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Implementation of Deep Learning for Early Detection of Skin Cancer: A Panoramic Review

Anderson Smith Florez-Fuentes[1,2], Everardo Vargas-Rodriguez[2], Rafael Guzman-Cabrera[3],*, Teodoro Cordova-Fraga[4], Johel Rodriguez Fernandez[1], Albenis Esther Florez Fuentes[5]

[1] Universidad Simón,
Facultad de Ingenierías,
Centro de Crecimiento Empresarial - MACONDOLAB,
Colombia

[2] Universidad de Guanajuato,
Departamento de Estudios Multidisciplinarios,
Mexico

[3] Universidad de Guanajuato,
Departamento de Ingeniería Eléctrica,
Mexico

[4] Universidad de Guanajuato. Campus León,
Mexico

[5] Universidad de Pamplona,
Grupo de Investigación en Bioprocesos y Alimentos,
Colombia

{anderson.florez, johel.rodriguez}@unisimon.edu.co, {as.florezfuentes, evr}@ugto.mx,
guzmanc@ugto.mx, theo@fisica.ugto.mx, albenis.florez@unipamplona.edu.co

Abstract. This article reviews a variety of open access documents related to pre-trained and proprietary architectures that contribute to the detection of skin cancer. This allows readers to freely access the referenced documents, and in some cases be able to replicate their implementations since most of the reviewed works consider open access databases, and therefore their metadata and their bibliographic references, which gave rise to their construction, are known. Moreover, in this review are described the efforts that have been made, and those currently being made for the early detection of any disease is a task that contributes to the improvement of human welfare. For this work, there were considered research manuscripts related to skin cancer, published within the last 5 years, that allow to extend the actions performed, replicating them to evaluate the results found and to improve the current diagnosis through the implementation of artificial intelligence (AI). The evaluation that is performed from the research to select from an extensive bibliography and select the works that from their expertise, manage to contribute to the detection and classification of skin cancer.

Keywords. Deep learning, skin cancer, melanoma, machine learning, segmentation.

1 Introduction

Skin cancer is one of the 10 most aggressive and studied cancers worldwide. According to the World Health Organization (WHO) [1] in 2022 cancers are in the 5th place with a high number of infected patients, not to mention the high number of deaths per year that occur due to this type of cancer. Each type of cancer has their own characteristics and difficulties to be diagnosed. For example, in breast cancer, which occurs in men and women, patients can have lumps or thickening in the breast or armpit. These characteristics can be analyzed initially with self-examination, and later the medical opinion can be supported with mammography. In colon cancer patients presents visual characteristics in the stool, change in bowel habits,

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abdominal pain, weight loss for no apparent reason, in the same way lung cancer is characterized by weight loss, in addition to difficulty in swallowing, swelling in the face and neck veins; even perform analysis of human aging [2], which also analyzes the habits of life of the person's facial features among others that can be easily detectable either by behavior, psychological changes, social among others; In the skin cancer some characteristics can be detectable at naked eye, such as asymmetry, color changes, change in size, unusual borders, among other characteristics on the skin that can be visually detected [3].

The skin is the largest organ of the human body with an estimated average area of 2 m^2 per person. Therefore, the skin cancer has large superficial area where it can develop, at any part of the body. Additionally, the skin cancer present characteristics variability such as Asymmetry, Border, Color, Diameter and Evolution (ABCDE) [4-6], and according to the Fitzpatrick scale it can be classified in 6 types, expanding the number of characteristics that can be found in the images.

The high number of characteristics that can be found in skin cancer, in addition to ABCDE and the existing multiple skin color characteristics established in the Fitzpatrick scale as well as the existing differences between the pigmentations of each lesion, it highlights the need for the addition of non-invasive techniques, as described in Silver et al [7].

Similarly, the use of non-invasive diagnostics remains a general concern for skin cancer detection, as vibrational optical coherence tomography (VOCT) is used to create 3D maps of skin lesions based on quantitative physical data, including changes in cellular and fibrous tissue stiffness and changes in vascular quality. Likewise, studies such as the one by V. Andreeva [8] are presented where deep learning algorithms are used to quantitatively evaluate the ability of fluorescence spectroscopy to differentiate between pathologies and normal skin, focusing the investigation to classify between normal skin, normal pigmented skin, benign lesions and basal cell carcinoma (BCC).

