Chapter 21
Towards an Effective Imaging-Based Decision Support System for Skin Cancer

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ABSTRACT

The usage of expert systems to aid in medical decisions has been employed since 1980s in distinct applications. With the high demands of medical care and limited human resources, these technologies are required more than ever. Skin cancer has been one of the pathologies with higher growth, which suffers from lack of dermatology experts in most of the affected geographical areas. A permanent record of examination that can be further analyzed are medical imaging modalities. Most of these modalities were also assessed along with machine learning classification methods. It is the aim of this research to provide background information about skin cancer types, medical imaging modalities, data mining and machine learning methods, and their application on skin cancer imaging, as well as the disclosure of a proposal of a multi-imaging modality decision support system for skin cancer diagnosis and treatment assessment based in the most recent available technology. This is expected to be a reference for further implementation of imaging-based clinical support systems.

DOI: 10.4018/978-1-7998-7709-7.ch021

INTRODUCTION

Skin cancer is a fast-growing health concern and threat for humans. Its diagnosis is still a challenge, and when made early, eases the consequences with appropriate treatment. Since 1980's technology has incrementally been adopted in daily medical practices to help in the management of health professionals, promotion of better care and aid in diagnostic procedures. Since skin cancer is thriving and the number of specialists is limited, the demand for an effective decision support system (DSS) to ease the burden of the existing experts is high.

This chapter is organized by presenting the problem of skin cancer, its types, the traditional diagnosis and treatment options, the promising imaging technologies that can facilitate a differential diagnosis, the existing freely available datasets that can be used for research, a review on the application of decision support systems in ~~the~~ skin cancer diagnosis, the proposal for an implementation of a generic effective DSS for skin conditions and remarks with a critical discussion and conclusion.

This research aims to present the current diagnosis and treatment options for skin cancer, the existing promising imaging technologies to improve it, disclose the existing free datasets for research, review the application of DSS in skin cancer and propose a generic technologically advanced effective DSS for skin conditions management.

BACKGROUND

Like any other cell in the human body, skin cells are subjected to different types of mechanisms that regulate their development and replacement, if considered needed.
Typically, physiological pathways are triggered to induce apoptosis of malfunctioning cells and destroy it before causing harm. If these defense mechanisms fail, the defective cell can grow out of control and generate a skin neoplasm. (Hunter et al., 2002a)

An abnormal cell grow is not inevitably indicative of the appearance of a cancerous tissue. Benign or malignant tumors can arise, and its differentiation should be clarified. Malignant masses are generally referred to as cancers and are histologically characterized by cells considerably dissimilar from the ones of its mother-tissue. There is a clear tendency to grow and multiply at an excessive rate, as well as to eventually infiltrate neighbor tissues and close-by vascular and lymphatic structures. This feature, i.e., metastization, allows it to spread to different organs and originate a new tumor focus, complicating its treatment and increasing the associated life-risk. Contrarily, benign neoplastic cells tend to be somewhat like its tissue of origin, presenting decent cell differentiation. Their growth rate is considered slower when compared to malignant ones, and the ability to metastasize is absent. In fact, these tumor types have a tendency towards local expansion, pushing adjacent structures. Thus, normally, it does not represent a threat for its host. (Crowley, 2013; L Kemp et al., 2015)

Anatomical changes are guaranteed to happen with the emergence of a tumorous mass. Still, the occurrence of physiological shifts is far more relevant, especially if in the presence of a cancerous lesions. (Baba & Catoi, 2007a) Contrarily to what most could hypothesize, the neoplastic mechanisms are not uniquely controlled by genes that underwent mutations. Genes that retained its "normal" structure can have a detrimental influence, as the promotion of the expression of proteins, normally included in regular cellular processes, but at inappropriate occasions and with the inappropriate extent. Thus, enhancing carcinogenesis. (Moasser, 2014)

At the beginning of neoplasm development, the tumor possesses low metabolic requirements than what could be expected. Still, to guarantee a continuous and interrupted growth, its constituent cells disseminate angiogenic growth factors (e.g., vascular endothelial growth factors (VEGF)) to avoid vasoconstriction and subsequent cancellation of blood supply. (Baba & Catoi, 2007b; Moasser, 2014) As cells multiply, eventually oxygen and nutrient deplete and neovascularization takes place, originating new blood vessels within the tumor. Blood perfusion is also triggered, by the neuronal messenger nitric oxide,

as it provokes vasodilation of surrounding vessels. All in all, boosting incessantly neoplastic growth and proliferation (Moasser, 2014).

The mutations responsible for the appearance of a skin cancer, can have exogenic and/or endogenic causes. Fitzpatrick skin phototype, hair, eye, and skin color, family history of skin cancer and excessive number of moles are all individual' traits that can suggest a person' predisposition for the development of the disease. For exogenic causes, contact with chemically aggressive elements, as arsenic, is an option. Though, excessive exposure to ultraviolet radiation is the most dangerous exterior cause, causing not only DNA defects on epidermal cells, but also the death of macrophages (Langerhans cells) responsible for the detection and elimination of malfunctioning ones. Based on the malignant mutations that take place, different types of skin cancers can arise and affect/infiltrate different skin layers, from epidermis to dermis and even subcutaneous fat (Hunter et al., 2002b; Gordon, 2013; Carr et al., 2020).

Distinction of melanoma and non-melanoma skin cancer

Despite sharing a common trigger-feature, i.e., the occurrence of a malignant mutation on skin cells, skin cancer takes several forms according to the mutated skin cell type. Normally, cancerous skin tumors are divided as melanoma and non-melanoma skin cancer. The latter encompasses squamous cell carcinoma (SCC), basal cell carcinoma (BCC) and Merkel cell carcinoma.

Before detailing each skin cancer type, it is worth to know that some "benign" skin neoplasms may be categorized as precursor lesions, if its existence is latter connected to the growth of malignant neoplasms. Keratocyte tumors, as thermal, tar or arsenical keratoses, depending on the mutagenic agent, are included in this group. Though, the most common of all is actinic keratosis (AK). (Fernandez Figueras, 2017) AKs are normally found in body areas frequently exposed to sunlight, hence, UV radiation is considered the critical etiological factor. It is represented by a papule with a gradient color from skin-tone to a brownish-yellow tone (Fig. 1). Histologically, AK are inflammations of the dermis combined with a proliferation of dysplastic keratinocytes in the epidermis, giving it a scale-like appearance that is rough to the touch. Its progression can lead to the malignant type of skin neoplasms: SCC. Nevi, benign melanocytic lesions, that present a dysplastic showing of melanocytes are also an increased risk for the development of skin cancer, in this case, melanoma. (Kang et al., 2019; Marks & Miller, 2019a)

As mentioned, skin cancer can be classed as melanoma and non-melanoma.
The first type is the deadliest form of all, particularly if detected at an advanced stage of development. As its benign "brother", i.e., nevi, it arises from an abnormal proliferation of melanocytes. Yet, its major disparities, lie on visual attributes. Melanomas are known to present considerable changes in size in shorter time intervals, being this growth accompanied by an amorphous contour with a combination of a variety of different pigmentations from brown tones to black (Fig. 1). Its differentiation from nevi is particularly difficult when at early stages of development. Despite with lower incidence than non-melanoma skin cancer, it possesses a high death rate associated to it (Table 1), due to its capability to metastasize, spreading malignant melanocytes to other organs to create additional cancerous sites. (Kang et al., 2019; Marks and Miller, 2019b; Ricotti et al., 2009; Schwartz, 2008a).

