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Various Types of Skin Tumors Lesion Medical Imaging (STLMI) of Healthy and Unhealthy Moles a Review and Computational of: Segmentation, Classification, Methods and Algorithms

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Abstract. Over recent decades, updates in the field of the imaging of skin tumor lesions and biomedical sensing at the side of its related clinical implementations have attracted the attention of scientists. The major aim is to develop an artificial bee colony algorithmic and other approaches to propose different types of skin cancer lesion medical imaging, utilizing medical images achieved through different imaging methods. The artificial bee colony is frequently used to get highly accurate analysis, which supports the early detection of that which poses a threat to life, and, this method can be a good area to examine for future research. We compared the achievement of many works that were developed specially to detect the skin tumours lesion of healthy and unhealthy nevi after the use of methods and algorithms to obtain good processing results and discussed the relevant conclusions. The paper presents develop various classification, segmentation, methods and algorithms to recognize benign and malignant nevi to help make an expert decision on dermatology. These methods would allow not just earlier detection of skin cancer cases, however, decreasing of the number of unnecessary of steps in image processing and costly process.

Keywords: Skin cancer, Lesion, Segmentation, Classification, Types of artificial methods, Dermoscopy, Diagnostic features.

1. Introduction
The malignant melanoma recognition procedure depends on the visual inspection of the pigmented skin tumor lesions (moles). There are numerous styles of analytical techniques utilized by dermatologists to distinguish between benign moles and malignant ones. These techniques contribute several ordinary principles depending on the branch of morphological features and benefits [1].

In the 1990s, death rates were noticed in several population groups around the world. This drew attention to a necessity for an enhanced early diagnosis of skin cancer, which is currently the major parameter for a more appropriate forecast. If malignancy is revealed at an initial level, while the cancer dimension is less than 0.1cm, it is extremely likely it can be treated [2]. In the USA, one person dies from malignant melanoma every hour [3].

According to the World Health Organization the details, regarding one hundred and thirty-two thousand skin cancer malignancies arise worldwide every year. The occurrence of unhealthy nevi in

the USA has risen significantly from one to one hundred thousand people per year in 1935[4]. Moreover, the occurrence of melanoma has been steadily rising since the 1970s in white inhabitants globally. In some countries, the occurrence rates rose from (three-four) cases per one hundred thousand populations at the beginning of the 1970s, and after that, the occurrence cases were from (ten to fifteen) at the same rates, since 2000[5]. Cohort research from many countries announced that phenomenon of rising occurrence rates will continue in the future [5].

Research concerning malignant melanoma from 1992-2006 established that occurrence rates for men and women were rising at yearly rate of about ten percent [6]. Intrusive malignancy has been evaluated as an occurrence of sixty-two thousand four hundred and eighty and overall of eight thousand four hundred and twenty deaths in the USA in 2008 [7].

An evaluated seventy-six thousand two hundred and fifty new cases of melanoma were detected in the USA in 2012, with an evaluated number of nine thousand one hundred and eighty that resulted in death [8, 9]. Melanoma is a profound infestation that can increase extensively in the body via the blood vessels. Australia has the peak rates for skin tumors in the world; the rates of melanoma are approximately one thousand eight hundred and ninety dying every year [10].

In 2013, skin cancer lesions were evaluated, which showed that seventy-six thousand six hindered and ninety people will be detected with malignant tumors and that nine thousand four hindered and eighty people will die from these malignant skin tumors in the USA [11].

Skin tumors have been predestined as one thousand and fifteen new cases of melanoma per year and extra fourth three thousand persons have been predicted to die from malignant lesions for each year in Australia 2014 [12, 13]. In this country it was announced that an additional four hundred and thirty thousand cases are processed for non-melanoma, and extra ten thousand three hundred persons are treated for melanoma with one thousand four hundred and thirty persons dying every year, which is highly expensive for processing [13,14]. Based on the American Cancer Society (ACS), approximately to seventy-six thousand three hundred and eighty (forty-six thousand eight hundred and seventy males and twenty-nine thousand fifty hundred and ten female) cases of malignant are evaluated to be determined in 2016 [15]. This year also, ACS also evaluated approximately to (ten thousand one hundred and thirty), deaths (six thousand seven hundred and fifty males and three thousand three hundred and eighty female) [16]. The occurrence of malignant has been increasing each year. Melanoma kills one thousand people every year in USA [17].