In addition, some authors have applied convolutional neural networks (CNNs) in dermatology for improving clinical pathways and enhance decision making by primary care physicians [9, 10]. Moreover, CNN-based applications can aid in the triage of skin lesions, ensuring that patients are treated by the appropriate clinical services and reducing unnecessary referrals to dermatologists. The models used for detection and classification of skin lesions are mainly CNN, such as GoogLeNet Inception v3 and ResNet, in databases such as ISIC. Furthermore, according to Salah et al a database of skin cancer images is used to train and test the neural network and neuro-fuzzy system [11]. The images are processed to extract features such as color variation, chromaticity and proportions. These features are used as inputs to the neural network and neuro-fuzzy system. The neural network system consists of four neural networks, each trained separately to classify different types of skin cancer. The neuro-fuzzy system combines neural networks and fuzzy logic to improve the accuracy of skin cancer diagnosis. The outputs of the neural networks are used as inputs to the fuzzy logic inference systems, which determine the type of skin cancer. An accuracy of 91.26% in skin cancer classification is achieved with the neuro-fuzzy system.

In a race for the early detection of skin cancer and more than that, to contrast the results of the implementation of skin cancer, seen from an analysis performed by experts and health professionals in comparison with the results obtained with the use of artificial intelligence in models or architectures that implement convolutional neural networks. Works such as the proposed by Hoffmann et al [12] who makes the comparison with professionals from different institutions in Europe, as well as in [13,14], where the combination between human and machine allows comparing and analyzing the results obtained, having as a variant the number of people interacting between the samples.

This same implementation is found in [15] with the variant of skin cancer detection, with the ISIC2016 images. In addition to databases such as ISIC 2016, 2017, 2018, 2019, 2020, images to which sound is applied to analyze the accuracy in the implementation of artificial intelligence and the others related here, one can also find databases such as DermIS and DermQuest [16,17] which are dermoscopic images with the variety that these images were manually segmented.

On the other hand, the implementation of own databases, as well as databases consisting of images that likewise contribute to the implementation of deep learning models such as VGG16 and ResNet50V2 [18], focusing efforts on early detection. For the improvement of the quality of life of patients. Each implementation using their own or adjusted datasets for medical center research, private research institutes, generate their contribution in artificial intelligence implementations, many times by building their own models [19,20] and others pre-trained models [9,21,22].

In several works [23-26] authors have demonstrated that systems based on IA have been capable to detect cancer by analysis medical images performed by digital tomography, histopathology [27], 3D lessons [7], among other types of images. In addition to this, multiple methodologies can be found to improve the results of the implementation of artificial intelligence for either the detection, the classification or both of skin cancer. For example, it has been described that skin cancer images can have high complexity [28, 29], and therefore it represents a significant challenge at the time of segmentation. In order to obtain a more appropriate segmentation for skin cancer classification different approaches were presented. For instance, [29] a hyperparameter optimization by means of a Full Convolution Encoder Decoder Network (FCEDN), whose network is designed for image segmentation using transposed convolution layers, has been proposed [29], which has the advantage that requires few convolutional layers.

Another important topic that recently has been broadly studied is the application of pretrained networks for cancer detection. As an example, [30] it has been proposed to use different pretrained networks for implement a cancer detection system and later perform their execution by changing the parameters in the image preprocessing. Moreover, on the one hand compares the pretrained networks with fewer parameters (light), performs the comparison with data augmentation, the comparison with CNN discriminant, the comparison with different loss measurement functions and finally the performance analysis compared with the best result obtained with the U-Net architecture, which requires a large number of parameters for feature extraction.

On the other hand, in [30] the examination of the efficacy of the Keystone Design Perforator Island Colp, (KDPIF) for the reconstruction of isolated skin cancer excision defects in the upper extremity is discussed. The study aimed to determine the size of repaired defects and complications associated with the trapezoidal flap procedure on the upper extremity, with the variety of features that have the images with skin cancer, the implementation of artificial intelligence, more precisely the implementation of Deep Learning for the detection and classification of the different types of skin cancer.

The early detection of skin cancer is fundamental to improve the survival rates of patients. Given the constant technological evolution, such as the constant improvement of processors, which has also contributed to advances in artificial intelligence, particularly in the field of deep learning, this has allowed testing different models of convolutional neural networks (CNN) with a high effectiveness in the classification of skin lesions, offering a valuable tool for dermatologists and physicians in general. It is important to highlight that in skin cancer, unlike other anomalies, a great advantage is the quality of many existing images in the detection of skin cancer, as well as the combination of existing artificial intelligence techniques.

