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Survey on Erythema Migrans, and Basal Cell Carcinoma in Computer-Aided Diagnosis

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Abstract. Lyme disease appears by various means one of the causes is infection from a bite of a black-legged tick which leads to the formation of a rash called Erythema Migrans (EM). This Lyme disease is the direct root of skin cancer and the primary phase is known as Basal Cell Carcinoma (BCC). Skin cancer causes pathological situations it integument the body's surfaces, including skin, hair, nails, and associated glands. Identifying EM and BCC in biomedical representation is a common platform known as biopsies and many works are done in the traditional methodology. But early detection of EM and BCC in the field of medical imaging using computer-aided diagnosis provides more accuracy and rapidity. This survey is classified under two categories; the first is EM detection and the second is the segmentation of BCC. The circumstances of this review are under the base of different algorithms, various methods used by the non-medicals appliance are discussed and compared by the several measures taken by increasing the parameters to improve the accuracy levels.

Keywords. Lyme disease, Erythema Migrans, Basal Cell Carcinoma.

1. Introduction

Medical image processing [1] is a vast field, researching in this area is a challenging task. Providing accuracy and time consumption are the keystone in image processing. Diseases identification, detection [2,3], classification, and clustering in this field are still not optimal. Various diseases (such as Tumors, Cancer, Skin, Retina, etc.) are still under evolution, and identifying them by computer-aided diagnosis is not ample. According to various reviews and studies on natural human calamities, the World Health Organization (WHO) gives an alert that skin disease is one of the most communal and stimulating sources of human illness. Very commonly, [4] it is known that the cause of cancer is not known for many cases but once it is identified at the beginning it can be cured. It is

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vulnerable to people and it appears through blood, bones, lungs, skin, and many other means. From numerous research and studies [5–7], it is come to know that the cause of cancer through the skin occurs primarily on areas of sun-exposed skin, involves all layers of the skin, and through many mediums (like the scalp, face, lips, ears, neck, chest, arms and hands, and on the legs too) and has several etiology (such as infections, tumors, or inflammation UV radiations, exposure of sunlight). Skin cancer [7, 8] through infections also ensues by insect bites. From the regions of northern Midwest and eastern coasts of the United States as well as in southeastern Canada insects so-called black-legged tick or deer tick bites trigger the bacteria Borrelia Mayonii and so engenders Lyme disease. The very foremost stage of Lyme disease [9] is a rash appearance recognized as [10, 11] Erythema Migrans (EM). Approximately 70 to 80 percent of people with Lyme disease have this kind of rash. Very often the rash looks like a bulls-eye and for some individual guises like a solid circle. And it is stated by doctors and many research specialists that Lyme disease is the direct cause of skin cancer. The very preliminary step of Lyme disease is [12–14] Basal cell carcinoma or Basal cell cancer (BCC) is an early category of skin cancer. This nature of cancer transpires by the formation of new cells inside the skin as old ones perish off. BCC often appears as a fairly transparent bump on the skin, though it can take other forms. Aspects that are stated and executed as previous work through various image acquisition techniques so-called noise reduction, implementation of various segmentation algorithms, feature extractions process (like Color Features: Min, Max, Mean, SD, and Entropy; and Textures Features: contrast, correlation, and energy), and classification of diseases have resulted in many downsides [15, 16].

2. Surveys

The review work in this field is categorized into two: detection of Erythema Migrans and feature extraction, and segmentation methods of Basal Cell Carcinoma to detect skin cancer.

2.1. Erythema Migrans

Based on the work of Philippe M. Burlina et al. [17], from various experimental analyses, it is proved that machine-based testing outcome better results than manual testing called biopsies. The work was implemented by the operations mean and rescale applied to the raw image to obtain pre-processed image through Image Net [18] and with various Deep Learning Techniques [12, 19–23]. Data augmentation functions flip, blur, color contrast, saturate, sharpen, and color balance are performed. [24] ResNet 50 a Deep Convolutional Neural Network model was implemented in the platform Keras and Tensor flow. In the training model, Stochastic Gradient Descent was used to improve the training speed and accuracy. The categorical cross-entropy loss function also named softmax loss function was used to train the Convolutional Neural Network model ResNet 50 to produce the probability-based classes. But entropy loss function stopped at every 10 epochs. So, the dynamic learning rate schedule was given as a constant. This training was held for four classes EM (Erythema Migrans), Normal, Tinea Corporis(TC), and Herpes Zoster(HZ). And later it was reduced to two class classifiers EM and Non-EM classes (Normal, TC, HZ). [25, 26] The training model of four class and two class classifiers was measured using the metrics accuracy, F1, sensitivity, specificity, positive predictive value, negative predictive value, kappa score, ROC. Implementation, training, and metric measurement were done with the data set of 1834 images (initially it was 6000 images before preprocessing).

