

Advanced Bio-inspired Point of Care for Skin Cancer Early Detection

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ABSTRACT

Background: The early detection of melanoma significantly affects the estimated 5-year survival rate of patients. The traditional manual visual methods used in the clinical screening suffer from clinician subjectivity, low sensitivity and specificity.

Materials and Methods: A method based on a combined approach that employs ad-hoc customised innovative hand-crafted image features together with a feed-forward Levenberg-Marquardt Neural Network System was tested on a dataset of 250 well classified dermoscopic skin lesion images.

Results: This “Point of Care” System was able to reliably predict the correct classification of dermoscopic skin lesion images with sensibility and specificity of 97 and 95%, respectively, giving appropriate indications for their management and follow-up.

Conclusion: Analysis of skin lesions by automated classification using computational methods may allow medical practitioners and patients to proactively track skin lesions and detect cancer earlier.

Introduction

Finding adequate and cost-effective clinical protocols for the early diagnosis of cancer is one of the major challenging tasks in oncology, especially for skin cancer. Skin cancer is the most common human malignancy [1,2]. Melanoma represents fewer than 5% of all skin cancers but accounts for approximately 75% of all skin-cancer-related deaths, and in the United States is responsible for over 10,000 deaths annually [2]. The early detection, or the medical discrimination, of primary skin lesions (nevi), is crucial since the estimated 5-year survival rate for melanoma drops from over 99% at the earliest stages to about 14% at the advanced stages [2].

The traditional visual method used in the clinical screening for the early detection of melanoma relies upon visual analysis of the skin lesion based on the so-called “ABCDE” (Asymmetry, Border irregularity, Color variegation, Diameter, Evolution) criteria, followed potentially by dermoscopic analysis, a biopsy and histopathological examination. However, this manual visual assessment strategy suffers from clinician subjectivity, low sensitivity and specificity, since it relies only on superficial, classical features that can

significantly affect the characterization of melanoma both in the screening and in the follow-up of suspected skin lesion phases.

Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions [3]. However, a computational method may allow medical practitioners and patients to proactively track skin lesions and detect cancer earlier.

Materials and Methods

The proposed method is a bio-inspired feed-forward automatic pipeline based on morphological analysis and evaluation of the image of skin lesion obtained by dermoscopy. Preliminary segmentation and pre-processing of the dermoscopic image by State Controlled-Cellular Neural Networks (SC-CNN) [4] is performed to obtain ad-hoc gray-level of the skin lesion image and applying to this image innovative mathematical processing by novel hand-crafted image features for related cancer risk assessment. At the end, pre-trained Levenberg-Marquardt Neural Network (L-MNN) [5] is used to perform ad-hoc clustering of these hand-crafted image features to obtain an efficient nevus discrimination (i.e. benign against melanoma) as well as a numerical array that is useful for the definition of the timing for the follow-up. Thus, a combined approach that employs ad-hoc customised innovative hand-crafted image features together with a feed-forward Levenberg-Marquardt Neural Network System (NNS) is proposed. This method could be easily implemented as a simple portable embedded system by introducing a "Point of Care" hardware solution based on the microcontroller device STM32 Microcontroller Unit (MCU) [6] for high-speed nevus discrimination. Figure 1 shows the proposed medical system and the related "Point of Care" for the early diagnosis of melanoma. The proposed "Point of Care" will perform automatic processing of the skin lesion image obtained by dermoscopy to discriminate a benign nevus from a suspected or malignant ones. An overview of the mathematical model inside the "Point of Care" is

described in Figure 2. The method was tested in a set of 250 well classified dermoscopic skin lesion images [7].

Results and Discussion

Some examples of dermoscopic skin lesions analysed by the "Point of Care" System along with related indications for their management and follow-up are reported in Table 1. The sensibility and specificity of the proposed method are reported in Table 2 and compared with those deriving from the other main automatic skin lesion analysis pipeline.

Recent methods for melanoma detection use image features, neuro-fuzzy or clustering (K-means, Support Vector Machine (SVM), etc...), approaches [8]. In some cases, they are based on the study of melanocytes distribution in the skin on histopathologic images and the probabilistic analysis as per Bayesian Classifier. Some promising methods use neural networks to classify skin lesions [9], or a method based on the adaptive thresholding analysis [10]. Further methods, with acceptable results, are based on pattern analysis combined with classical statistical dermoscopy image features. However, the methods reporting high accuracy have been validated with a few number of skin images, whilst those tested with a consistent number of images exhibit lower accuracy, sensibility and specificity [8]. Several methods were proposed for the classification of skin cancer lesions based on the use of global and local features combined with different classification systems such as the SVM, the classical Artificial Neural Networks (ANN), K-nearest and Naive-Bayes algorithm. In particular, one method combined some hand-crafted image features with a deep-learning algorithm for handling other image features [8-14]. These methods used a score-based approach to perform classification of the image features. However, limited sensibility and specificity were reported with the dataset of images analysed [7-14].

