

## Introduction

Melanomas, which are the deadliest form of skin cancer, are less common but they represent the most fatal cancer since they can quickly spread to other parts of the body. A melanoma arises through a malignant transformation of melanocytes causing about 60,000 cancer deaths in 2018. It represents as 0.7% of all cancer deaths. The incidence rate from 1973 to 2009 shows a rise in the number of cases which is particularly worrying.

A particular interest in creating automated systems for melanoma inspection has been the challenge of the healthcare management community. It is now crucial to use supportive imaging to identify melanomas at an early stage when the odds of curing it are completely high, thereby reducing mortality.

Computer-Aided Diagnosis (CAD), has been designed to improve and facilitate a quick and accurate diagnostic process based on strategies invented and already used by physicians. One widely used clinical clue is the ABCDE signs, which is a useful indicator for melanoma. The ABCD of dermatoscopy, based on multivariate analysis of only four criteria was introduced by Stolz et al., it represents an analytical method for the evaluation of melanocytic lesions that clinicians and the general public can utilize to help detect melanoma. Melanoma often manifests some or all of the ABCDE features, namely asymmetry (A), border irregularity (B), color variability (C), diameter greater than 6 mm (D).

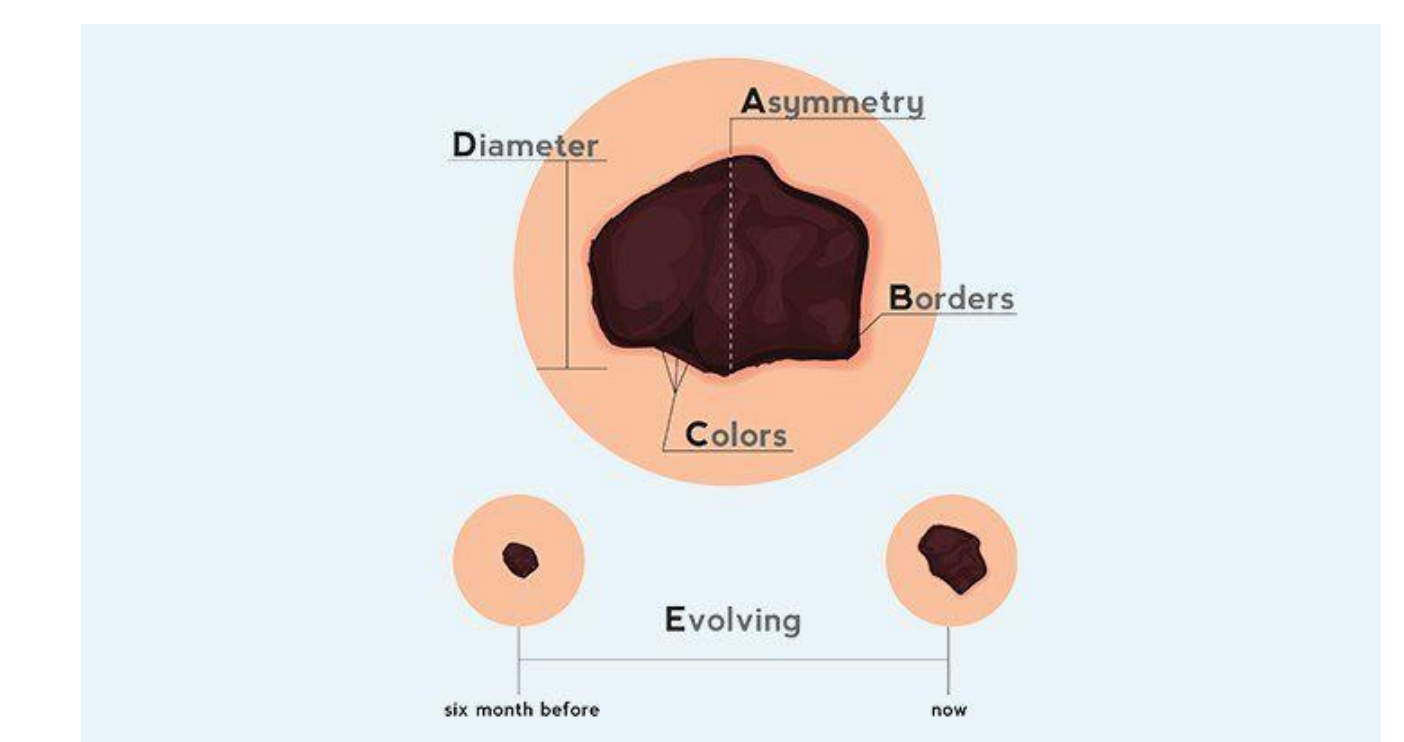


Fig 1. The ABCD Rule for Melanoma inspection

## Proposed Approach

The CAD systems rely on handcrafted features and traditional machine learning techniques. However, other systems rely on deep learning techniques, which detect the skin lesion from images and automatically learn a feature representation from a large number of skin lesion images.