Table 1 *–Incidence and mortality numbers of melanoma and non-melanoma skin cancer for world population during the year of 2020.*

		World
Incidence	Melanoma	324 635
	Non-melanoma	1 198 103
Mortality	Melanoma	57 043
	Non-melanoma	63 731

The non-melanoma type squamous cell carcinoma is one of the most common forms of skin cancer. Its development is often linked to pre-existing lesions, e.g. keratoses, having a greater malignant potential when from thermal, tar and arsenical dysplasia's. An over-proliferation of keratinocytes fuels its expansion, having a clear tendency to infiltrate the dermis, while retaining the ability of keratin production. Normally, SCC invade its host tissue and only multiply into its surrounding healthy skin. Still, some tumors can grow in several directions and even metastasize. In terms of anatomical features, it is somewhat like AK tumors, but with greater size and thickness, with a protuberant growth that can originate a horn-like structure (Fig. 1) (Hunter et al., 2002a; Ricotti et al., 2009; Schwartz, 2008b).

Basal cell carcinomas are constituted by aggregates of basal cells that proliferate into the dermis. It is usually a local infiltrator as SCC, presenting several forms. The most common one is noduloulcerative, followed by superficial, morpheaform and pigmented. The first possesses a node-like structure with a dome that frequently ulcerates. Superficial BCC and morpheaform are usually quite similar, being the first a more pinkish, well demarked structure while the second one can seem like scar tissue (Fig. 1). As the name implies, pigmented BCC is characterized by a heavily pigmented papule and can sometimes be confused with a melanoma tumor (Kang et al., 2019; Ricotti et al., 2009; Schwartz, 2008c).

The last type is not as frequently diagnosed as its associates. Still, Merkel cell carcinoma presents a life risk 2 to 3 times higher than melanoma. The mutated Merkel cells originate a pink/purplish nodule that assimilates to an insect bite (Fig. 1). It is fast growing, and commonly late detected, so spreading to additional organs is plausible to happen (Schwartz, 2008d).

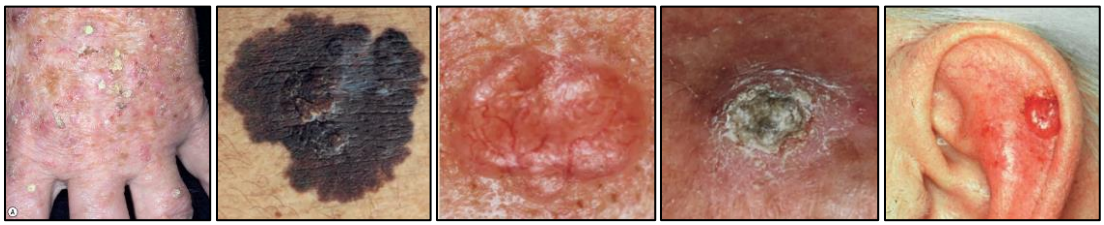

Figure 1 *- Examples of pre-cancerous and cancerous skin neoplastic lesions. From left to right: AK, melanoma, BCC, SCC, Merkel cell carcinoma.*

Current diagnosis

Nowadays, it is fair to say that the gold-standard procedure for diagnosis of skin neoplasms is composed by two stages: visual assessment and histological identification.

The first has remained almost unaltered over the years, being based on a visual examination performed by a physician, as a dermatologist or plastic surgeon. Lesion anatomical traits are essential here, as well as patient description of lesion behavior over time (e.g. size alteration, bleeding, shape variation) . Usually, a Dermoscopy device is utilized by clinicians to have a better visualization of lesion characteristic features invisible to the unaided eye. Also known as skin surface microscopy, epiluminescence microscopy or incident light microscopy, this non-invasive technique uses, at least, 10-fold magnification to facilitate the observation of shape, vascular structures, and color patterns from the epidermis to the upper dermis. Lesion is normally covered with a liquid medium (e.g. water, alcohol) to prevent the appearance of reflection artefacts, unless the system includes a polarized light source. Different gadgets can be used, as handheld dermoscopes, that are cheaper but present low magnification capacity, or digital dermoscopies, more expensive but with greater amplification and the possibility of image storage for lesion comparison over-time. Though, it can also be of assist for evaluation of lesions with little to no pigment, this tool is normally used for the assessment of pigmented lesions. When in the presence of the latter, the observer first distinguishes melanocytic (melanoma, melanocytic nevi) from non-melanocytic ones (e.g., pigmented BCC, angioma, seborrheic keratosis). Then, a preliminary diagnosis is reached based on lesion' characteristics. In the case of melanocytic neoplasms, different methods can be used for visual inspection,

as the ABCDE rule, Menzies method and 7-check-point list. The first strategy is normally preferred. The physician assesses lesion Asymmetry at different axis, followed by the evaluation of neoplasms Borders to check for unexpected terminations of pigmentation throughout lesion' contour. Then, the presence of different Colors is validated, as well as the existence of Differential structures (brown globules, dots, pigmented network, streaks). Finally, lesion Evolution is analyzed, either by previous registries with digital Dermoscopy or by patient report (Fig 2). A positive assessment for each one of these characteristics, strongly indicates the presence of a malignant melanocytic lesion, i.e., melanoma (Kato et al., 2019; Schwartz, 2008e, Yélamos et al., 2019). Despite, being the preferred technique for skin cancer assessment, Dermoscopy accuracy is highly dependent of physician experience and training. Thus, teaching and practice regarding its use is extremely necessary, to take profit from it, during patient diagnosis (De Bedout et al., 2021; Fee et al., 2020).

When there is uncertainty regarding the malignancy of a skin tumor, a biopsy procedure is usually scheduled to remove it entirely (excisional) or partially (incisional) and confirm diagnosis. In incisional procedures, i.e., needle or punch biopsy, only a small sample of the suspicious neoplasm is removed for histopathological analysis. It is only preferred when the lesion is considerably large and/or located in a sensible area, as face. Yet, it is not widely used due to the idea that the technique can disrupt malignant cells to adjacent tissue, promoting metastization.

Surgical excision can be executed with several techniques. The most traditional one, simply involves lesion removal with an elliptical excisional margin that can vary from 1 to 6 plus mm, followed by a biopsy. When tumor is diagnosed as malignant, additional skin margins needs to be removed and analyzed, to guarantee a tumor-free margin. Thus, several surgeries might be needed. To avoid this, the use of Mohs' micrographic surgical technique is preferred, as it allows a thorough histopathological analysis of the neoplasm' edges during the procedure. As skin tissue is excised, the surgeon performs a microscopical analysis of the removed tissue and performs additional re-excisions of the remaining neoplasms until a tumor-free margin is attained. Thus, allowing, a maximal preservation of healthy tissue while removing the cancer completely.

