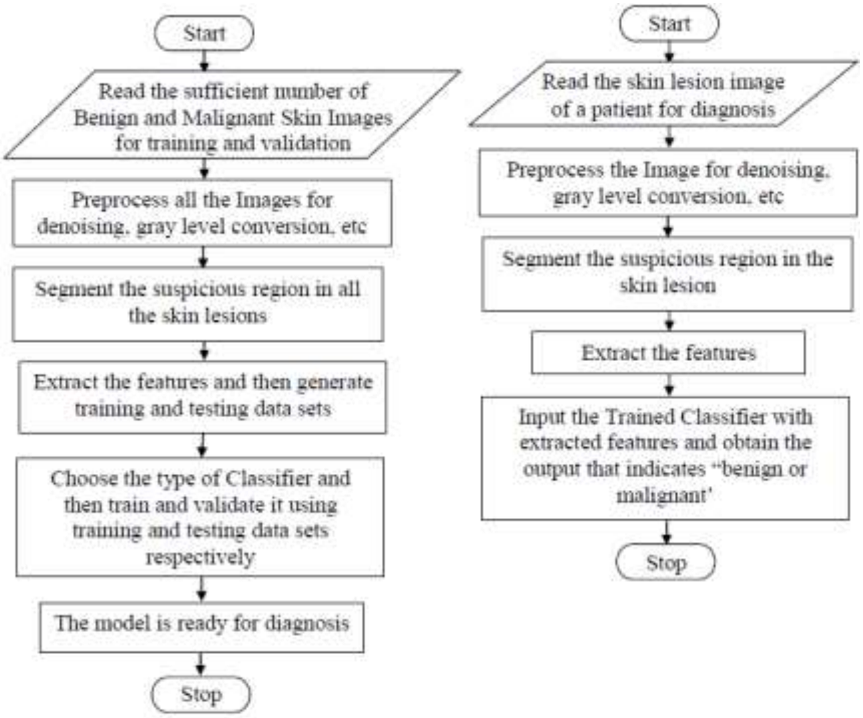


Figure 9: Computer Aided Diagnostic System (CADS)

At the outset, the model is constructed by first training and then validating a classifier using a preexisting set of image data. After the model has been trained and then verified, it will be ready to be used for diagnosis. The flow charts in Figures 9(a) and 9(b), respectively, explain the flow of processes that occur during the construction of the CADS as well as the application of the CADS for diagnosis. Image preprocessing, segmentation of the suspicious region, feature extraction, and classification are all included in these steps.

Pre-processing

The first step in expert systems used for skin inspection involves the acquisition of the tissue digital image for skin cancer detection. The skin cancer images usually contain fine hairs, noise and air bubbles. These feature that is not part of the cancer cell and would reduce the accuracy of the border detection or segmentation. The first step to do is apply some image processing techniques to the images. Thus pre-processing used to referring to remove the unwanted features on the skin and post-processing referring to enhancement to the shape of image.

The available methods such as Karhunen-Loève (KL) transform histogram equalization and different kinds of filter are used to achieve these goals. In addition, contrast enhancement can sharpen the image border and improve the accuracy for segmentation. Since the image database consists of both digital photo and dersmocopy. These images are obtained from different source and the size of the images is non-standard. The first step is to resize the image to have a fixed width 360 pixels but variable size of height. The second step is to remove the background noise from the pictures. The method used here is wavelet de-noise by two-dimensional bior3.3 wavelet. Biorthogonal (bior) is a linear wavelet which advanced used in image reconstruction and decomposition.

Segmentation Process

In this stage, the enhanced skin image is segmented to separate the tumour from the background (skin). Segmentation removes the healthy skin from the image and finds the region of interest. Usually the cancer cells remains in the image after segmentation. Segmentation used here is Threshold Segmentation. Thresholding provides an easy and convenient way to perform the segmentation on the basis of the different intensities or colors in the foreground and background regions of an image. The input to a thresholding operation is typically a grayscale or color image. After segmentation, the output is a binary image. Segmentation is accomplished by scanning the whole image pixel by pixel and labelling each pixel as object or background according to its binarized gray level.

Segmentation algorithms are based on one of two basic properties of intensity values discontinuity and similarity. First category is to partition an image based on abrupt changes in intensity, such as edges in an image. Second category is based on partitioning an image into regions that are similar according to predefined criteria. Histogram Threshold approach falls under this category.

The interesting features of melanoma are included within the border since most of the cancer cells are nodule structure. The border structure provides vital information for accurate diagnosis. Many clinical features including asymmetry and border irregularity are calculated from the border. In this thesis, threshold and statistical region merging (SRM) are implemented and compare their accuracy with 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 as shown in Figure 4.7 which 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

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.