This article shows the evolution that artificial intelligence has had with the presentation of different actors, the dataset used for the classification or detection of skin cancer, as well as the comparison between the quality of the medical images of skin cancer, as well as the implementation of these datasets in different implementations for the detection and classification of skin cancer with the use of artificial intelligence.

2 Methodology

For this research we consulted the sciencedirect, google scholar and pubmed databases, due to their large scientific literature references data, particularly in the medical areas. In order to delimit the set of elements that can yield a query, we use

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a group of keywords which allow us to reduce by eliminating the definite and indefinite articles that have the sentences in a normal search for this we use the words: 'skin cancer', 'skin cancer' and 'artificial intelligence', 'skin cancer' and 'deep learning' and 'skin cancer' and 'convolutional neural network'. This query was also performed in Spanish.

In addition, the temporality of the published work was defined for the period of the las last 5 years. Furthermore, the PRISMA-COSMIN [31] approach/ method/ algorithm/ procedure was used for carry out the for the process of selection, identification and integration of the consulted document (Fig. 1) to focus only on those regarding imple-mentation techniques and tools for the detection and classification of skin cancer.

2.1 Selecting a Query

The elaboration of an effective query is the first crucial step in the search for relevant scientific articles for a literature review. Through an analysis of the papers consulted during the research, the most relevant keywords are identified. In the case of studies related to skin cancer detection, selecting terms such as: “skin cancer detection”, “seg-mentation”, “classification”, “neural network”, “dermatology”, “deep learning”, “transfer learning”, “image classification” and “convolutional neural network (CNN)” are fundamental for the construction of this review.

These terms serve as the basis for building a broad search strategy in scientific databases. Moreover, by combining these keywords strategically, it is possible to refine the results and obtain a selection of articles that address the most relevant aspects of the topic. In addition, the use of Boolean operators (AND and OR) allowed to broad or narrow the search as needed. A well-structured query not only saves time, but also ensures that the literature review is based on the works consulted in the defined exploration window (last five years). As a result of this selection of terms related to skin cancer and the boolean operators there are obtained the sentence: 'SKIN CANCER’ OR MELANOMA’ OR ‘DESMATOSCOPY’ OR ‘DERMATOLOGY’ OR ‘SKIN LESION’ AND ‘SEGMENTA-TION’ OR ‘CLASSIFICATION’ OR ‘MACHINE LEARNING’ OR ‘DEEP LEARNING’ OR ‘TRANSFER LEARNING’ OR ‘IMAGINE CLASSIFICATION’ OR ‘CONVOLUTIONAL NEURAL NETWORK’ OR ‘CNN''. This sentence is used in the selected databases in order to obtain an effective bibliographic reference for the construction of this article.

2.2 Delimitation

The selection of the correct keywords is not enough to obtain the specific articles for a systematic review, because it was obtained an initial selection of 10990 documents, including journal and conference research articles, review articles, articles in different languages, review conferences, among other types of documents. After filtering this first selection, there were remaining 5975 scientific articles, in which all the different subareas were left active.

2.3 Ranking

In order to ensure the quality and relevance of the selected articles, a comprehensive search strategy was implemented that combined multiple criteria, such as the title, keywords, authors, journals and the period of publications comprised between the year 2019 and 2025. Here, open access articles there were prioritized, as well as specialized databases. To perform this task advanced search tools were used. In this way, it was obtained a set of 209 relevant articles related to the detection and classification of skin cancer, which I served as a starting point for a detailed analysis.

2.4 Selection

In order to guarantee an exhaustive and updated review of the state of the art in skin cancer detection and classification based on deep learning techniques, a rigorous selection and analysis process was carried out over the 209 scientific articles obtained in the classification process. Beyond a simple search by title and keywords, a detailed analysis of each article was performed, evaluating aspects such as the abstract, the data sets used, the convolutional neural network architectures implemented, the pre-training techniques and the results obtained. This level of analysis made it possible to identify those

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articles that can made a major contribution for our review. By focusing on the analysis on pre-training techniques, the best practices were identified and also laid the foundation for the development of more robust and efficient deep learning models. As a result of this process, a database of 105 highly relevant articles was formed, which were systematically organized to facilitate their consultation and subsequent analysis. This detailed structuring of the information allows not only to understand the current state of research, but also to identify trends and future research opportunities, which contribute to generate more accurate and accessible diagnostic tools for skin cancer.

