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Techniques for Malignant Melanoma Diagnosis: A Systematic Literature Review

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Abstract:* Malignant melanoma is the deadliest type of skin cancer. If melanoma detection and diagnosis is performed in its early stages, the probabilities of recovery and survival are higher. Dermoscopy is a manual method which is applied by doctors to diagnose this disease, but it strongly depends on the experience of the specialist who performs this skin assessment. Although, many proposals have been made for automated detection and diagnosis of malignant melanoma based on images processing, there are still improvement opportunities for melanoma diagnosis. This paper aims to identify the current status of the latest researches related to techniques for malignant melanoma diagnosis based on images analysis, considering the three research questions that have been elaborated for the systematic literature review: Q1) Which are the latest methods for malignant melanoma detection? Q2) Which systems for malignant melanoma diagnosis have been implemented in the last 5 years? And Q3) Which CAD systems for malignant melanoma detection have been developed? Furthermore, a cross-analysis of the outcome was performed. The results propose the implementation of systems using Inception V3 and the classifier Support Vector Machine, which achieved high accuracies in malignant melanoma diagnosis based on images processing.

***Keywords*: CAD Systems for Melanoma Diagnosis, CNN for Melanoma Detection, Dermoscopic Images Processing, Melanoma Detection, Support Vector Machine.**

I. INTRODUCTION

"Melanoma is a tumor that affects cells called melanocytes, these cells produce melanin, which is the pigment that colors our skin and protects it from the ultraviolet radiation. Most melanoma cases are found on the skin and it is because of the great sunlight exposure", Márquez et al. [1]. "Malignant melanoma is the deadliest type of skin cancer because of its great ability to metastasize and its high chemo resistance", Herrera et al. [2]. According to the World Health Organization (WHO) [3], "it is estimated that every year there are 132000 malignant melanoma cases and approximately 66000 people die due to this disease and other types of skin cancer". Melanoma is the deadliest type of skin cancer, even though it only represents 4% of all skin cancer cases, it causes 75% of skin cancer deaths, Jain et al. [71]. If melanoma is detected and diagnosed in its early stages, the probabilities of recovery and survival are higher [21]. Nowadays, there are traditional methods and techniques that are used by doctors in order to detect and diagnose malignant melanoma, such as dermoscopy, which is a manual assessment of the skin performed by experts, but it only has an accuracy of 75-84%, and strongly depends on the experience of the doctor who performs the examination [21]. In this way, given the importance of the early melanoma diagnosis, in the last years many proposals have been made to detect and diagnose malignant melanoma in its early stages based on images analysis. For this reason, in the present paper, a systematic review of the literature related to techniques for malignant melanoma diagnosis based on images processing has been made, according to a proposed taxonomy, in order to identify future researches. This paper is organized as follows. Section II describes the research methodology that has been used to perform the systematic literature review related to techniques for malignant melanoma diagnosis based on images processing. Section III presents the proposed taxonomy, considering the analysis of the studies that were selected from the systematic literature review. Section IV consists of the analysis of the obtained results. Finally, Section V presents the conclusions.

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II. RESEARCH METHODOLOGY

The research methodology that was used to perform the systematic literature review related to techniques for malignant melanoma diagnosis based on images processing, has been made based on the work of Wong et al. [4], considering the guidelines used by Kitchenham et al. [5], which consists of three phases: (A) Planning the review: in this phase, the research questions are elaborated and the review protocol is defined. (B) Developing the review: in this phase, the primary studies are selected according to the selection and exclusion criteria. And (C) Results of the review: in this phase, the statistics and the analysis of the selected studies are presented.

A. Planning the review

In the review planning, three research questions were elaborated, and a research protocol was defined, which are mentioned below:

Q1: Which are the latest methods for malignant melanoma detection?

Q2: Which systems for malignant melanoma diagnosis have been implemented in the last 5 years?

Q3: Which CAD systems for malignant melanoma detection have been developed?

In order to perform the systematic review, the following databases were mainly used:

ACM Digital Library and IEEE Xplore Digital Library, the research covers the period from 2015 to 2020. The keywords that have been applied to perform the research were: "CAD Systems for Melanoma Diagnosis", "CNN for Melanoma Detection", "Dermoscopic Images Processing", "Melanoma Detection". After performing the research using the defined keywords, the selection and exclusion criteria showed in Table I were applied.