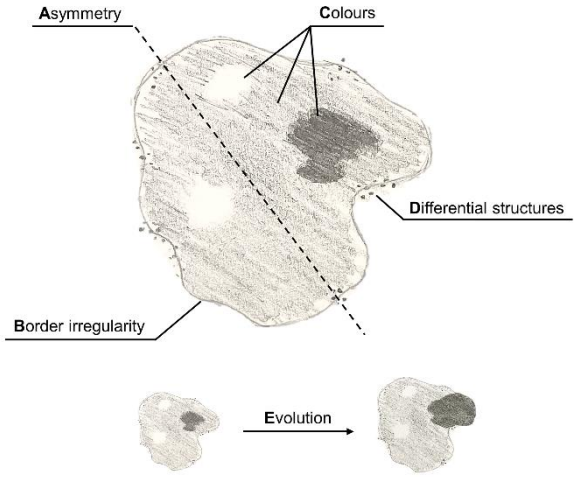

Figure 2– Scheme of melanocytic lesion assessed with ABCDE rule: asymmetrical lesion, irregular borders, presence of three different shades of color, presence of differential structures, e.g., brown globules, dots, pigmented network, and lesion evolution over time.

Despite being a very precise strategy, the gold-standard procedure for skin cancer lesions possesses several downfalls. The experience dependency associated to the Dermoscopy stage is the first hurdle, being this half the battle to determine a correct diagnosis or highly imprecise analysis. The biopsy stage involves consequences and disadvantages, as patient' suffering and discomfort, sometimes deemed unnecessary. The

produced wound can cause cosmetic imperfections, like scarring and bruising, as well as infections, depending on its size and postoperative care. Additionally, the time gap between the surgical procedure and the release of biopsy results can encompass several weeks, increasing stress associated to diagnosis (Doolan et al., 2019; Hoorens et al., 2019; Weinstein et al., 2017; Yagerman and Stevenson, 2018).

To avoid the performance of unnecessary biopsies, as well as the failure of not carrying histological examination when needed, complementary diagnosis techniques with a non-invasive approach are of clinical interest. Always with the goal of maximizing diagnosis accuracy, while being cost-effective and patient thoughtful.

Treatment

Different treatment modalities are offered for skin cancer lesions. After a primary evaluation, it is up to the physician to define the best course of actions based on lesion size, site, invasiveness and metastatic potential and anatomical and physiological features. The optimal treatment is always the one that eliminates malignant cells while favoring the best cosmetic outcome.

Excisional surgery is probably the most frequent treatment prescribed, as it serves two purposes: lesion removal and pathological analysis. Though, as previously mentioned, sufficient margins are needed for success, which can be difficult in certain body areas as eyelids, nose, and ears. If not possible, alternative treatments should be considered to avoid recurrences and subjection of patient to unnecessary pain and scaring. From the available options, performance of lesion excision is always preferred with Mohs technique to guarantee minimal disfiguring while maximizing margins (Schwartz, 2008; Shriner et al., 1998).

For other treatment alternatives, topical chemotherapy is particularly of interest when dealing with large regions affected by actinic lesions. Topical agents as retinoids, diclofenac and topical 5-fluorouracil are applied to the neoplasm for a prescribed period, eliminating completely or partially the tumors. It has the advantage of being a localized treatment, as oppose to traditional (systemic) chemotherapy, thought the leased skin tends to be extremely delicate and tender for a period after treatment (Sahu et al., 2019; Orthaber et al., 2017; Simoes et al., 2015). A similar approach is followed in photodynamic therapy, where a topical agent is applied to the tumorous area, accumulating in cancerous cells. Later, the region is irradiated with a light source to induce the production of reactive oxygen species toxic to the target tissue. In some cases, the topical agent might be substitutes by a drug administrated via blood stream or in the form of a tablet, depending, per example, on lesion size or location. It is usually faster and less aggressive than excision, being the main side effect a burning sensation, normally tolerable (Kapek et al., 2020; Papakonstantinou et al., 2018) Another light-based method is laser therapy, only used for pre-cancerous lesions and small malignant neoplasms. A high intensity narrow beam, e.g., CO_2 laser, irradiates and destroys the tumor, in a very precise manner, thus delivering a good cosmetic outcome. (Soleymani et al., 2017; Mirza and Khatri, 2017). Tumor destruction is also attained with cryosurgery. Cryogenic agents at extremely low temperatures, typically liquid nitrogen, are used to induce necrosis of a specific skin area through freezing of its constituent cells. It is not indicated for deeply penetrating tumors and usually not preferred for melanoma treatment. Caution also needs to be taken if implementing it in patients with Fitzpatrick 5 skin type, as hypopigmentation may occur following the treatment. (Pasquali, 2015; Buckley et al. 2020) When dealing with small skin cancers, curettage and electrodesiccation is usually chosen by most physicians. As the name indicates, the tumor is curetted, and an electrode is used immediately after on its edges to kill neoplastic cells that remained outside the curetted area. The process of electrodesiccation is completed when no tumor is visible, being very effective. Though, wound healing should be carefully controlled to avoid infections. Lastly, radiotherapy is usually applied as and adjuvant technique to other treatments for metastatic or highly invasive tumors, and never as a solo treatment option (Goldman, 2002; Lin et al. 2019).

Emerging non-invasive diagnostic technologies for skin cancer

Innovations on the field of skin cancer detection occur as a way of fighting deficiencies of current approaches. When lesions are detected early, better prognosis is projected, so new tools that assist in this task are attractive to improve patient' survival rate. Particularly, innocuous methods have gain interest and attention, as more and more, non-invasive treatment options are preferred to traditional approaches, to reduce scarring and avoid highly disfiguring outcomes.

Several adjunct tools, beyond visual assessment, have been investigated. Certain techniques have already been applied in a different clinical setting and are now exploited as a potential tool for skin cancer diagnosis (Table 2).

Ultrasounds are widely used as a diagnosis tool for numerous pathologies since the 1950's. The emitted sound waves allow the assessment of structures' heterogeneity within the body based on different echogenic properties. The application of High Frequency Ultrasonography (HFUS) refers to the use of an ultrasound probe that emits waves with frequencies above 10MHz. The shorter wavelength waves are rapidly absorbed and do not reach deeper tissues, delivering images with improved resolution of upper skin layers. Thus, allowing its effective application in the dermatological field. For skin tumor diagnosis, the assessment of characteristic inner components is possible and can even assist surgery as it exposes tumor invasiveness. For melanomas, it has been reported a lower rate of echogenicity, contrarily to benign neoplasms, allowing a clear detection of tumor margins (Botar-Jid et al., 2016). Other skin malignancies, as BCC, follow the same line, showing hypoechoic patterns when compared to its surrounding tissue (Barcaui et al., 2014). Its non-invasiveness and appealing price make it attractive for skin neoplasms evaluation. Though, its sensitivity is limited when used to evaluate ultra-fine tumors (Wortsman and Wortsman, 2010) or extremely thick ones (Mandava et al., 2012). Additionally, it is an operator-dependent technique, as Dermoscopy, requiring extensive training for good diagnostic performance (Zmudzinska et al., 2008; Polańska et al., 2017; Zheng, 2005; Catalano et al., 2019).