In 2017, also in the USA, the ACS evaluated the number of diagnose melanoma on approximately eighty-seven thousand one hundred and ten people with nine thousand seven hundred and thirty people having the possibility of death [18]. About 1.7 million new cancer cases are expected to be detected in 2018.

This evaluate include basal cell or squamous cell skin cancers (Tumours) [19]. Rohrer et al. [20] introduced research that mainly depended on characteristics chosen for malignant detection and showed a high raise with recognition rate. On the other hand, the accuracy of professional dermatologists in malignant detection was until now evaluated and will be approximately from (seventy-five to eighty-five) percent [21].

To raise survival rates and to diagnose melanomas, it is paramount to suggest the study of ABCDE when shown, to be alerted to nevi and be certain of changes (dimensions, bleeding, shapes, sizes, and colors) and to show any suspicious nevi to a physician [22]. Stanley et al., [23] offered the fuzzy analysis method for the distinction between benign lesions and malignant melanomas. Khan et al., [24] presented a technique depends on the structureless regions to distinguish malignant from benign skin lesion images.

Persons with lighter leathers and weak immune function are normally more at risk of developing skin tumors lesion [25].

The traditional multilevel thresholding image segmentation methods comprehensively study for the optimal thresholds to enhance impartial functions, which as described in survey, are mathematically high costs. Meta-heuristic methods for results optimal thresholds have increased the observation of scientists in this arena to address multilevel thresholding difficulties meanwhile the computational time for results multiple thresholds produce exponentially with the total of chosen thresholds [26].

There are many varies methods of classification for medical imaging lesion skin cancer as shown in Table1[26]. Researchers have shown that dermatoscopic detection has an accuracy of (seventy-five to ninety-seven) percent; however, for macroscopic detection this range is (sixty-five to eighty) percent [27, 28].

Fuzzy method in image processing is utilized in the regions for filtering, boundary detection, enhancement, segmentation, model recognition, and clustering [29].

Iyatomi et al. [30] modified the advance by adding numerous manual edges that match with every lesion into one utilizing method [31].

The definitions of image malignant viewing can be affected through the utilization of the computer-aided detection (CAD) of skin tumors. These computer algorithms obtain a picture of the skin lesion area as a key and extract a group of helpful characteristics.

The characteristics are applied to recognize the skin lesion such as melanoma [32].   Research by Burroni et al. established that even easy utilizing for the CAD algorithm formed dependable analytical results [33, 34]. The pictures are sent to a dataset where they are analyzed and detected, and the results are sent to support the injury [35].

The level set technique is used with active curve as explained in [36] and generates a pattern of the contour that cannot use any border recognition function to finish the developing curvature on the border; however, utilizing a finishing term is supported by the Mumford- Shah segmentation methods [37].

A technique named Japan Society of Engineering Geology (JSEG) [38] which depends on color quantization and steps of segmentation, has been used for skin tumor images in [39]. The JSEG utilize J-images and is related to the calculations of the limited homogeneities at various levels to evaluate the edges of the border positions in this image [40]. Statistical region merging (SRM) is a color pictures segmentation method which prepares to utilize an area growing and a merging procedure with synthesis cases.

The major benefits of SRM are its simplicity and enhanced analysis; however, this technique is noise sensitive and has an unidentified theoretical picture [41]. The results established for Modified Quick Artificial Bee Colony (MQABC) are extremely effective at the time of implementation with the improvement of the threshold image segmentation [42]. Support vector machines (SVMs), which means a machine learning model depends on numerical learning hypothesis, and algorithms have been described in the medical imaging lesion area literature review [43]. The drawback of SVMs is that the categorization result is simply opposition, and no possibility of class membership is known [44]. Celebi & Zornberg [45] utilized a machine-learning method to the automated classification (healthy and unhealthy nevi) of clinically important colors in dermoscopy pictures, subsequently utilizing a K-means to decrease the number of color characteristics.