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 images, and image classification are the three primary uses for this tool. CNN is a good tool for collecting and learning global data as well as local data by accumulating simpler features such as curves and edges to produce more complex features such as shapes and corners [28]. CNN is a fantastic tool for collecting and learning global data as well as local data. Convolution layers, nonlinear pooling layers, and fully linked layers are the components that make up CNN's hidden layers [29]. 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].

A CNN is a subset of the neural network discussed previously. As in a typical neural network, a System consisting of one or more convolutional allayers, sometimes with a sub sample layer, following by one or more fully connected layers. The finding of a visual process in the mind, the visual cortex, inspired the creation of a CNN. The visual cortex has a large number of cells that sense light in small, overlapped sub-regions of the visual field known as visual field. The more sophisticated cells have wider receptive fields, and they operate as local filters across the input space. The function of the cells in the cerebral system is accomplished by the convolutional in a CNN [69]. Fig.4 is a typical CNN for identifying traffic signs. Each layer's feature takes messages from a group of characteristics called a local receptive field that are placed in a tiny neighbourhood in the preceding layer. Characteristics can extract basic visual features, such as oriented edges, end-points, corners, and so on, using local receptive fields, which are subsequently integrated by protocol stack. A hand-designed feature extractor gathers significant data from the input and removes irrelevant variations in the classic concept of pattern/image recognition. After the extractor, a trainable classifier, which is a typical neural network that divides feature maps into classes, is used.

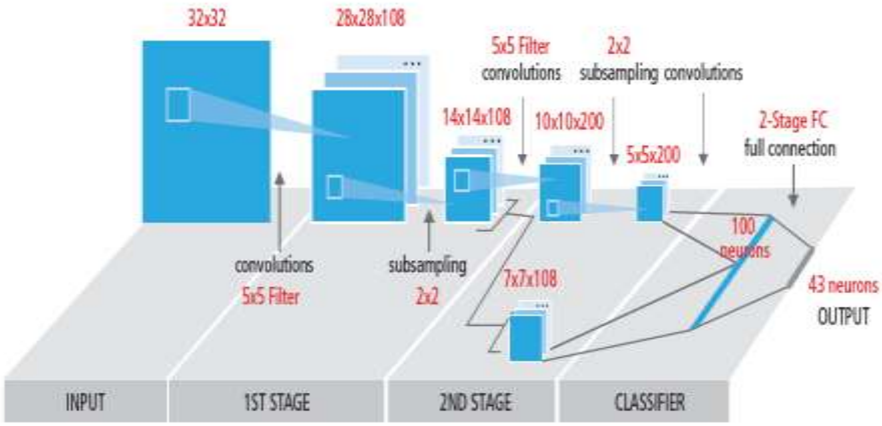


Figure 10: Typical block diagram of a CNN

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

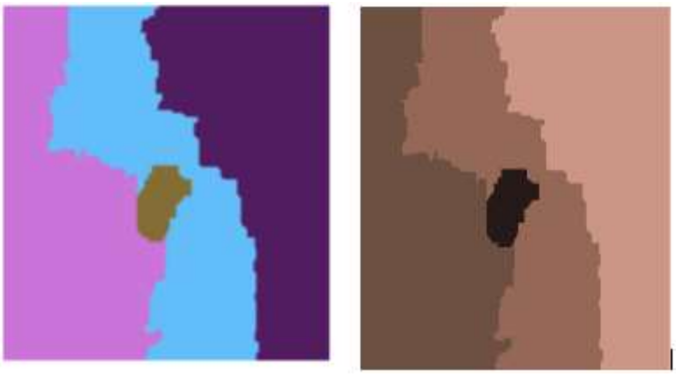
This step of thesis intends to rank the available extracted features by attention to their impact on skin cancer detection.

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.