The characterization of skin tumors can also be performed through Confocal Scanning Laser Microscopy (CSLM). A low-power laser beam strikes a focal skin point, after passing through a lens. The reflected light is detected as an electrical signal and ultimately translated into grayscale images. The images can depict different histopathological features and associate it to distinct types of skin tumors, being something referred to as an "optical skin biopsy". For the most aggressive form of tumor, i.e., melanoma, CSLM assists in its diagnosis through the visualization of atypical melanocytic cells in the epidermis, particularly in patients with many melanocytic lesions or with potentially cancerous tumors that do not follow the common ugly duckling traits. (Carrera et al., 2012; Rajabi-Estarabadi et al. 2019) Different traits characteristic of BCC have been specified in CSLM, with basal cells appearing as bright spots encircled by darker holes. These findings have been correlated with histopathological results (Que et al., 2015; Lupu et al., 2014). The assessment of both SCC and AK tumors has proven to be challenging, as images often appear mostly white, due to the great amount of reflection caused by tumor structures filled with keratin. Its distinction is more easily done when tumorous cell aggregates are found on the dermis (Que et al., 2015; Aghassi et al., 2000). The greater advantage of CSLM over Dermoscopy is the ability to detect melanoma lesions that do not present the typical features described by the ABCDE rule. Additionally, it aids in estimation of excision border and tumor recurrences, as well as treatment monitoring. Despite its advantages, it is very expensive, a bit time-consuming and demands expertise for its application, complicating its dissemination in a hospital setting (Parsons et al., 2011; Ilie et al., 2019:).

Optical Coherence Tomography (OCT) appears as an imaging modality that offers cross-sectional images of subcutaneous tissue with the use of scattered and reflected infrared light. Conventional equipment possesses a penetration depth of 2 mm, while high-definition OCT can go down to 0.57 nm, allowing the visualization of single cell units. Its application for skin cancer evaluation is well-studied for BCC diagnosis, as well as the assessment of neoplasm border during Mohs, reducing the possible cosmetic defect (Hussain et al., 2015; Chan and Rohrer, 2012) For pigmented lesions, nests of atypical cells close to the dermis haven been documented in higher quantities for melanoma tumors when related to benign melanocytic lesions (Gambichler et al., 2015). In regards of SCC, a clear thickening of the epidermal layer is present, though its differentiation from AK remains challenging, as with CSLM. (Reggiani et al., 2015) The advantages of OCT, include real-time assessment of skin tumor morphology the need to remove any

tissue sample, as neoplasm is scanned laterally with the light beam. Despite presenting a penetration depth inferior to that of US, it shows greater resolution and does not require physical contact with the specimen. It presents lower resolution than CSLM and its efficiency can also be affected by tumor thickness (Ferrante di Ruffano et al., 2018; Levine et al., 2017).

Adhesive patch biopsy (APB) is the closest approach to a traditional biopsy procedure. Yet, without the pain and scaring involved. It is the only innovative method, presented here, that is not image based. The outermost skin layer, i.e., stratum corneum, is removed with the aid of adhesive tape pressed onto the lesion site. RNA from the harvested cells is analyzed to detect specific gene profiles and differentiate, mostly, pigmented skin lesions. This technique rests on the idea that mRNA is scattered to this skin layer by melanocytes through the same channels as melanin is. When combined with visual assessment using ABCDE rule it can improve diagnostic sensitivity and specificity, allowing the early identification of melanomas, though several sample stripping might be needed. (Gerami et al., 2014; Hughes et al., 2021; Fried et al., 2020).

The 3D imaging of epidermal and upper-dermal structures is feasible with Multiphoton Laser Scanning Microscopy (MPLSM). Endogenous fluorophores present in skin neoplasms, emit a fluorescence signal after two-photon excitation, normally with near infrared light. The autofluorescence images present high resolution, allowing the study of melanoma and non-melanoma lesion with high sensitivity and low light damage. Different morphological features were found for SCC and superficial BCC, as the presence of hyperkeratosis and palisading of cancerous cells, respectively. (Paoli et al., 2008) For melanoma lesions, it has recently shown its usefulness for the identification of sentinel lymph nodes (Kantere et al., 2020). When compared to CSLM it has a higher penetration power, though if the lesion is considerably thick, out-of-focus fluorescence can interfere with the collected images (an issue non-existent in CSLM due to the use of a pinhole) (Paoli et al., 2009; Multiphoton Excitation and Microscopy, 2006).

Different tissues present different properties, and electrical impedance is no exception. The technique of bio-electrical impedance (BEI) uses a spectrometer to quantify this property at different frequencies. The measured current is influenced by water content of the assessed tissue, varying when cells endure malignant mutations. This technique has already been applied for the diagnosis of melanoma and BCC with good diagnosis metrics. The acquired impedance spectra delivered sufficient information to distinguish benign nevi from melanoma (80% specificity and 92% sensitivity) and basal cell carcinoma (86% specificity and 96% sensitivity) (Aberg et al., 2005). This technique has also been successfully implemented for the monitoring of melanoma scars after surgery. The property of bio-electrical impedance can be measured on the excision site, to monitor and guide a proper tissue regeneration stage (Logothetis et al., 2019). Apart from complementing data collected from dermatological examination, one of its great advantages is that it can be carried out multiple times to perform lesion surveillance throughout time. Still, specificity is not great, keeping biopsy numbers elevated.

Infrared thermal (IRT) imaging is the only emerging method that does not require direct contact with the patient or irradiation with light sources to assess skin tumors. This technique exploits the capability of the human skin to irradiate infrared heat naturally and continuously, capturing it with thermal cameras. Distinct temperature patterns are expected from unadulterated skin tissue when compared to neoplastic regions, with increased metabolic and vascular activity, and consequently, heat dissipation. Practical studies are found for the identification of thermal patterns characteristic of melanoma and nevi, with melanoma presenting higher temperature values than healthy skin tissue (Magalhaes et al., 2019). When stimulation is included, i.e., dynamic implementation instead of a static approach, by mechanical, chemical, or thermal means, this difference is accentuated, easing skin tumor identification (Pirtini Çetingül and Herman, 2011). Additional skin lesion types, as BCC, SCC and AK have also been analyzed with IRT imaging to adjuvant diagnosis (Baek et al., 2019; Godoy et al., 2017) The main set-back of this technique concerns the need of a controlled environment, to guarantee correct temperature measurements (Ammer, 2003; Ring and Ammer, 2015; Ring and Ammer, 2012).

Another technique, not widely used on day-to-day practices, is photodynamic diagnosis (PDD). This methodology consists of the application of topical agents onto the lesion, followed by excitation with a light beam to stimulate the production of photosensitizers. These fluorescent compounds present a greater

accumulation rate on skin neoplasms compared to healthy skin. PDD is recent for skin cancer applications, but surely promising. Its recent use is found for the diagnosis of metastatic melanoma. (Naidoo et al., 2019) Due to the induction of the production of fluorescent compounds, it is a very helpful tool to guide tumor' excision, while being non-invasive and extremely target-precise. Thought, PDT is not without limitations as it cannot be applied to patients with specific blood diseases (Krammer and Verwanger, 2016; Lipiński et al., 2015).