The method proposed herein showed promising results in terms of sensibility and specificity that need to be confirmed in a prospective study.

Furthermore, we are going to extend the proposed method by using a specific photo-multiplier sensor

Table 1: Examples of dermoscopic skin lesion images analyzed by the “Point of Care” System.







<i>PH² image</i>	<i>Classification by proposed method</i>	<i>Correct Classification</i>	<i>Proposed Follow-up Timing</i>
	Common Nevus (Benign Nevus)	Common Nevus (Benign Nevus)	>= 6 months
	Common Nevus (Benign Nevus)	Common Nevus (Benign Nevus)	>= 6 months
	Common Nevus (Benign Nevus)	Common Nevus (Benign Nevus)	>= 1 year
	Dysplastic Nevus (Benign Nevus)	Dysplastic Nevus (Benign Nevus)	>= 6 months
	Melanoma (Cancer lesion)	Melanoma (Cancer lesion)	Contact physician as soon as possible
	Melanoma (Cancer lesion)	Melanoma (Cancer lesion)	Contact physician as soon as possible

Table 2: Sensibility and specificity results of the proposed method compared with main automatic skin lesion analysis pipelines.

Method [Reference]	Performance Indicators	
	Sensibility (%)	Specificity (%)
<i>Proposed method</i>	97	95
Global Method (Color) [7,11]	90	89
Global Method (Textures) [7,11]	93	78
Local Method (Color) [7,11]	93	84
Local Method (Textures) [7,11]	88	76
Global Features C1-kNN Classifier [7,11]	88	81
Global Features C6 – SVM [7,11]	84	78
Global Features C6 – AdaBoost [7,11]	96	77
Local features BoF [7,11]	98	79

Abbreviations: BoF (Bag of Features); kNN (k-Nearest Neighbor); AdaBoost (Neural Network) SVM (Support Vector Machine)

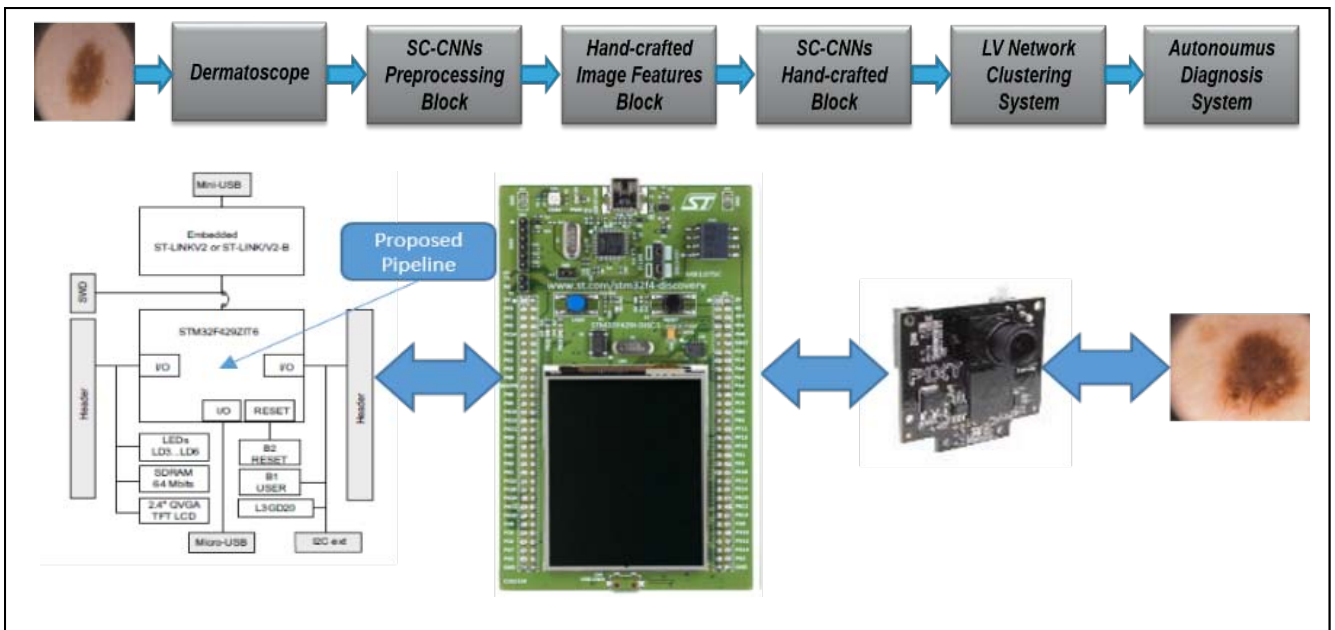


Figure 1: The proposed “Point of Care” System for efficient skin lesion analysis.
 Abbreviations: LV; Levenberg-Marquardt; SC-CNN; State Controlled-Cellular Neural Networks