Pegah Kharazmi et al. [27] detected and segment vascular structure from dermoscopy images (dataset of 759 images from three different sources). [28] Independent Component Analysis (ICA) method was applied to decompose the [29] dermoscopic images. Due to this edge detection was conceivable from input images termed image decomposition. The skin layer components melanin and hemoglobin are retrieved [30]. This hemoglobin component extracted achieved a better performance to get RGB values calculated through the Mahalanobis distance. The values of RGB assisted to perform K-means cluster to segregate three different classes [28] termed as pigmented, normal, and erythema migrans.

This study from Ramy Abdlaty et al. [31] states the possible measures of Erythema was assessed from Hyperspectral Images (HSI) [13]. The background segregation of the hyperspectral images shaped from the preprocessed image and the segregation of and the white standards from the preprocessed image lead to spectral reflectance images. Image registration was boosted by two inputs digital images (RGB) and the output from spectral reflectance image. [32, 33] The Visual Assessment (VA) declares the erythema regions through the X-OR correlation to produce the corrected images. [34] The performance evaluation was analyzed by the contradiction of colored digitalized images Red-Green-Blue (RGB) pigments. The [6] Hyper Spectral Images (HSI) and the RGB pigments are analyzed and classified via the smoothing of images by a low pass filter called Savitzky-Golay and the results are compared with colored images. From the analysis, two major work phase was stated; firstly it was known that to remove low informative bands column subset selection was framed based on the matrix rank [35] representation by Frobenius. In the second phase, the Weiner filter was applied for the noise removal from the outputs spectral reflectance images, registered images, and corrected images.

Examined by Philippe M. Burlina et al. [36] on skin lesions and detecting Erythema Migrans (EM) [9,11,37] using Artificial Intelligence (AI) and Deep Learning (DL) methods [38,39] is the main approach of this study. Early accurate identification of EM avoids rheumatology, neurology, and complications in cardiac. Comparison of the clinical-based skin conditions with Erythema Migrans detection using Artificial Intelligence models and Deep Learning methods was implemented and tested. The clinical skin conditions are tinea corporis, cellulitis, erythema multiforme, herpes zoster, and non-pathogenic normal skin. Complications of multi-class classification with high complexity along with incorporations of clinical-based binary classifications are taken into consideration [40]. The models and methods of AI and DL were trained and tested with images available publicly and also tested with images obtained from clinical data. These trained models and implemented methods were measured by ROC and with the gold standard. According to the metrics [4], public images in DL models produced an accuracy level of 71.58% to 94.23% for classification of 8- class problem [41] (having EM and other skin pathology) with binary classification (of EM and non – pathological skin). From the study, it was defined that the [42] DL system helps in prescreening for EM diagnosis as per the dataset [43].

2.2. BCC Segmentation and Feature Extraction

By Wangting Zhou et al. [44] Malignant Melanoma (MM) and Basal Cell Carcinoma (BCC) [45] tumor growth detection were measured by the functional and structural variations and the study of biopsies in dermatologic condition was the mean in this paper. The apparent skin features and the required parameter data were lacking from the conventional optic imaging techniques to describe the skin disease pathophysiology correlations. Due to the issue [46, 47], All Optically Integrated Photoacoustic / Optical Coherence Tomography (AOIP / OCT) preclinical device was suggested. This AOIP / OCT device provided a free label of certain features. Table 1.1 describes the features list for the growth of the tumor by pathophysiologic correlations in MM [48, 49].

Table 1. Feature extraction and classifiers used in BCC classification.

Methods	Features	Classifiers
AOPA / OCT [44]	Vascular, Blood flow velocity, Heterogeneity of blood flow, Tissue microstructure changes, Pigment structures, Cytologic features.	-
Auto Encoder [50]	Patient profile, SAE feature leaning	SoftMax
Otsu's Method [27]	Vascular Features	Simple Logistics, Naïve Bayes, MLP, Random Forest

[51] By the measurable metrics of this device, the functional and morphological parameters are rehabilitated due to the impact of spatial-temporal heterogeneity of MM and BCC. Distinguishing the validation criteria of vivo [52, 53] from the imaging biomarkers and ex vivo from MM was also provided by the correlation analysis. The device was measured by the ROC analysis had AOIP / OCT parameters improved with the accuracy of MM with 68.4% and BCC with 95.8% correspondingly. As a result, this paper indicates that the accurate diagnosis of clinically translatable technologies was possible.

Early detection by Komal Sharma et al. [54] and segmentation of the BCC by Ramandeep Kaur et al. [55] to detect skin cancer was suggested in this work and also analyzed with [8] previous methods with the flow of preprocessing, feature extraction [1], classification, and measures. [56, 57] The input image was preprocessed and smoothly segregated the foreground and the background of the image by the k-means cluster along with the Particle Swarm Optimization (PSO) to improve the quality of background separation of the image. Speed Up Robust Features (SURF) and Scale Invariant Feature Tra nsform (SIFT) were implemented for feature extraction. Artificial Neural Network was trained to get better performance with the classification strategies and also measured with the metrics precision, accuracy, True Positive Ratio (TPR), and False Positive Ratio (FPR).