Ultraviolet (UV) imaging can be considered the most recent technique for skin cancer assessment. Its application presents two variants with reflected-UV imaging and fluorescence-UV imaging. The first involves the use of an UV excitation source that results in the acquisition of an image representative of the UV radiation reflected at the same wavelength by the irradiated object. In the case of the second, a UV light is used as an excitation resource to promote the reemission of longer wavelength rays, often in the visible area of the electromagnetic spectrum. Thus, it is passible of being imaged with a standard digital camera. Though, recent, UV fluorescent photography has been indicated as a valuable tool for the evaluation of tumor margins in BCC cases, while UV reflectance has shown good input in the appraisal of skin photoaging (Mojeski et al., 2020; Crowther, 2020; Pratt et al., 2017).

Table 2 *– Emerging non-invasive techniques and its associated advantages and drawbacks.*

Technique	Advantages	Drawbacks
High frequency ultrasonography	Evaluate tumor invasiveness Aid with excision planning	Low sensitivity for very thin/thick melanomas User-dependent
Confocal scanning laser microscopy	Diagnose melanoma in absence of Dermoscopy features Assist in estimation of excision border Non-invasive treatment monitoring Detection of tumor recurrences Surveillance of lesions over time High sensitivity and specificity	Very expensive Time consuming Demands expertise
Optical coherence tomography	Assist in estimation of surgical borders Contactless Higher resolution than HFUS High sensitivity and specificity	Lower resolution than CSLM Performance affected by tumor thickness
Adhesive patch biopsy	Reduce number of biopsies No-scarring Early diagnosis of melanoma	Multiple stripping might be needed Destined for melanocytic lesions
Multiphoton laser scanning microscopy	High resolution High sensitivity Low light damage High penetration power than CSLM	Poorer resolution for thicker lesions Excitation wavelength needs to be refined to guarantee fluorescence while innocuous for the tissue

Bio-electrical impedance	Assist in estimation of surgical borders Surveillance of lesions over time	Low specificity Poor performance in given body areas
Infrared thermal imaging	Contactless Real-time measurement Cost-effective (when compared to other imaging modalities) Surveillance of lesions over time	Need of controlled examination room conditions
Photodynamic diagnosis	Extremely target-precise Assist in estimation of surgical borders	Not suited for patients with specific blood diseases
Ultraviolet imaging	Evaluation of tumor margins Contactless	Extremely expensive equipment Need for artificial light sources

Existing freely available skin cancer datasets

To date there were only found 7 freely available skin cancer datasets through a search on the main repositories of data, Kaggle (https://www.kaggle.com) and UC Irvine Machine Learning Repository (https://archive.ics.uci.edu/ml), which are characterized on table 3.

Table 3 *– Freely available skin cancer datasets.*

Dataset name	Data type	Samples (N)
ISIC 2019 challenge	Images and 15 attributes	25331
Dermnet	Images and diagnostic	19500
HAM10000	Images and 7 attributes	10015
Melanoma Image Data (U.Porto)	Images and 15 attributes	435
SKINL2	Images and diagnostic	376
Dermoscopy Skin Lesion Multispectral Image Database	Images and diagnostic	30
Dermatology Data Set	34 attributes	336

The ISIC 2019 challenge dataset (ISIC, 2019) contains 25,331 (2017 and 2018 are also included) images available for the classification of dermoscopic images among nine different diagnostic categories: Melanoma, Melanocytic nevus, BCC, AK, Benign keratosis, Dermatofibroma, Vascular lesion, SCC and None of the previous. It has a total of 15 attributes consisting of the beforementioned categories, patient age, sex, lesion anatomical location, lesion id and image reference.

The Dermnet (Dermnet, 2020) dataset is composed of 19500 images of 23 types of skin diseases. All images are in JPEG format with 3 color channels, e.g. RGB, with variable resolution. The lesion categories include acne, melanoma, Eczema, Seborrheic Keratoses, Tinea Ringworm, Bullous disease, Poison Ivy, Psoriasis, Vascular Tumors.

The HAM10000 ("Human Against Machine with 10000 training images") dataset (Tschandl et al., 2018) consists of 10015 dermatoscopic images of pigment lesion released for academic research involving machine learning methods. Along with the images there are 7 attributes: image id, lesion id, diagnostic, diagnostic type, patient age, patient sex, and lesion anatomical location. More than 50% of the sample include histology results, lesion included in the database are: AK, BCC, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions.

At the University of Porto there it was developed a project of a melanoma PH^2 dataset (Mendonça et al., 2013), which is composed of a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. All images have a magnification of 20x and are 8-bit RGB color images with a resolution of 768x560 pixels. It also includes attributes such as: clinical diagnosis, asymmetry, pigment network, presence of dots, streaks, regression areas, presence of blue whitish veil and mention of all colors present at the lesion.

Another dataset also developed in Portugal, the light field dataset of skin lesions (SKINL2) (Faria et al., 2019) consists of 376 plenoptic camera with extended depth of field images, which were categorized as melanoma, melanocytic nevus, BCC, seborrheic keratosis, hemangioma, dermatofibroma, psoriasis and other.

The Dermoscopy Skin Lesion Multispectral Image Database (Lézoray et al., 2014) has 30 multispectral dermoscopic images with resolution 800x600 and are composed of 6 spectral bands (3 in visible spectrum light and 3 in infrared light).

The Dermatology Data Set (Güvenir et al., 1998) has 336 samples of 34 attributes, being 12 clinical and the remaining histopathological. It also includes the patient demographic data and his family history. The skin conditions present at the database are psoriasis, seboreic dermatitis, lichen planus, pityriasis rosea, cronic dermatitis, and pityriasis rubra pilari.

It can be observed that all freely available datasets are of a single nature of data, being a multispectral imaging dataset with clinical, histological, patient and family record multisource dataset missing.

Existing Skin Cancer Decision Support Systems

Since the general application of clinical DSS in the mid 1980's, they spread from general to specific applications, in this section attention will be given to the Skin Cancer oriented DSS, which were retrieved from literature sources such as PubMed and Scopus after screening the abstracts.

The aim of the clinical DSS is to be able to process more data and achieve a better sensitivity, and specificity than human experts, dermatologists, trainee, and general practitioners (table 4).

Table 4 *– Average sensitivity and specificity of human experts, dermatologists, trainee, and general practitioners (Przystalski et al., 2010).*

	Sensitivity	**Specificity**
Expert	90%	59%
Dermatologist	81%	60%
Traine	85%	36%
General practicioner	62%	63%

A melanoma DSS was implemented using 152 Dermoscopy images with features extracted from ABCDE rule and texture segmentation and a multi-classifier with a combination of LDA, Decision Tree and kNN with a voting system for the best result achieved 81% sensitivity and 74% specificity (Sboner et al., 2003).

A performance of a spectrophotometric DSS system based in ANN involving 1794 samples was tested, achieving a sensitivity of 88% and a specificity of 80%, recognized 95% of the cutaneous melanoma cases. The ANN training procedure was based on the backpropagation and conjugate gradients algorithms. The images acquisition consisted of images at 15 different spectral bands (30 nm bandwidth) between 483 and 950 nm. Having the images, a useful area of 18×14 mm^2 (spatial resolution of 33 pixels mm^{-1}) (Carrara et al., 2007).

A melanoma DSS using 2851 dermoscopic images based in the ABCD rule and ANN showed a sensitivity of 75% and specificity of 84%, which was lower than achieved by experts that was 97% and 93% respectively but analyzed much less samples (Dreiseitl et al., 2007).