Table- I: Selection and exclusion criteria

Selection criteria	Exclusion criteria
Studies related to the state of art and motivation.	Studies that do not belong to the selected databases.
Studies that present Algorithms, Architectures, CAD Systems, Frameworks, Methods, Models and Systems to diagnose malignant melanoma based on images processing.	The study language is different from English.
	Studies that were not published between 2015 and 2020.
	Studies that present techniques for melanoma detection, but which are not oriented to Software Engineering.

B. Developing the review

After the research was performed using the defined keywords in the selected databases (ACM Digital Library and IEEE Xplore Digital Library), the studies that met the selection and exclusion criteria (see Table I) were selected. Fig. 1 shows the research process applied, 540 potentially eligible studies were found, from which, 19 studies met the defined requirements and were selected.

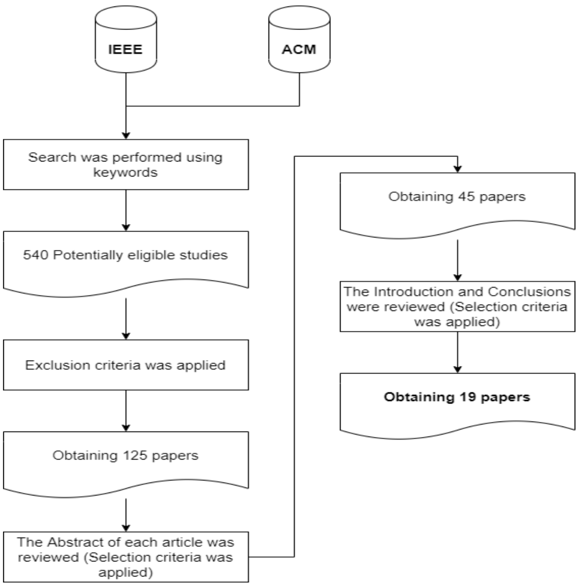

Fig. 1: Systematic literature review process

C. Results of the review

The studies that have been selected from the systematic review process, contained information related to different techniques which were used to process images in order to diagnose malignant melanoma. Table II shows the distribution of the selected studies according to the database to which they belong, where it is observed that most of the selected papers correspond to IEEE Xplore Digital Library with a total of 14 studies.

Table- II: Potentially eligible studies and selected studies

Source	Potentially eligible studies	Selected studies
ACM Digital Library	200	5
IEEE Xplore Digital Library	340	14
Total	**540**	**19**

Fig. 2 shows the number of selected studies per year between 2015 and 2020, and it is observed that most of the studies which proposed different techniques for malignant melanoma diagnosis based on images processing were published in 2018.

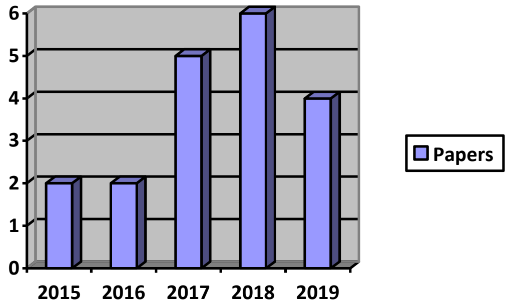

Fig. 2: Papers per year

III. TAXONOMY

In order to perform the analysis of the selected studies that have been found in the systematic literature review related to techniques for malignant melanoma diagnosis based on images processing, a taxonomy has been defined (see Fig. 3) according to the research questions that were elaborated in the planning of the review: "Methods" (Q1), "Systems" (Q2) and "CAD Systems" (Q3). The classification "Methods" corresponds to the studies that proposed different methods to detect and diagnose malignant melanoma based on images analysis. The classification "Systems" is related to the studies which implemented different kinds of systems to automatically diagnose malignant melanoma based on images processing. In the classification "CAD Systems", the studies that developed specialized Computer Aided Diagnosis Systems to diagnose malignant melanoma based on images processing are found.

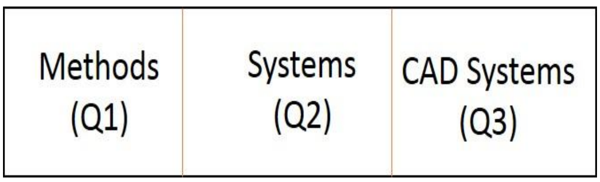

Fig. 3: Proposed taxonomy

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In summary, Table III shows the selected studies that were found in the systematic review according to the proposed taxonomy (see Fig. 3).

Table- III: Classification of studies

Classification	References	Total
Methods (Q1)	[6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 24]	11
Systems (Q2)	[16, 17, 18, 19, 20]	5
CAD Systems (Q3)	[21, 22, 23]	3

The analysis of the selected studies according to the proposed taxonomy is presented below.