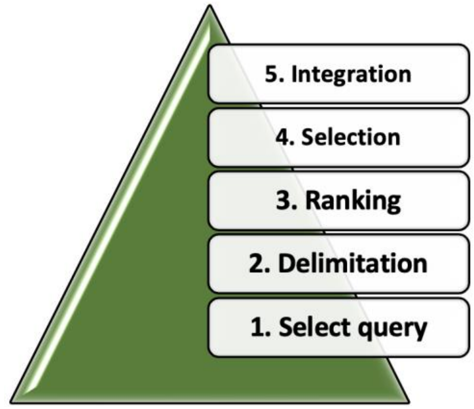

Fig. 1. Diagram of the methodology used for building the present review

2.5 Integration

The integration phase constitutes the fundamental pillar of the review, since at this point all the generated knowledge by each individual study is consolidated. Through a meticulous and selective process, the most relevant elements of the 95 articles are extracted and subjected to a comparative and critical analysis. This process not only involves identifying the main findings, but also evaluating the methodological quality of each research, the relevance of its conclusions with respect to the general objective of the review and its contribution to the existing body of knowledge.

Integrating the results of multiple investigations facilitates the identification of patterns, trends and possible contradictions in the findings. This holistic perspective makes it possible to detect causal relationships, establish connections between variables, and construct a coherent narrative that guides the reader through the literature. In addition, integration makes it possible to evaluate the consistency of the results and to detect possible biases or limitations in the individual studies. In this way, the reliability of the overall conclusions of the review is strengthened.

The main criteria for selecting the research articles used in this review was to choose those based on artificial intelligence in any of its methodologies and implementation for skin cancer detection. Another criterion applied was to select articles available on free access basis since these can be downloaded by all readers for deeper analysis. By taking this into account, many documents are obtained among web pages, articles, theses, clinical cases and others with the previously selected requirements.

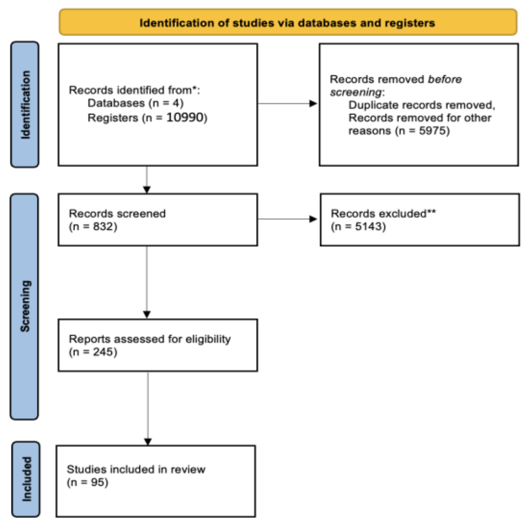

Fig. 2. PRISMA methodology diagram

This work focused on the acquisition of 95 documents in the selection of keywords and proceeds to perform the debugging of the downloaded documents, limiting only those articles that are specific to the detection and / or classification of skin cancer, leaving aside the revised articles and focusing on those articles that have implementations of some type of artificial intelligence model or use any of the public domain databases.

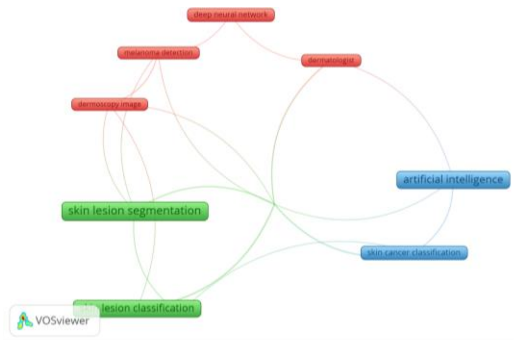

Fig. 3. Skin cancer co-occurrence nodes

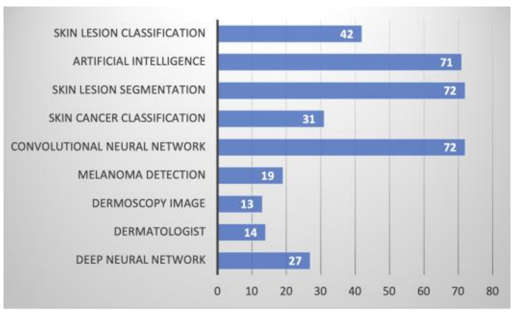

Fig. 4. Co-occurrence histogram

The occurrences of similar terms among the literature consulted allow us to see the behavior of similar terms among the most common words in the abstract or keywords.