A skin cancer DSS system composed of 110 Dermoscopy images using a ABCDE rule, achieved an accuracy of 92.15% on the cooperation of a NB and MLP-7 classifiers (Ruiz et al., 2008).

Using 152 images from the Dermnet dataset consisting of 55 features of the ABCDE rule and texture classified with NB model achieved 86% accuracy. This model also used age, skin type, lesion location and sex as features (Alcón et al., 2009).

An automated Content-Based Image Retrieval (CBIR) system for the diagnostic of dermoscopic images of pigmented skin lesions consisting of 24804 dermoscopic images corresponding to 20491 pigmented lesions with known pathology, using the ABCD rule, a hierarchical multi-scale computation of the Bhattacharyya distance and SVM classifier achieved a maximum precision of 94.1% in the benign nevi identification (Baldi et al., 2009).

The best result was obtained for linear SVM – 97.44% for 70/30 train to test ratio on 5189 color dermatoscopic segmented images (Przystalski et al., 2010).

A Melanoma DSS consisting of 187 samples of Multiple-Scattered Light Spectroscopy (MSLS) images achieved 89% sensitivity, 89% specificity, and 89% accuracy with NB (Li et al., 2014).

A computer-aided diagnosing (CAD) system was developed for skin cancer diagnosis consisting in pre-processing, segmentation, features extraction and classification using Self-advisable SVM on 168 dermoscopic images based in the ABCD rule achieved an 90% accuracy with 91% sensitivity and 89% specificity (Masood et al., 2014).

A CAD for melanoma diagnosis based in color analysis and probabilistic model Correspondence-LDA of 482 Dermoscopy images and classified with an AdaBoost algorithm achieved an average precision of 84.9% (Barata et al., 2015).

One DSS based in 200 dermoscopic samples used a classifier based in self-advised SVM with a radial basis function and presented an accuracy of 89% (Masood et al., 2015).

A dataset composed of 160 ultrasound images with parameters selected according to Mahalanobis distance and linear SVM classification, was able to differentiate malignant from benign melanoma presenting 82.4% accuracy (Andrėkutė et al., 2016).

Using feature selection with a Genetic Algorithm for classification with kNN on a database composed of 167 fluorescence images achieved an accuracy of 94% (Odeh & Baareh, 2016).

A DSS using a classifier composed of Deep Learning based ANN and Hybrid Adaboost-SVM algorithms in a database of 992 Dermoscopy images presented an accuracy of 93% (Premaladha & Ravichandran, 2016).

Using a ABCDE rule were applied to Genetic Algorithms for feature selection and classification with SVM on 1300 Dermoscopy images achieved an accuracy of 88% (Tan et al., 2016).

A multicenter DSS for discriminating Melanocytic Nevi from Malignant Melanomas using a training database of 1300 samples achieved an accuracy of 94.1% using a ABCD rule input to an ANN (Kostopoulos, 2017).

To a dataset containing 200 Dermoscopy 8-bit RGB channel images at 768x560 resolution, a classification was applied using ANN, SVM, kNN and DT based in the parameters of ABCD rule assessment presented an accuracy of 92.50%, 89.50%, 82.00% and 90.00% respectively (Ozkan & Koklu, 2017).

A classification of the skin cancers using ECOC SVM with deep convolutional neural network on a total of 3753 images achieved a maximum average accuracy of 95.1% for SCC (Dorj et al., 2018).

Histogram analysis and segmentation parameters of 294 images were processed and selected as input to ML methods, which were compared, and the best achieved result was of RF with 77.26% accuracy (Gautam et al., 2018).

A DSS for detection and localization of Cutaneous Vasculature in Dermoscopy images using a database of 200 images having shape, size, color and architecture vascular features classified with data-driven feature learning framework based on stacked sparse auto-encoders (SSAE) presented 91.1% accuracy (Kharazmi et al., 2018).

Using the ISIC 2017 skin lesions images database composed of 2000 samples, a DSS with ABCDE rule and texture features classified using SVM achieved a 93.95% accuracy (Saleem, 2019).

A hyperspectral imaging DSS employing 125 spectral bands captured between 450 and 950 nm used a database of 76 images with features labeled using Spectral Angle Mapper algorithm and classified with a SVM Linear classifier presented 89% accuracy (Leon et al., 2020).

At table 5, the existing skin cancer DSS sensitivity and specificity values can be observed that only six outperform the expert sensitivity, but all overachieved the general practitioner sensitivity. In terms of specificity all published DSS present better performance when compared with human experts, dermatologists, trainees, and general practitioners.

Table 5 *– Sensitivity and specificity reported for existing skin cancer decision support systems.*

	Sensitivity	**Specificity**
Sboner et al. 2003	81 %	74 %
Carrara et al. 2007	88 %	80 %
Dreiseitl et al. 2007	75 %	84 %
Ruiz et al. 2008	79.13 %	93.72 %
Alcón et al. 2009	94 %	68 %
Li et al. 2014	89 %	89 %
Masood et al. 2014	91 %	89 %
Barata et al. 2015	78.9 %	76.7 %
Masood et al. 2015	90 %	88.3 %
Andrėkutė et al. 2016	85.8 %	79.6 %
Odeh & Baareh 2016	96.7 %	91.3 %
Tan et al., 2016	83 %	89 %
Kostopoulos 2017	82.9 %	96.5 %
Ozkan & Koklu 2017	87.08 %	94.86 %
Dorj 2018	96.9 %	94.17 %
Gautam et al. 2018	70.38 %	83.54 %
Kharazmi et al. 2018	85.3 %	94 %
Saleem et al. 2019	93.27 %	98.47 %
Leon et al. 2020	87.5 %	100 %

PROPOSED IMPLEMENTATION

A Decision Support System (DSS) has three main components: Dataset, Inference Engine and User Interface and should have as main goal to support its users in aiding their decision making in a bias free and transparent manner (Sauter, 2014).

For an effective skin cancer DSS the data should be of multiple sources, as more and detailed data will provide better insights for the decision-making process and better characterization of the problem. Relying only on ABCDE dermoscopic rule has been exhaustively tested and has limited accuracy, as seen in the previous section. With new emerging imaging modalities presenting promising results, a multispectral based DSS is expected to perform better, although it also brings new challenges and complexity. This added with histology, patient clinical history (probably obtained for an existing Electronic Health Record), patient socio-demographic data and patient family history of skin conditions will provide full data to build information and knowledge to aid for better decisions. Based on this the proposed infrastructure showed in fig. 3 will have all the mentioned sources. Though, it is important to refer that not all the imaging modalities are available in the Digital Imaging and Communications in Medicine (DICOM) standard and stored in the Picture Archiving and Communication System (PACS), so proprietary data storage implementations must be considered. Each imaging modality (Dermoscopy, HFUS, CSLM, OCT, APB, MLSM, BEI, IRT, PDD and UV) will be a data source along the histology, patient health record, patient socio-demographic and patient family skin condition history datasets. The data will be processed by

an Extract, Transform and Load (ETL) system to correct data ambiguity, discrepancies, and outliers. Additionally, it will be stored into an offline Datawarehouse (DW), being divided in different tables, i.e. Datamarts (DM) and correspond to the original multiple source data that are linked through a fact table (fig. 4), which facilitates the data selection for the Data Mining tools and Visualization at the Dashboard.