A. Methods (Q1)

Table IV presents the proposed methods that were found in the selected studies related to malignant melanoma diagnosis based on images processing. Each method consists of different algorithms, architectures, datasets, and techniques that were used for images preprocessing, features extraction and selection, and classification in order to diagnose malignant melanoma.

Table- IV: Applied methods to diagnose malignant melanoma

ID	Methods	Source
M01	Otsu's Thresholding, ABCD Rule, CFS, ReliefF, Linear Forward Selection, Greedy, SVM, Naive Bayes	[6]
M02	Otsu's Thresholding, GLCM, MRF, LBP, LIPU	[7]
M03	HSV, GLCM, SVM	[8]
M04	G-Opt, Bilt-Sp, FCM, Otsu's Thresholding, Fractional Poisson, SVM, AdaBoost-M1, k-NN	[9]
M05	FCRN, SVM, SoftMax	[10]
M06	ResNet-50, Inception V3	[11]
M07	VGG, ResNet-50, Inception V3, SVM, Logistic Regression, Naive Bayes, AdaBoost, Random Forest	[12]
M08	Flood-filling, Otsu's Thresholding, Canny	[13]
M09	SMOTE, VGG19	[14]
M10	Finlayson, VGG19-UNet, DeeplabV3+	[15]
M11	ResNet-50, FV, SVM	[24]

Rosado et al. [6] used an adaptative algorithm for images segmentation based on Otsu's Thresholding [25]. In order to perform features extraction, ABCD Rule [26, 27, 28] was applied. Four methods were applied for features selection: Correlation based Feature Selection (CFS), ReliefF, Linear Forward Selection and Greedy [29,30]. Finally, two classifiers were used for classification task: Naive Bayes and Support Vector Machine (SVM). Rosado et al. [6] achieved a Sensitivity of 86.0%, a Specificity of 73.0% and, an Accuracy of 80.0%. Sáez et al. [7] classified melanoma lesions according to their thickness. Otsu's Thresholding [32], Gray level co-occurrence matrix (GLCM) [33], Markov random fields (MRF) [34] and Local binary pattern (LBP) [35] were used for features extraction. To perform the classification, Logistic regression using Initial variables and Product Units (LIPU) was applied, which is a combination of a logistic regression model with a Product Unit Neural Network (PUNN) [36, 37]. The Accuracy was 77.6% in the first case (two classes) and 68.4% in the second case (three classes). Waheed et al. [8] for features extraction analyzed the Color, using the HSV color space (Hue, Saturation and Value), and the Texture, applying GLCM. An SVM classifier was used. The Accuracy was 96% when used MATLAB and 95% when used Weka. Al-abayechi et al. [9] during the images preprocessing applied morphological operations and Median filters to reduce images noise. For images segmentation, G-Opt [38], Bilt-Sp [39], fuzzy c-mean (FCM) [40] and Otsu's Thresholding [41] were applied. To perform features extraction, texture was analyzed using the fractional Poisson process proposed by Laskin [42]. In the classification task, an SVM classifier with Radial basis function (RBF) as its kernel function [43] was applied, also AdaBoost-M1 [44] and k-NN [45] were used. AdaBoost-M1 achieved the best results with a CCR, Sensitivity and Specificity of 100% in the three proposed models. Yu et al. [10] built a fully convolutional residual network (FCRN) [47], its input consisted of images with different sizes and its output were score masks with the same size. Data augmentation was applied to increase the robustness and reduce the overfitting. SVM and SoftMax were used for classification. The FCRN was tested with different depths, the best was the FCRN-50, which had and Accuracy of 94.9%.

Shanin et al. [11] applied data augmentation to increase data and reduce network overfitting. They assembled two Deep Learning architectures: ResNet-50 [47] and Inception V3 [50], the optimization algorithm Adam and a batch size of 16 were used for training. The Accuracy achieved was 89.9% in the classification of seven skin diseases.

Maia et al. [12] extracted the Region of Interest (ROI) of each image and standardized the images size. For features extraction, VGG16 and VGG19 [52], ResNet-50 [47] and Inception V3 [53] were used. Six different classifiers were tested: Logistic Regression [54], Support Vector Machine [55] with Linear and Radial kernels, Naive Bayes [56], AdaBoost [57] and Random Forest [58]. The best Accuracy was 92.50%, achieved by the combination of VGG19 with Logistic Regression, and Inception V3 with Logistic Regression. Gupta et al. [13] built a methodology for skin lesions segmentation. They converted RGB images to gray scale, then applied flood-filling and Otsu's Thresholding. Finally, to perform the segmentation, a border detection operation based on Canny was used. Also, morphological operations such as closing were applied to detect a complete lesion. The Jaccard Index was 89.24%.