The work by Kharazmi P et al. [50] is classified into two; To learn the framework of unsupervised features using the [58] Sparse Encoder (SE), and to study the vascular features directly from the given image with its hidden characteristics. [59] Feature maps are derived from the filters that are considered by the individual weights of the learned kernel. Table 1 illustrates the features extracted from the sparse encoder. These feature maps helped to diminish the dimensions and to relate with the records of the patients. The outcome of the feature maps was fed to the SoftMax classifier for classifying the BCC.

From the author, Luca Fania et al. [60] it was explained that due to exposure to sun and age population skin cancer has become a common occurrence worldwide. Non-melanoma skin cancer has a subtype [7, 61, 62] Basal Cell Carcinoma (BCC) is a very common type worldwide and started to spread globally. [63] People with an illness caused by this tumor die low in number. Individuals who cross to the next stage without perceiving are more in numbers. A survey in this field started with the pathophysiology till the novel approach therapeutic was taken. The diagnosis for BCC improved with different prognostic values along with the improvement in device strategies like reflectance confocal microscope, and recent dermoscopy images [19, 64, 65] and clinical features [13, 14]. Even though the initial stage of treatment was surgical to BCC many local non-surgical treatments are available. Depending on the patient's environmental and genetic behavioral collaborations BCC formation is possible. To treat the advanced level BBC or metastatic BCC hedgehog signaling like sonidegib, and vismodegib are represented in this pathogenesis.

3. Result and Discussions

As per the above survey on Erythema Migrans, Feature extraction, and BCC segmentation its performance analysis is discussed according to the methods applied and the accuracy levels obtained based on the data set used. According to Figure 1 The Hyperspectral

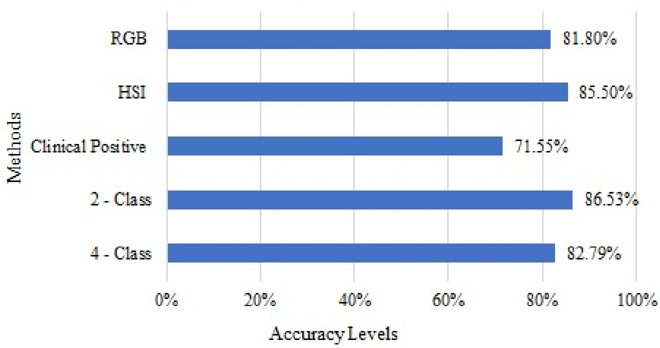

Figure 1. Erythema migrans performance.

Image (HSI) [31], and the Red – Green - Blue (RGB) pigment extraction for the erythema migrans detection resulted in an accuracy level of 85.5% and 81.8% respectively. The class-based optimization [17] in 2 class, 4 class, and clinical positive classifiers produced the accuracy outcome in the range of 86.5%, 82.79%, and 71.55% respectively. Methods and techniques used to segment Basal Cell Carcinoma for skin cancer have resulted by Artificial Neural Network with an accuracy of 97.9%, Sparse AutoEncode (SAE) feature extraction obtained an accuracy of 84.7%, HD-OCT performed the four different models as AlexNet, GoogLE Net, VGG-16, and VGG-19 outcome with the accuracies of 91.6%, 74.4%, 93.5%, and 89.1% respectively. The shape and erythema methods produced an accuracy of 79.1% and 66.7% which is represented in Figure 2.

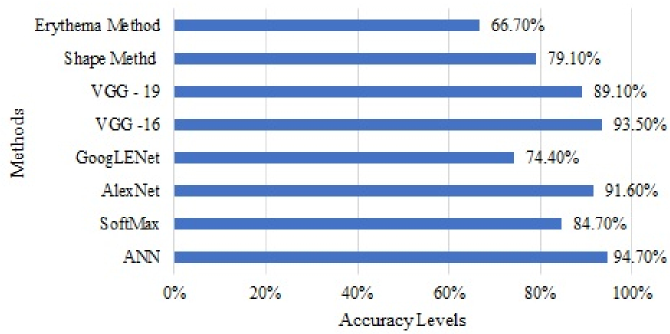

Figure 2. Basal Cell Carcinoma Performance.

4. Conclusion

From the consideration of previous work, analyzing various Deep Neural Network for segmentation (Fast RCNN, Faster RCNN, and U-Net) is considered to be the further study in this area. The keynote in measuring the outcome of medical image processing is accuracy and rapidity. Not enough statistics were done on these circumstances. The vision of this proposal is to analyze the techniques of Deep Learning algorithms to provide the best algorithm using the measurement parameters with various comparison studies. Skin diseases are a massive problem in the world, and there is an alarming necessity to get them into rheostat at the primary stage. so the actual actions can be taken up as soon as possible. Furthermore, the number of dermatologists is quite low as associated with the subjects, which is the scope. So, computer-aided analysis is a boon in such situations as they not only dilute the job of dermatologists but also add effects to their work by reducing the diagnosing time.

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