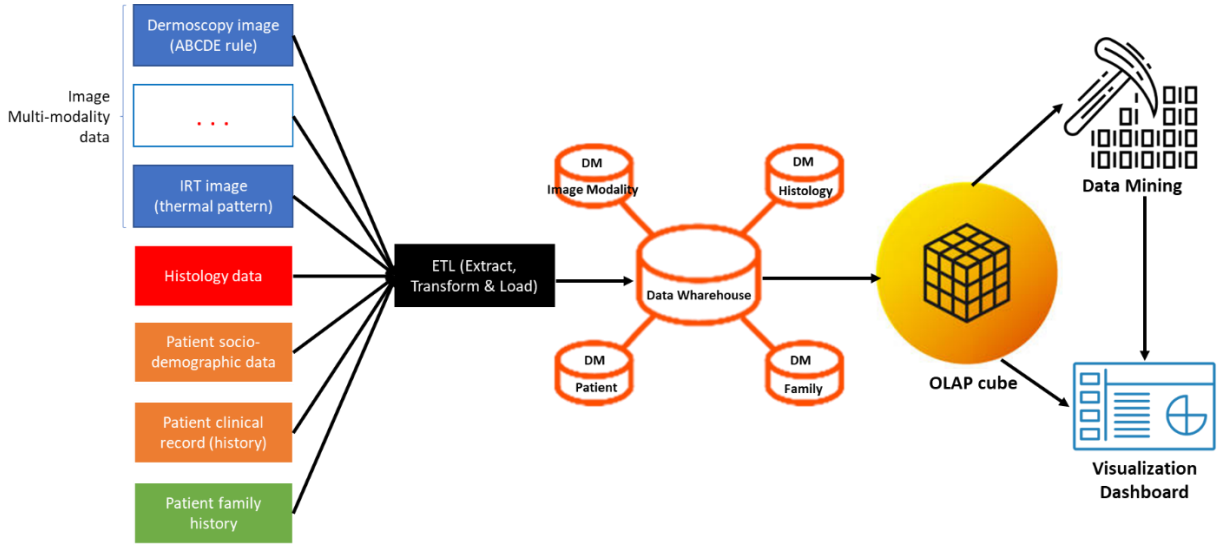

Figure 3 – The proposed skin cancer Decision Support System general infrastructure.

The data can be presented in several forms. It can be a raw image, a processed image (e.g. segmented, histogram analysis, region of interest analysis, cross-section analysis), text, numeric, binary, date type or categorical.

In the Data Mining tools several operations may be applied to the data, which can be supervised or unsupervised learning algorithms. For some datamining operations binarization or normalization of an attribute might be required.

With the unsupervised learning methods. Clustering and Data Association can be practiced. The clustering can be performed through KMeans or Hierarchical clustering, this helps to establish groups among selected data. The association is normally based in rules of different attributes association to identify patterns and normally employs the Apriori algorithm (Witten et al., 2016).

The supervised learning approach is based in prediction/regression methods and classification. The prediction/regression methods use the input data to through a linear (all numeric data) or logistic (numeric and categorical data) formula, estimate a new output. This can be achieved using linear regression methods, which can be simple or multivalued or a logistic regression. For classification, there are several methods available to be employed, all based in diving the dataset in two groups: the training set and the testing set. Commonly, a division of 70/30% is selected, although other configurations can also be applied. The training will be used to train the model built with the selected algorithm, and respective parameters adjusted. The accuracy value obtained will represent the probability of a given new record of the dataset to be correctly classified. Among the most common classification methods there are: MLP, also known as ANN, SVM, NB networks, DT, Random Trees, RF, kNN, GA, Fuzzy Logic, Logistic Regression and the AdaBoost (Witten et al., 2016). Based in the previous section the already used in a single modality classification, that proved its utility, are ANN, SVM and NB.

Once the data is stored in a clean and correct form in the DW and DM, through the OLAP cube, it will be possible to perform different views and queries on the related data. The fact table (fig. 4) is indispensable in this task, as it maintains the correspondence between the related data. With the OLAP cube it is possible to perform the operations Roll-up (reducing dimension through aggregation), Drill-down

(fragment data into small parts, increasing a dimension), Slice (selecting one dimension of data), Dice (selecting only two or more dimension, but smaller than the original cube) and Pivot (rotates the data axes to provide a substitute presentation of data) (Sauter, 2014).

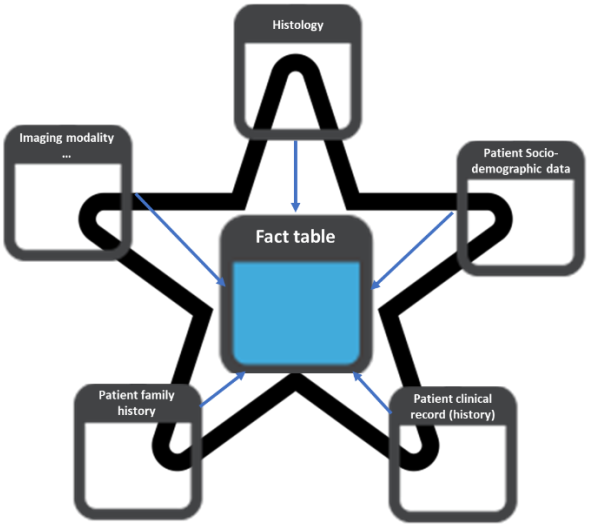

Figure 4 – The representation of the Datawarehouse fact table and its relationship in star with the DataMart tables in the support to the OLAP cube.

It is important to mention that, despite the main goal of a skin cancer DSS being focused the production of a prognosis for a patient examination, it should also support that indication with more data representation and visualization tools, such as charts. This is important because, at the end, the responsibility of the diagnosis is entirely of the physician and not of the system, as it only gives him a hint.

The produced dashboard should be operational, reflecting the actual state of the patient lesion and its relationship with history. It must enforce simplicity, readability, and focus. The dashboard should use different shades of the same color, avoid using any logo, avoid using data navigation, use 2D graphics instead of 3D graphics, use lines and borders sparingly, use rounded metrics and simplified details, use the same font, color palette and style, use some space between the elements, avoid multiple views, scale sections according to the same space and group data logically.

In terms of charts at the dashboard, they depend in the objective of showing them. For comparison between items: if there are two variables per item, it should be used the variable with column chart; if there is only one variable per item, but many categories, it should be used the table with embedded charts; with few categories, but many items, it should be a bar chart; for few items, a column chart. For overtime comparison: if there are many periods and cyclic data should be a circular area chart, or non-cyclic data a line chart; if there are few periods and single of few categories, a column chart is recommended or with many categories, a line chart. For data distribution: if there is a single variable and few data points it is recommended a column histogram, or many data point a line histogram; if is two variables, a scatter plot should be used, and for three variables a 3D area chart. For data composition: if static and a simple share of total, it should be used a pie chart; if accumulation or subtraction of total, a waterfall chart; with changes over time if there are few periods, a stocked column chart is recommended, if there are many periods, a stocked area chart. Finally, for relationship between data: if there are only two variables, it should be used a scatter plot, if three or more a bubble plot is recommended.