Jaworek-Korjakowska et al. [14] presented a methodology for melanoma thickness analysis. During the images preprocessing, noise removal was performed, also segmentation masks and Synthetic Minority Oversampling TEchnique (SMOTE) [59] were applied to generate more data. For classification, VGG19 [52] with a densely-connected classifier [60] was used. The Average Accuracy was 87.2%. Ali et al. [15] proposed a novel methodology for skin lesions segmentation.

The Shades of Gray method proposed by Finlayson [61] was used for images preprocessing. Data augmentation was applied to reduce overfitting.

They assembled two new Deep Learning architectures: VGG19-UNet and DeeplabV3+. The Accuracy was 93.5% in the segmentation of skin lesions.

Yu et al. [24] standardized the images size, then normalized the images and applied data augmentation to increase images quantity. ResNet-50 [47] was used for features extraction. Fisher Vector Encoding Strategy (FV) [49, 51] was applied to encode features. An SVM classifier with Chi-squared (chi2) kernel [46, 48] was trained. The best Accuracy was 86.54%, which was achieved by the fusion DCNN-FV using ResNet-50.

B. Systems (Q2)

The second classification corresponds to the selected studies which implemented "Systems" to detect and diagnose malignant melanoma based on images analysis. Table V shows the proposed systems that were found in the systematic literature review.

Table- V: Developed systems to diagnose malignant melanoma

ID	Systems	Source
S01	Mobile application	[16, 20]
S02	Visual recognition system	[17]
S03	Completely automated system for skin lesions diagnosis	[18]
S04	Automated system for melanoma detection	[19]

Abuzaghleh et al. [16] developed a mobile application with two components: the first one sent alerts to prevent sunburn with UV radiation [62], and the second one was a module that classified dermoscopic images in real time, using SVM [63], the Accuracy was 96.3%, 95.7% and 97.5% in the classification of benign lesions, atypical and melanoma respectively. On the other hand, Alizadeh et al. [20] proposed a mobile application for images classification into melanoma or no melanoma, which consisted of two methods, the first one performed all of its operations in the same mobile device using a Normal Bayesian Classifier [64], and the second one sent extracted features to a server where an SVM classifier [55] was applied, the second method achieved the best Accuracy of 96.67%.

Codella et al. [17] proposed a visual recognition system which consisted of two components: dermoscopic images segmentation and classification. A fully convolutional network structure [65] was used for lesions segmentation. To perform the classification, they assembled Deep residual networks [47], convolutional neural networks (CNN) [66], fully convolutional U-Net architecture [67] and used an SVM classifier. The Accuracy was 80.7%.

Hasija et al. [18] implemented a completely automated system for skin lesions diagnosis. Data augmentation was performed using SMOTE, also noise was removed from each image. VGG19 was used for classification, but its last layer was an SVM classifier. The Accuracy was 95.3%.

Mustafa et al. [19] developed an automated system for melanoma detection based on the analysis of skin lesions pictures. Image enhancement was performed and GrabCut [68] was used for segmentation. ABCDE Rule [69] was considered for features extraction. An SVM classifier [70] was applied, the Accuracy was 86.67%.

C. CAD Systems (Q3)

This classification corresponds to the selected studies which implemented Computer Aided Diagnosis Systems ("CAD Systems"), which are specialized systems for clinical use, in order to diagnose malignant melanoma based on images processing. Table VI shows the "CAD Systems" that were found in the systematic review of the literature.

Table- VI: CAD Systems for malignant melanoma diagnosis

ID	CAD Systems	Source
CAD01	CAD System with k-NN	[21]
CAD02	CAD System with Convolutional Neural Network (CNN)	[22]
CAD03	CAD System with SVM	[23]

Moussa et al. [21] proposed a CAD System for skin lesions images classification intro cancerous (melanoma) or not cancerous. Thresholding was applied for lesions segmentation. ABD Rule was considered for features extraction. K-NN was used for classification, and the Accuracy was 89%.