In Fig. 3 it is shown the co-occurrence between the keywords of each selected article in this verification, the segmentation into 3 groups is done automatically, this implementation was done with the VOSviewer application, which allows selecting the consulted source, from some databases or directly from a bibliography file already selected, in this case the implementation is done with the selected bibliography, taking the keywords and combining the co-occurrence between the words. This graph gives a clear relationship and frequency of the references selected for the construction of this article; by means of this graph it is possible to observe the frequency that each keyword has among all the selected articles.

The selection of 15 most used keywords is presented in Fig. 4, which can be useful at the time of selecting the keywords to consult on skin cancer and the implementation of artificial intelligence, the selection of words such as melanoma, skin cancer, deep learning, artificial intelligence and CNN allow to reduce the search to papers with higher number of citations and papers with good results in the implementation of AI in the detection and classification of skin cancer.

3 Image Database Analysis

Currently different types of skin cancer image databases are available. Additionally, in several works different types of skin cancer images have been presented. Table 1 provides a list of free databases.

For example, the international skin imaging collaboration (ISBI) provides a robust database of skin cancer images. It should be noted that ISBI is focused on obtaining solutions for the detection and classification of skin cancer in collaboration with several researchers across the world.

This collaboration has generated skin cancer images databases from 2016 to 2020 contributing with the cancer research. In another example of databases, Jinnai et al have pointed out the acquisition of approximately 120000 medical images was performed, for 17 years, by the staff of the Dermatological Oncology Department of the National Cancer Center Hospital [32].

This large data set is the result of extracting the images from medical records and patients directly. All image records have been manually labeled.

Another relevant dataset is the PH2 which was integrated with the collaboration of 200 expert dermatologists [33].

This dataset contains a manual segmentation, clinical diagnoses, as well as the identification of various dermoscopic structures. In an effort for early detection of skin cancer, considering the high number of people affected by this cancer, PH2 image set [34] is relevant.

The image groups stored in PH2 contains 80 images of normal nevi, 80 atypical nevi and 40 melanomas, which allows from the beginning not only to recognize melanomas and non-melanomas or skin cancer detection, but also to perform skin cancer classification. This dataset has been used and evaluated in several works such as [28,34-40], among others, obtaining accuracies ranging from 80% to 94% in the cancer classification.

Table 1. Dataset implemented in skin cancer classification or detection

Dataset	Authors	Number of images	Number of diseases	Types of cancers	Image quality
HAM10000	[13,34,41–49]	10015	7	akiec, bcc, bkl, df, mel, nv, vasc	Excellent
DDI	[24,50–52]	656	78	Melanoma (18 diseases) / Non-melanoma (60 diseases)	regular
MED-NODE	[39,53,54]	170	2	Melanoma, melanoma nevus	good
ph2	[28,34,36,38,39,55–57]	200	3	Atypical Nevus, Common Nevus, Melanoma	Excellent
derm7pt	[39]	1011	20	Melanomas / Non melanomas	Excellent
ISIC2016	[15,29,34,56,58–62]	1279	2	Benign / malignant	Excellent
ISIC2017	[28,29,34,57,61–67]	2750	3	Melanoma, nonmelanoma and seborrheic keratosis	Excellent
ISIC2018	[41,48,55,62,64,66,68–70]	11720	7	akiec, bcc, bkl, df, mel, nv, vasc	Excellent
ISIC2019	[39,71–76]	33569	8	ak, bcc, bkl, df, mel, nv, scc, vasc	Excellent
ISIC2020	[71,75]	44108	2	Benign, malignant	Excellent

The quality of images is given by their general conditions in each data set. Here images can be classified as regular, good and excellent. Regular images contain different factors in the skin in different photographs, this means that either the affected areas are demarcated with ink, or present objects, such as clothes, tables and other objects. Good images are free of external factors or are slightly visible, but present a great variety in the sizes of each image. Excellent images have good characteristics and present standardized format.

The implementation of artificial intelligence in skin problems, not only presented in the detection of melanomas and non-melanomas [54], presents the analysis and prediction of 134 skin anomalies, within them are presented the detection of melanomas and non-melanomas with MED-NODE data, but does not emphasize on the classification or detection of skin cancer, mentioning that it is necessary to continue with these procedures in the limitations that were presented in this research.