This proposal for DSS is generic, as it always depends on the question that the system must give a response. Still, the proposed infrastructure, if well parameterized, can respond to more than a single

question. For a more intelligent dashboard, some interactivity can be implemented, presupposing, per example, a pressing of a chart or text to show more related detail to it.

DISCUSSION AND CONCLUSION

There is no doubt of the valued contribution of DSS to aid health professionals with the growing rise of skin cancer and shortage of specialists. Most of the developed solutions, ~~which~~ are mainly research oriented and institution self-solutions are based in a single modality of diagnosis. Only one implementation was multicenter (Kostopoulos, 2017), but based in the simple dermoscopic image ABCDE rule. The majority of the skin cancer DSS implemented to date focus on this rule, which is also the common practice in daily clinical setting. Although for better discrimination, on a confounding lesion, relying in this rule is not enough and selecting a histology lab test is costly and dilatory. This leds to the emergence of promising imaging techniques, which are now becoming to be adopted. Still, some require validation against the histology gold standard, which, with the absence of a multi-source dataset freely available, is limited in terms of time and funds.

It is important to mention that a DSS to become useful, must surpass the performance of a specialist (Przystalski et al., 2010). The best reported results for the ABCDE rule DSS are using SVM (Baldi et al., 2009; Masood et al., 2014; Premaladha & Ravichandran, 2016; Dorj, 2018; Saleem, 2019), even when combined with another ML algorithm such as Adaboost (Przystalski et al., 2010). Other supervised ML algorithm that performed with an accuracy over 90% was the MLP or ANN (Dreiseitl et al., 2007; Kostopoulos, 2017; Ozkan & Koklu, 2017), a proposal result was achieved when combined with NB (Ruiz et al., 2008). On other imaging modalities, the best achieved accuracy was obtained for a spectrophotometric DSS using ANN (Carrara et al., 2007), followed by the fluorescence images using kNN (Odeh & Baareh, 2016), MSLS using NB (Li et al., 2014), hyperspectral imaging with SVM (Leon et al., 2020) and ultrasound images with SVM (Andrėkutė et al., 2016).

The proposed DSS implementation is generic and conceptual, being out of scope of this publication to constrain it to a specific technology or development environment, as it can be implemented on most of the current available development and storage tools. From this research, it is clear that with the existing freely available datasets on skin cancer, an effective DSS for skin conditions using a multi-imaging approach it cannot be implemented. The majority of the existing DSS only addressed a specific and simple question, but future practice may demand more information, in specific for the differential diagnosis. The proposed open architecture is dynamic in allowing multiple questions, which through OLAP and data mining is possible to add and adjust questions. In a multi-modality data source approach, different data mining and visualization tools can be used for different modalities, making the proposed system flexible. To the authors knowledge, there is no implementation of this kind for dealing with skin cancer, being the proposed more comprehensive and could cope with other dermatological conditions. This is the first step towards a technological need. It is important to enforce the idea to health professionals that it is easier to engage with new advanced computational tools than being afraid of losing a job to a smart system, showing resistance to their adoption, becoming these technologies a facilitator in their practice.

At this publication, the current diagnosis and treatment options for skin cancer, the existing promising imaging technologies to improve it and the existing free datasets for research were presented, the application of DSS in skin cancer were reviewed and a generic technologically advanced effective DSS for skin conditions management was described.

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KEY TERMS AND DEFINITIONS

Accuracy: parameter that represents the number of individuals correctly diagnosed among a given group, by a clinician or decision support system.
Basal cells: epidermis skin cells responsible for producing new skin cells.
Business Intelligence: software tools that can analyze large data quantities and retrieve information to reach knowledgeable conclusions.
Datamart: Subset of a data warehouse focused on a specific topic of information, per example, patient information.
Data Mining: Process involved on the harvesting of information from unprocessed data.
Datawarehouse: electronic system for the collection and manipulation of large amounts of data.
Decision support system: computational system employed to assist, sustain decisions, and select the best course of action. In a clinical setting, these systems are commonly referred to as **Computer Aided Diagnosis**: system that supports medical diagnosis and helps in treatment selection.
Deep learning: subfield of machine learning that mimics the workings of the human brain in process of data analysis, interpretation and decision making.

Dysplasia: abnormal cell development, normally associated to the appearance of pre-cancerous or cancerous lesions.
Echogenicity: the capability of a given tissue to bounce an echo. This ability is low for hypoechoic structures (denser) and high for hyperechoic structures.
Expert Systems: computational system build to mimic the capability of a human specialist to perform a decision.
Fluorophores: fluorescence compound that can radiate light upon excitation with a light source.
Inference Engine: section of a machine learning system destined to logically interpret a given data set and retrieve information from it.
Keratinocytes: epidermis skin cells that originate from the differentiation of basal cells, composing approximately 85% of epidermis. It is the skin constituent responsible for the synthesis of vitamin D and keratin production.
Langerhans cells: epidermis skin cells with immunological functions.
Machine learning: scientific area of Artificial Intelligence focused on the development of algorithms and/or systems with the ability to learn, modify in an automatic manner and reach decisions, based on data patterns.
Melanocytes: epidermis skin cells that produce and store melanin, a pigment that absorbs ultraviolet rays, blocking its nefarious actions.
Merkel cells: epidermis skin cells that play a role in human sensing and work as mechanoreceptors.
Metastization: the ability of malignant cells to infiltrate neighbor tissues and close-by vascular and lymphatic structures to spread to distant organs.
Neoplasm: atypical growth and agglomeration of cells.
OLAP cube: array with large amounts of data used for multidimensional analysis.
Sensitivity – measure of the ability of a clinician or decision support system to correctly identify those who have the disease.
Specificity: measure of the ability of a clinician or decision support system to correctly identify those who do not have the disease.
Supervised learning: a machine learning algorithm that learns from labeled data included in a training set.
Unsupervised learning: a machine learning algorithm that learns from unlabeled data, learning and detecting characteristic data patterns on its own.
User Interface: platform created for the interaction of a human operator with a computer.

ACRONYMS

AK – Actinic Keratosis
ANN - Artificial Neural Network
APB – Adhesive Patch Biopsy
BCC – Basal Cell Carcinoma
BEI – Bio-Electrical Impedance
CBIR – Content-Based Image Retrieval
CSLM – Confocal Scanning Laser Microscopy
DICOM – Digital Imaging and Communications in Medicine
DT – Decision Trees

ECOC – Error-Correcting Output Coding
EHR – Electronical Health Record
ETL – Extract, Transform and Load
GA – Genetic Algorithms
HFUS – High Frequency Ultrasonography
IRT – Infrared Thermal
kNN – k-Nearest Neighbor
LDA – Linear Discriminant Analysis
MLP - Multilayer Perceptron
MPLSM – Multiphoton Laser Scanning Microscopy
NB – Naive Bayes
OCT – Optical Coherence Tomography
OLAP – Online Analytical Processing
PACS – Picture Archiving and Communication System
PDD – Photodynamic Diagnosis
RBG – Red Blue and Green
RF - Random Forest
RT – Random Trees
SCC – Squamous Cell Carcinoma
SSAE – Stacked Sparse Auto-Encoders
SVM - Support Vector Machines
UV - Ultraviolet