Ge et al. [22] proposed a CAD System for melanoma images segmentation and classification. To extract the Region of Interest (ROI), a fully convolutional neural network (FCN) was applied, then a convolutional neural network (CNN) and GLCM were used to extract features. A Multi-Layer Perceptron (MLP) was used for classification, and the Accuracy was 93%.

Hameed et al. [23] developed a CAD System for skin lesions detection based on images processing. Otsu's Thresholding was applied for segmentation, and GLCM [31] was used for features extraction. Different classifiers were used: SVM, k-NN, decisions trees and assembled classifiers. The best Accuracy was 92.3% in the classification of three classes, and 83.0% in the classification of six classes, both achieved by Quadratic SVM.

IV. ANALYSIS OF RESULTS

A. Methods (Q1)

According to the results that were obtained from the systematic literature analysis, 11 studies correspond to different "methods" for malignant melanoma diagnosis based on images processing, which represents 58% of the total number of revised studies (see Table III). It is observed that the most used method for skin lesions segmentation was Otsu's Thresholding, which was applied in the studies [6, 7, 9, 13]. Considering the methods for images classification, Support Vector Machine (SVM) was the most used, which was applied in the studies [6, 8, 9, 10, 12, 24].

Furthermore, all the revised studies consist of hybrid methods, is that is, they combined different algorithms and techniques for preprocessing, segmentation, features extraction and selection, and classification [6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 24].

B. Systems (Q2)

Regarding the revised studies that proposed "systems" for malignant melanoma diagnosis, 5 were found, which represents 26% of the total number of revised studies (see Table III). It is observed that all proposed systems used the classifier Support Vector Machine (SVM), which was applied in the studies [16, 17, 18, 19, 20], and achieved the best Accuracy of 97.5% in malignant melanoma classification [16]. Furthermore, two of the revised studies proposed mobile applications for malignant melanoma detection [16, 20], and one of them [16] implemented a novel component to send alerts in order to prevent sunburn with UV radiation.

C. CAD Systems (Q3)

Finally, 3 studies proposed "CAD systems" for malignant melanoma diagnosis based on images processing, which represents 16% of the total number of revised studies (see Table III). It is observed that all these studies implemented a component for skin lesions segmentation [21, 22, 23]. Furthermore, the 3 studies that correspond to "CAD systems" used different classifiers, from which, Multi-Layer Perceptron (MLP) achieved the best result with an Accuracy of 93% in melanoma classification [22].

D. Cross analysis

In order to obtain a deeper analysis about the different proposals that have been analyzed previously, a cross analysis has been made between: "Methods", "Systems" and "CAD Systems" (see Table VII). As we can observe, the most used method for classification was Support Vector Machine (M03, M04, M05, M07), while LIPU (M02), Inception V3 (M06), Canny (M08) and VGG19 (M09) were the least used methods for malignant melanoma diagnosis. Regarding the systems and CAD systems, most of them used different combinations of techniques for both images preprocessing (image enhancement, segmentation, features extraction and selection), as for classification, (S01, S02, S03, S04, CAD02, CAD03). On the other hand, CAD01 was the only system that did not combine different techniques for malignant melanoma diagnosis.

Table- VII: Cross analysis

	Systems				CAD Systems		
	S01	S02	S03	S04	CAD01	CAD02	CAD03
M01	✓	✓	✓	✓			✓
M02						✓	✓
M03	✓	✓	✓	✓		✓	✓
M04	✓	✓	✓	✓	✓		✓
M05	✓	✓	✓	✓		✓	✓
M06							
M07	✓	✓	✓	✓		✓	✓
M08							✓
M09			✓			✓	
M10		✓	✓			✓	
M11	✓	✓	✓	✓			✓

V. CONCLUSIONS

This paper presented a Systematic Literature Review of 540 articles related to techniques for malignant melanoma diagnosis based on images processing, from which, the abstract of 125 studies were reviewed, which helped to obtain 19 relevant articles for this study (see Fig. 1). The selected articles were analyzed considering the proposed taxonomy (see Fig. 3). The conclusions of this work have been made according to the research questions that were elaborated in the planning of the review (see Section II). Most of the revised studies, with a total number of 11 studies, presented different "methods" for malignant melanoma diagnosis, and the most used method for images classification was Support Vector Machine. Regarding the "systems" and "CAD systems", most of these studies used two main components: images preprocessing and classification. Furthermore, a cross analysis has been made between the components of the proposed taxonomy (methods, systems, CAD systems), where it was identified that the Architecture of Convolutional Neural Networks (Inception V3), has not been used by any of the studies that implemented systems, which suggests new research applying this technique.

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