Texture Distinctiveness Lesion Segmentation (TDLS), which is implemented, is utilized for the pictures to obtain with a PH2 dataset, later it is changed for the illumination distinction. The segmentation algorithm utilizes a group of educated texture distributions parameters [46, 47].

The Artificial Skin Lesion Merging (ASLM method), is implemented by Pennis and Bloisi, which consists of four steps for the process segmentation image with the considered different types of skin lesion and their dimensions and color. The analysis of melanoma detection for this method has got the best sensitivity and higher accuracy when compared to other methods used for the database [48].

The artificial bee colony method(ABC) is more suitable for detecting melanoma in the skin, and this method has superior parameters in a specificity of 98.00 and an accuracy of 91.00, but it is not favoured for other considered algorithms [49,50].

There are numerous problems in choosing an appropriate algorithm, for example, image processing, and the number of factors whose standards will require a Maglogiannis [51]. Table1 shows a summary of different skin tumor lesion for medical imaging techniques and some applications. Dolianitis et al. [52] presented, in a comparative survey, that the Menzies method obtained the maximum sensitivity, 88.66 percent, for the detection of malignancy, contained by the 7-point checklist 83.44 percent, the ABCD rule 79.75 percent, model of analysis 68.48 percent, and evaluation of a macroscopic picture 62.69 percent. The pattern analysis and estimation of the macroscopic image presented the peak specificity, (88.00 and 86.37) percent.

This paper explains a normal automatic for detection pigmented skin lesions which is dependent on the semantic analysis of malignant pictures. The goals of this review are to summarize, and study developed dermoscopic algorithms utilized for the classification of varieties in skin lesions and explain the significant problems affecting the success of the categorization. A summarized and overall review of the characteristics for the investigation of different papers is achieved about many norms, such as, lesion segmentation, design methods and algorithms. and in section1 provides information according to the types of various methods of classification of medical imaging of skin cancer lesions and provides a literature review on this method This article is organized as follows: In section2, we explain the principles of the proposed methodology in the system to recognize skin cancer detection and material used from PH2 dataset images. Section3 we explain the effectiveness of the parameters in many methods, segmentations, Classification and algorithms after that compared to ABC method is proposed and this value are evaluated with literature review on this method. The study is some relevant conclusions are given in Section4.

2. Methods

Every picture of the 200 PH2 datasets is categorized into healthy moles and unhealthy moles from Figure1 the histological identification is just obtainable for several of the pictures; meanwhile the histological check is only achieved for those lesions measured extremely suspicious by dermatologists.

Three diagnostic types of common and atypical nevi (healthy of skin Tumours equal to 160 cases) and malignant melanoma (MM) lesions of skin Tumours (unhealthy nevi equal to 40 cases) will make it possible to complete a better checkup.
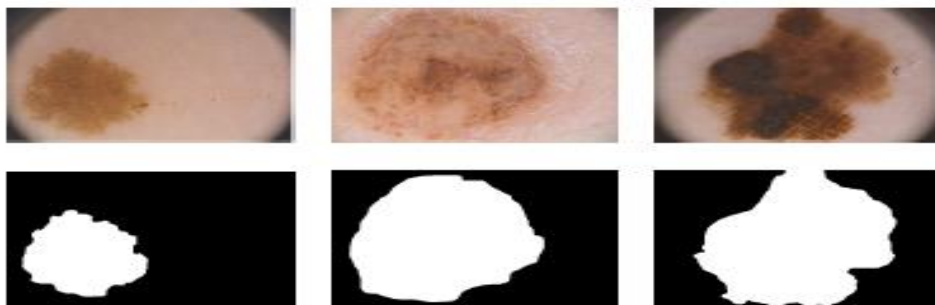
Figure 1. Samples of segmentation of three skin cancer lesions: common nevus (first column), atypical nevus (second column) and melanoma (third column) [53].

The main field of this paper is to apply various and new methods, segmentation, classification and algorithms (for example ABC method) on a computer-add system (CAS) forming different experimental techniques. For that purpose, it is valuable to estimate and detect the healthy and unhealthy nevi. The selected features are categorized to measure the accuracy degree and estimate the performance of that technique.