Diverse Dermatology Images (DDI) is a data set built with images taken from the pathology reports of the Stanford clinic [51]. The selection of these images took 10 years, in this selection and given the nature of the information the authors managed to reflect in detail 18 different types of melanomas and 60 non-melanomas, making it the data set with the largest number of samples, taking into account that it has a differential approach, but the nature of the analysis that can be implemented, is the detection of skin cancer in melanomas and non- melanomas.

One of the smaller skin cancer image datasets is MED-NODE [40,54], which consists of 70 melanoma images and 100 nevus images, as detailed in studies such as [9, 25], and [77]. While this dataset has been utilized in various research endeavors, its size presents certain constraints. Firstly, the restricted number of images can limit the ability of machine learning models to learn robust and generalizable features. With a smaller dataset, there is a higher risk of overfitting, where the model becomes too tailored to the specific images in the training set and struggles to accurately classify new, unseen images. Secondly, the limited diversity of skin lesions within MED-NODE may not fully capture the wide range of

Table 2. Implemented architectures

References	Models	Best-performing model	Dataset	Measurement best result
[60]	MobileNetV1	MobileNetV1	ISIC2016	AUC 83.0%
	DenseNet-121	DenseNet-121		Accuracy 83.7%
[64]	inception-ResNet-V2, Inception-V3, ResNet-50, DenseNet-201	inception-ResNet-V2	ISIC2016 ISIC2017 ISIC2018	Accuracy 89.28%
[63]	GoogleNet AlexNet ResNet VGGNet SMV SMP ω(1)SMP ω(2)SMP	ω(2)SMP	ISIC2017	AUC 93.0%
[66]	NABLA-N $R2U-Net_B$ ∇^2-Net_A ∇^2-Net_B ∇^2-Net_{AB} $\nabla^2-Net_{AB}+TL$ $\nabla^2-Net_{AB}+TL+Data\ Aug.$	$\nabla^2-Net_{AB}+TL$	ISIC2018	Accuracy 96.36%
[68]	SVM SVM and HOG	SVM SVM and HOG	ISIC2018	Precision 84%
[72]	DenseNet201,MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, GoogleNet	GoogleNet	ISIC2019	Accuracy 76.08%
[77]	SVM Random Forest RF KNN NB	SVM	ISIC2016	Accuracy 85.19%
[78]	own	own	HAM10000	Accuracy 79.94%

variations observed in clinical practice. This can hinder the development of models that are capable of accurately detecting and classifying a broad spectrum of skin cancers, including rare and atypical types.

The first ISBI that is implemented is the 2016, in this challenge the participants are presented with the set of 900 images for training and 379 images for testing, in this challenge the detection of benign cancer is handled with 727 images and malignant cancer with 173 images only for the training group.

The ISIC2019 dataset presented at the ISIC challenge contains the cancer types of Melanomas, Melanocytic nevus, Basal cell carcinoma, Actinic keratosis, Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis), Dermatofibroma, Vascular lesion, Squamous cell carcinoma, being a dataset containing 33569 images, al-lowing the selection of images for AI implementation. The variety of cancer types makes it tentative for implementation in CNNs. On the other hand, ISIC2020 contains a much larger dataset of images with a total of 44108 images, the vast majority of which are classified as benign nevi skin cancer, and therefore it is unbalanced for classification and can be further implemented for the detection process.

Research in skin cancer detection using dermoscopic imaging has been driven by the availability of a wide variety of public datasets. These datasets present characteristic differences in terms of size, cancer types, image quality and patient characteristics.

Despite this great diversity, their implementation in artificial intelligence focuses on a common goal, which is to facilitate the development and evaluation of machine learning algorithms for the early detection of malignant skin lesions. The quality of the data, ranging from regular to high quality images, which is crucial for the correct training of robust and highly accurate convolutional neural network models.

4 Artificial Intelligence Implementation with Public Databases

Proprietary implementations that implement artificial intelligence for skin cancer detection and classification. Some implementations with proprietary networks and pre-trained networks are listed in Table 2. Here, the datasets used in each work are also listed. These examples present significant results in the detection and classification of skin cancer.

Early detection of melanoma is essential to improve patient survival. However, the high prevalence of benign lesions such as melanocytic nevi (NV) and benign kerato-sis-like lesions (BKL) can overwhelm dermatology practices.