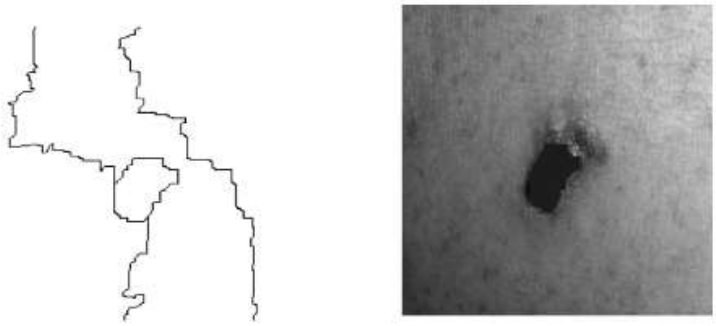


Figure 16 : Some training image results of detected skin cancer

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	83.5	56.7	64.8	73.6
1	20	98.6	61.4	65.6	86.4
1	30	101.2	53.7	78.3	89.5
1	40	99.6	52.3	76.8	88.6
2	10,5	81.4	48.2	55.9	68.5
2	20,10	98.8	53.1	74.7	87.2
2	30,20	99.1	56.4	71.3	86.7
2	40,20	99.7	51.9	76.4	87.4
3	10,8,6	96.3	61.7	68.7	85.2
3	20,12.8	98.5	63.1	77.1	88.8
3	30,20,10	98.7	62.4	72.7	89.4
3	40,25,10	99.8	61.4	79.9	91.3

Table 2: CNN classification results with size of neurons

Layer 1 to 4	Training	Validation	Testing	Total
10, 4 10, 4	87.7	58.9	70.1	77.9
10, 5 10, 4	83.3	56.5	69.2	73.5
20, 4 20, 4	88.9	58.8	69.1	79.1
20, 10 20, 10	90.9	62.1	69.5	81.3
30, 4 30, 4	90.1	58.8	72.8	79.8
30, 10 30, 4	87.4	56.2	64.2	77.1

40, 4 40, 4	89.3	64.1	68.5	80.1
40, 20 40, 4	89.7	54.3	63.3	78.3
40, 10 30, 4	44.5	38.2	39.4	41.3

V. 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.

REFERENCES

[1] Ashraf, R.; Afzal, S.; Rehman, A.U.; Gul, S.; Baber, J.; Bakhtyar, M.; Mehmood, I.; Song, O.Y.; Maqsood, M. Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection. IEEE Access 2020, 8, 147858–147871.
[2] M. Celebi, H. Kingravi, B. Uddin, H. Iyatomi, Y. Aslandogan, W. Stoecker, and R. Moss, A methodological approach to the classificationof dermoscopy images, Computerized Medical Imaging and Graphics, vol. 31, pp. 362–373, 2007
[3] Byrd, A.L.; Belkaid, Y.; Segre, J.A. The Human Skin Microbiome. Nat. Rev. Microbiol. 2018, 16, 143–155.
[4] S.Mohammad Seyyed Ebrahimi, HosseinPourghassem,Mohssen Ashourian .Lesi on Detection in Dermoscopy Images using Sarsa Reinforcement Algorithm. IEEE 2010.
[5] Elgamal, M. Automatic Skin Cancer Images Classification. IJACSA 2013, 4.
[6] Key Statistics for Melanoma Skin Cancer. Am. Cancer Soc. Available online: https://www.cancer.org/content/dam/CRC/PDF/ Public/8823.00.pdf (accessed on 8 February 2021).
[7] R. Garnavi, Computer-aided diagnosis of melanoma, Ph.D. dissertation,University of Melbourne, Australia, 2011
[8] Khan, M.Q.; Hussain, A.; Rehman, S.U.; Khan, U.; Maqsood, M.; Mehmood, K.; Khan, M.A. Classification of Melanoma and Nevus in Digital Images for Diagnosis of Skin Cancer. IEEE Access 2019, 7, 90132–90144.
[9] Maryam Sadeghi,David Mclean ,Harvey Lui ,M stell Atkins.Detection and Analysis of Irregular Streaks in Dermoscopic Images of Skin Lesion.IEEE 2013.
[10] Jaleel, J.A.; Salim, S.; Aswin, R. Artificial Neural Network Based Detection of Skin Cancer. Int. J. Adv. Res. Electr. Electron. Instrum. Eng. 2012, 1, 200–205.
[11] Aswin, R.B.; Jaleel, J.A.; Salim, S. Hybrid Genetic Algorithm: Artificial Neural Network Classifier for Skin Cancer Detection. In Proceedings of the 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kanyakumari, India, 10–11 July 2014; pp. 1304–1309.
[12] Choudhari, S.; Biday, S. Artificial Neural Network for SkinCancer Detection. IJETTCS 2014, 3, 147–153.
[13] Hasan, M., Barman, S. D., Islam, S., & Reza, A. W. (2019). Skin cancer detection using convolutional neural network. In Proceedings of the 2019 5th international conference on computing and artificial intelligence (pp. 254–258).
[14] Hobbs, L., Hillson, S., Lawande, S., & Smith, P. (2011). Oracle 10g data warehousing. Elsevier.
[15] Hoshyar, A. N., Al-Jumaily, A., & Hoshyar, A. N. (2014). The beneficial techniques in preprocessing step of skin cancer detection system comparing. Procedia Computer Science, 42, 25–31.

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