Consequently, several researchers [54-59] are trying to improve efficient automatic and semi-automatic detection systems with 7-point norm and model of analysis being used. Many techniques for extracting characteristics from clinical leather lesions pictures have been planned in the research as in Figure5 this represents the distribution of the characteristics utilized in dermoscopic tool research. Many studies have confirmed the efficiency of boundary shape descriptors for the diagnosing of melanoma or non- melanoma on both clinical and CDA estimation techniques [60, 61].

Table1 many researchers have studied analyzing the achievement of the comparison of several existing checking methods as referenced Table1.
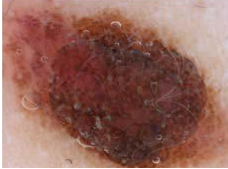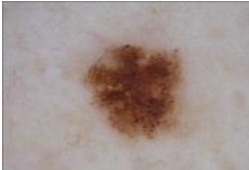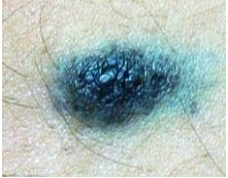
Every method has advantages and disadvantages, by using the dermoscopy and novel technique have supported of the cutaneous skin cancer lesions imaging devices. The dermoscopy norm utilized consists of the models of skin cancer lesions are detected. The models are 7 categories of dermoscopy modes introduced from Table2 [62, 63]. Random selection of classifiers (categories) achieved the best

analysis labeling clinical observations with pain calculation information, compared to other classifiers and methods [64, 65].

Table 1. Summary of the different skin tumor lesions of medical imaging techniques.

Technique	References	Descriptions	Drawbacks
Traditional Photography(TP)	[66-69]	Simple data organization for monitoring injuries in several cases. This technique provides the top layer of the skin lesion pictures.	Restricted morphologic data.
Dermoscopy Imaging Technique(DIT)	[70-82]	Improved results and distinguishing concentration of melanoma to support doctors.	Using for detection applications method.
Ultrasound Visualization(UV)	[83,84]	Ultrasound visualization is generally utilized to calculate the depth of skin cancer. When a doctor detects malignancy, in that case, it utilizes the frequency around 30 MHz	The values of the tumor thickness; accuracy of results based heavily on the anatomic location of the lesions.
Multispectral Imaging(MI)	[85-88]	MI scope can support the detection of lesions about 2mm and the distribution of tumors.	Various explanations for the difficulty of the visual procedure of scattering and absorption.
Laser Based Enhanced Detection (LBED)	[89-93]	Imaging of the skin lesions at a change able depth, examination, and high resolution.	These methods are very sensitive and expensive to use in clinical applications. .
Skin Lesion Boundary Tracing(SLBT)	[94,95]	It was established that Mat lab is a useful instrument and the automatic diagnosis for skin lesion behaviour.	Several of the digital processing methods are boundary and picture segmentation.

Table 2. Models of dermoscopy classes in case of database images.

Models	Characterizations	Classify	Image
Starburst	It is described by the existence of dyes streaks and red moles.	Nevi	
Multiple component	This model's detection of melanoma and depends of existence three of dermoscopy characteristics	Melanoma	
Reticular model or pigmented network	It is consisting of 3 Nevis types	Melanoma	
Globular	It existence several have varies colors and moles lesions.	Nevi	
Parallel Ridge Model(PRM)	The mode includes of benign moles.	Melanoma lesions	
Cobblestone	It is identical to globular model however, they are huge.	Melanoma	
Homogeneous	The homogenous dyes are existence of blue moles.	Blue nevi	

3. Results

Each segmentation algorithm is used to the corrected pictures, and the resulting values are compared to the ground truth table for the PH2 database image.

To quantify the performance of each algorithm and methods categorizing the pixel correctly, accuracy (Acc %), specificity (Sep %), positive predictive value (PPV), negative predictive value (NPV), and sensitivity (Sen %) are determined. The quantitative investigation of the performance of all the techniques has been implemented by the various parameters is given in the equations below: -

$$\mathrm{Sen\%} = \frac{True\ detected\ melanoma(\ malignant)cases}{All\ melanoma\ (malignant)cases} \tag{1}$$

$$\mathrm{Sep\%} = \frac{True\ detected\ non\ melanoma(\ benign\ )cases}{All\ non\ melanoma\ (benign)cases} \tag{2}$$

$$\mathrm{Acc\%} = \frac{True\ detected\ cases}{All\ cases\ (malignant+benign)} \tag{3}$$

$$\mathrm{PPV} = \frac{True\ detected\ melanoma(\ malignant)cases}{Detected\ melanoma\ (malignant)cases} \tag{4}$$

$$\mathrm{NPV} = \frac{True\ detected\ non\ melanoma(\ benign\ )cases}{Detected\ non\ melanoma\ (benign)cases} \tag{5}$$