By delegating the management of these benign cases to appropriately trained general practitioners, dermatologists can spend more time identifying and treating potentially malignant lesions.

This redirection of care allows for earlier detection of melanoma, resulting in less invasive treatments and better patient outcomes. In addition, early detection can prevent metastasis and significantly reduce melanoma-associated mortality.

5 Image Segmentation and Processing

In this section, it is presented an analysis of different techniques implemented by researchers, to be able to perform more efficient classifications. Several authors [80-90] have performed preprocessing tasks to the selected medical images [79–90]. At this first stage a depilation procedure of the selected images is performed, removing all the noise that does not need to be analyzed, leaving only in the image the region of interest as it names it. It also performs the segmentation of the images integrating two networks, the U-Net and RP-Net, which is called U-RP-Net. This process is combined with the fusion model based on the Jaccard similarity and an increase of the selected data in order to classify the images with the SqueezeNet architecture. In the combined implementation of filters, networks for segmentation [90-92] and the proposed architecture for melanoma classification.

The YOLO3 (You Only Look Once) model has been used for localized lesion detection in the implemented image [28]. This implementation was realized because it is a fast and accurate algorithm that is also used to detect objects in real time. It also implements the GrabCut algorithm for lesion area segmentation, as a semi-automatic segmentation technique that uses a graph-based approach to find the best segmentation of the image. The algorithm implements Gaussian mixture models (GMM) to represent foreground and background regions and iteratively updates the segmentation based on the color in-formation of the image.

The implementation of full resolution convolutional networks FrCN (full resolution convolutional networks) has been applied to segment the images and performs an overlay on the already segmented images and the real images [56,58,64]. Although the implementation used different types of ISIC data sets with differences between the existing cancer types, for example the ISIC-2016, ISIC-2017 and ISIC 2018 have different cancer types between the groups. This has allowed to perform implementations of different types of pre-trained networks for classification after segmentation. In these procedures the In-ceptionV3, ResNet50, InceptionResnetV2 and DenseNet201 have been used for detection and classification according to each type of data set implemented, in this implementation the best result was obtained with the data set ISIC-2018 with the ResNet50 architecture with an accuracy equal to 89.28 %.

Another way to implement the segmentation is the use of fuzzy networks called Fuzzy U-network in [92,93] in which the noise from the images was eliminated by implementing bilateral filters, the result of this implementation base superimposed on the images and are implemented as input to the fuzzy network. This method allows the user to remove the features of the images and leaves only the affected area that is the interest of analysis, this procedure runs it with different pre-trained networks, achieving a result equal to 97.57% in accuracy with the fuzzy U-network.

6 Conclusions

Skin cancer, being one of the most common and aggressive cancers, presents unique challenges for detection due to the variability in lesions and the extent of the affected skin. Artificial intelligence, particularly Deep Learning, has emerged as a promising tool to support dermatologists in the detection and classification of skin cancer, offering greater accuracy in a short time and efficiency in diagnosis. One can observe the models that are developed, the variability between classification and detection, allowing for the most part the comparison of pre-trained networks and eigen-networks. The current importance is the synchronization that can be achieved for the benefit of patients, being able to combine or compare the experience of dermatologists with artificial intelligence, favoring the diagnosis as well as the early detection of any type of cancer. It is necessary to mention that, for the implementation of skin cancer is essential to have a database that has excellent conditions, images that can contemplate each of the visual characteristics that a dermatologist can have when observing the affected area, by containing these features can improve the diagnosis, for this it is necessary to perform several processes, such as segmentation, electronic depilation, and each of the preprocessing treatments that the authors implement. Moreover, early detection of skin cancer requires synergy between disciplines such as dermatology and data scientists who bring complementary knowledge and skills to find practical solutions. Dermatologists offer their expertise in visual identification of skin lesions and interpretation of clinical findings. Computer engineers and data scientists develop machine learning algorithms and image processing techniques to analyze large data sets and extract relevant patterns. Collaboration between professionals is essential to overcome the challenges of early detection of skin cancer. On the one hand, dermatologists can provide high-quality data and accurate labels to train machine learning models. On the other hand, engineers and data scientists can develop assisted diagnosis tools that help dermatologists make more informed decisions and detect lesions at earlier stages, when they are more treatable.

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**Corresponding author is Rafael Guzman Cabrera.*