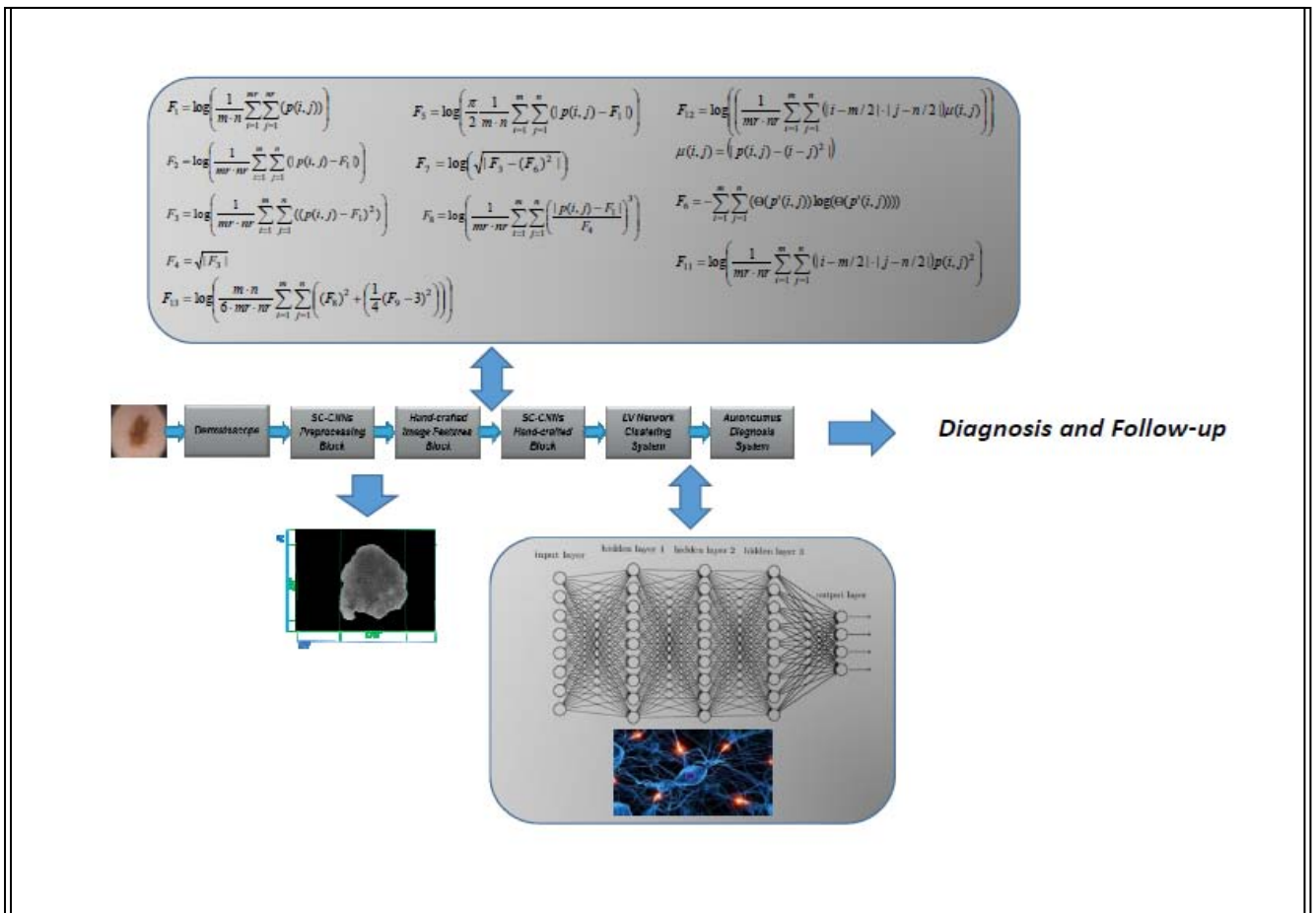


Figure 2: An overview of the mathematical model inside the “Point of Care” System.
 Abbreviations: LV; Levenberg-Marquardt; SC-CNN; State Controlled-Cellular Neural Networks

coupled with LED device at a specific wavelength, aiming to integrate dermoscopic image analysis with tissue characterization by this coupled photo-sensor platform.

Conclusion

A combined approach that employs ad-hoc customised innovative hand-crafted image features together with a feed-forward Levenberg-Marquardt NNS demonstrated efficient nevus discrimination on a set of 250 well classified dermoscopic skin lesion images. This method, that needs to be confirmed in a prospective clinical study, could be easily implemented as a simple portable embedded system by introducing a “Point of Care” hardware solution for high-speed nevus discrimination.

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Conflict of Interest

The author has no relevant affiliations or financial involvement with any organisation or entity with a financial interest in or financial conflict with the subject matter or materials discussed in the manuscript. This includes employment, consultancies, honoraria, stock ownership or options, expert testimony, grants or patents received or pending, or royalties.

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