Table 3. shows the estimation of the parameters of several kinds of skin cancer detection techniques and the classification of the skin cancer is melanoma or non- melanoma image processed that prove the validation of the all algorithm and methods are used. And the parameters estimation of several types for skin cancer detection techniques and algorithms

Segmentation Technique	Reference	Sum images	Malignant (melanoma)	Benign (non-melanoma)	Moles (non-melanoma)	Sep %	Sen %	Acc %
ANN	[95,96]	240	50	33.3	16.7	86	75	83
KNN	[97]	536	1.8	18.8	79.8	92	87	
SVM	[43,44, 98]	564	15.6	85.3	85.1	95	85	90
LDA+KNN+	[99]	152	27.6	72.5	------	74	80.5	------
Decision tree	[55,56]	154	30.7	88	12	80	75	55
Multivariate model +ROC	[100]	132	17.4	82.3	-------	95.6	63.3	89.4
Multilayer Perception+ fuzzy	[101]	102	50	50	------	87.8	69.9	76
Mumford-Shah	[37]	564	32	85	18	68	84	82.54
Canny	[102]	100	50	50	-----	90	78	-----
Genetic	[103]	244	15	50	-----	97	51	-----
Snake models	[104]	260	1801	64.2	18	80-90	90	----
Active contours without edges	[105,106]	102	50	50	-----	86	70	74
Gradient Vector Flows [GVF]	[107]	977	5.15	94.88	------	87.12	96.3	-----
SRM	[41]	200	40	80	80	87.5	10.3	67.6
Level Set	[36,37]	200	40	80	80	80.0	71.8	78.4
JSEG	[38-40]	200	40	80	80	97.1	71.0	89.4
Otsu	[108]	200	40	80	80	70.6	50.3	42.4

KPP	[109]	200	40	80	80	42.3	95.3	54.6
K-mean	[110]	200	40	80	80	84.8	72.4	66.7
TDLS	[46,47]	200	40	80	80	92.6	84.3	88.6
ASLM	[48]	200	40	80	80	97.2	**80.2**	89.6
Proposed Method(ASIT)	[49,50]	200	40	80	80	**98.0**	72.8	**91.0**

From Figure 2. Shows that clarification of classification methods as utilized by existing detection tests systems.

Figure 3 shows the relationship between the numbers of percent of new cases and the   ages of people for incidence melanoma [112 [113]. And from the comparison chart of methods of segmentation [114].
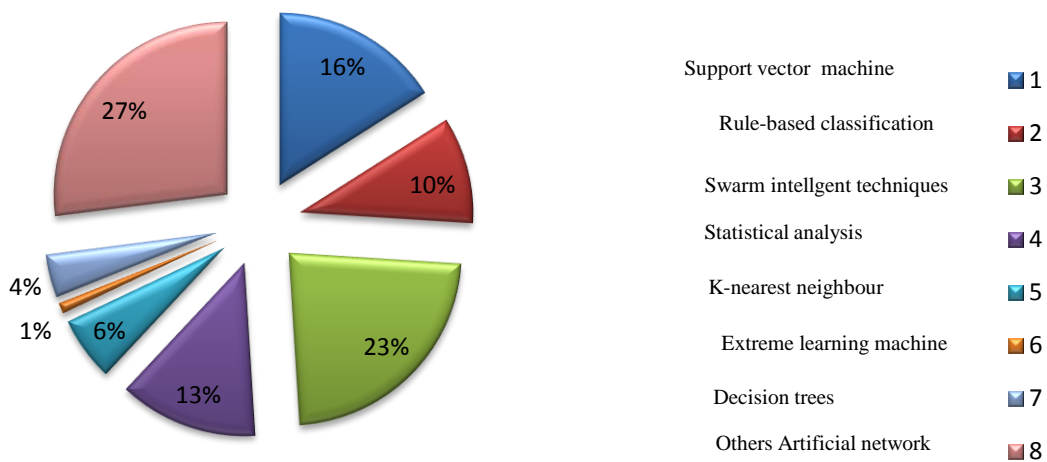
Figure 2. Clarification of classification methods as utilized by existing detection tests systems [111].
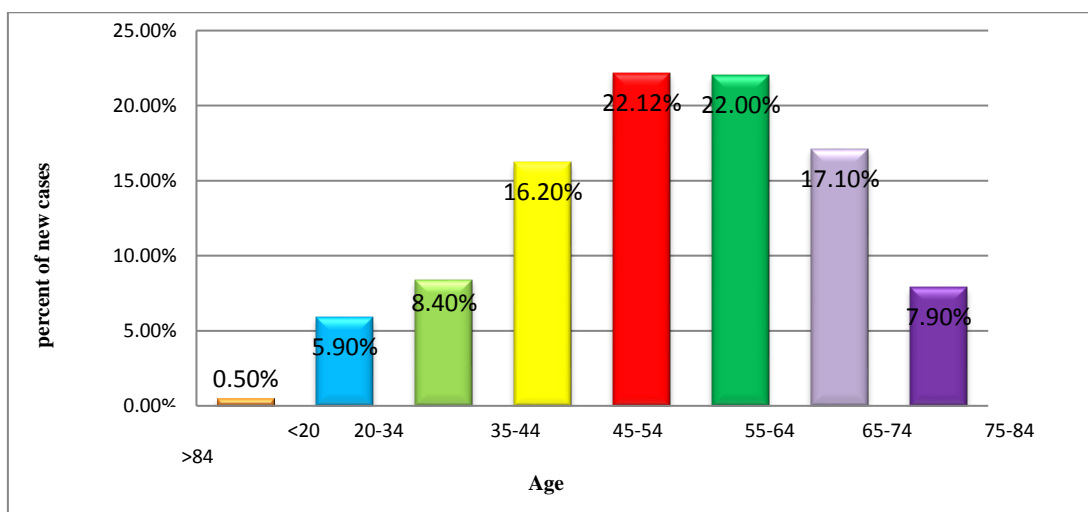
Figure 3. The relationship between the numbers of new cases and the age of patient people melanoma [112,113,114].

4. Conclusions

Recent research has involved developing automated computer algorithms to investigate the images of skin cancer lesions and assess the risk of melanoma. Our research allows a significant improvement in this area of study for many reasons. It is a survey that merges the study being prepared associated with all the steps required for improving automatic detection images for skin cancer diagnostics and categorization. It introduces information that aids scientist with the significance of the high stage characteristics election technique of benign and malignant skin cancer lesions. It suggested a construction that uses standard methods for sample effectiveness which in previously published studies is generally related to algorithms and methods. The quantitative investigation of the performance of all the techniques has been implemented by considering five various parameters. The results show that the artificial swarm intelligence technique (ASIT) can obtain superior accuracy in extracting the section of the dermoscopic pictures involving the skin tumors lesion compared to other segmentation methods and algorithms. Furthermore, the ABC and ASLM methods present a motivating performance when used on the pictures from the PH2 dataset or samples of hospital training examinations. All methods, which may be appropriate, will be utilized when a branch of a computer-aided diagnosis (CAD) for segmentation and classification system also can recognize healthy and unhealthy nevi by applying these methods and algorithms. The improvement of higher technologies in the fields of image processing, classification and segmentation have given us the capability to allow discrimination of malignant from the many benign. In certain, ABC algorithm indicates that the value of the accuracy and specificity increased when compared with other methods, (i.e. this procedure made it easy to detect the unhealthy Melomnana).

These novel techniques would allow not just earlier detection of skin cancer cases, however, decreasing of the number of unnecessary of steps in image processing and costly process. Moreover, we have studied and distinguished the main actors in many using and   applications for malignant detection. To overcome the problem of trapping the resolution in restricted optimal is solved by classification and segmentation depend on a biologically algorithms and methods was advanced, until we be able to use in the future study.

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