Both systems are proved to be very efficient in melanoma inspection, for that, we have proposed a method that combines image processing and machine learning techniques, and deep learning techniques in ameliorating the melanoma inspection process. Thus, fusing the decision of many systems using majority voting ameliorate their performance. The need of using such a concept comes from the limitations that have been proved from the deep learning techniques due to the lack of a large-scale dataset. They will fail in learning a distinctive feature representation on real data.

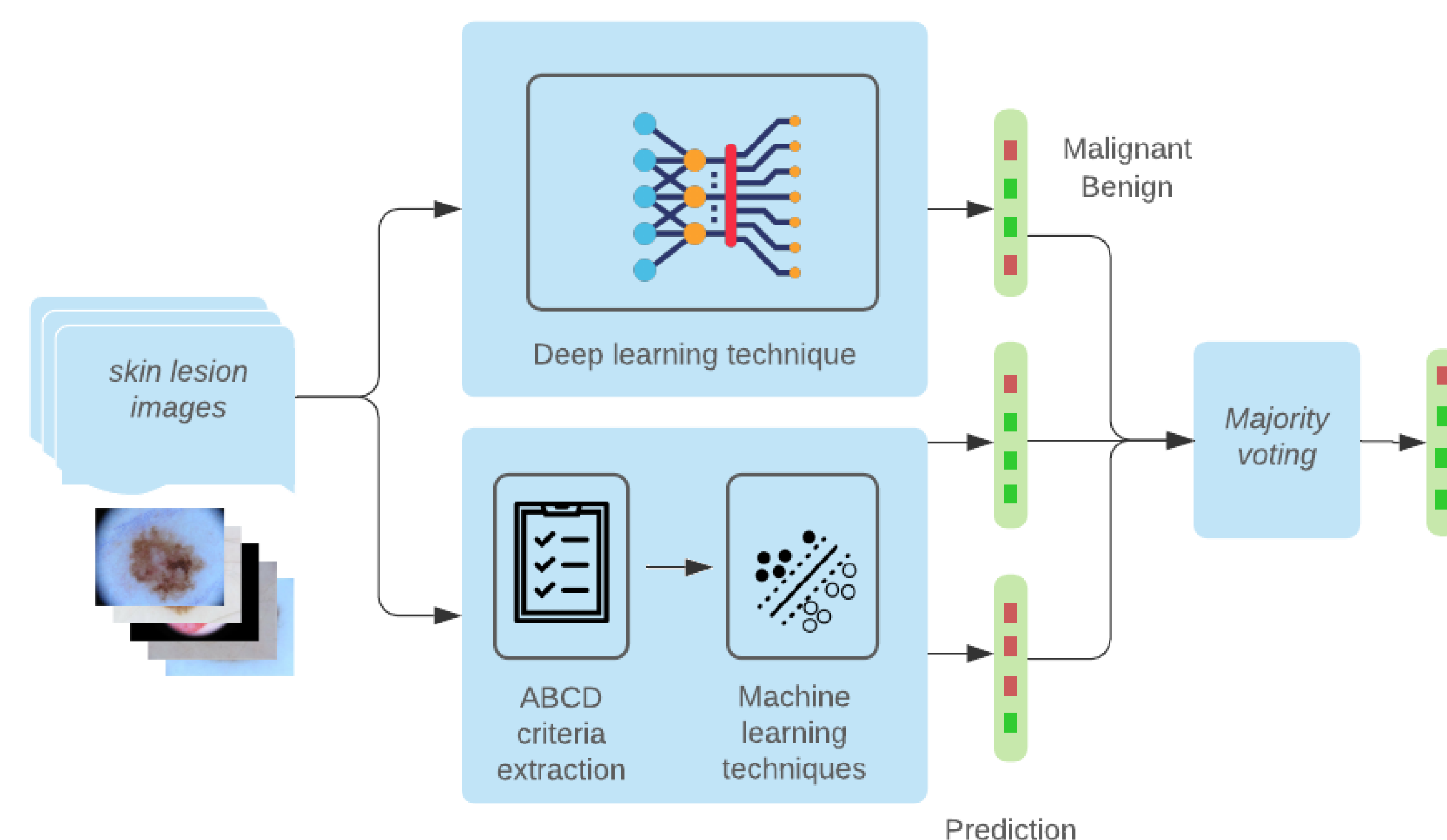


Fig 2. Layout architecture of the proposed method for melanoma inspection

After preprocessing the skin lesion images, Regions Of Interest (lesions) are segmented and a set of features are extracted describing the ABCD rule to finally classify a skin lesion as malignant or benign. The extracted low-level features describe some visual components: the border, the color, and the texture looking for some differential structures.

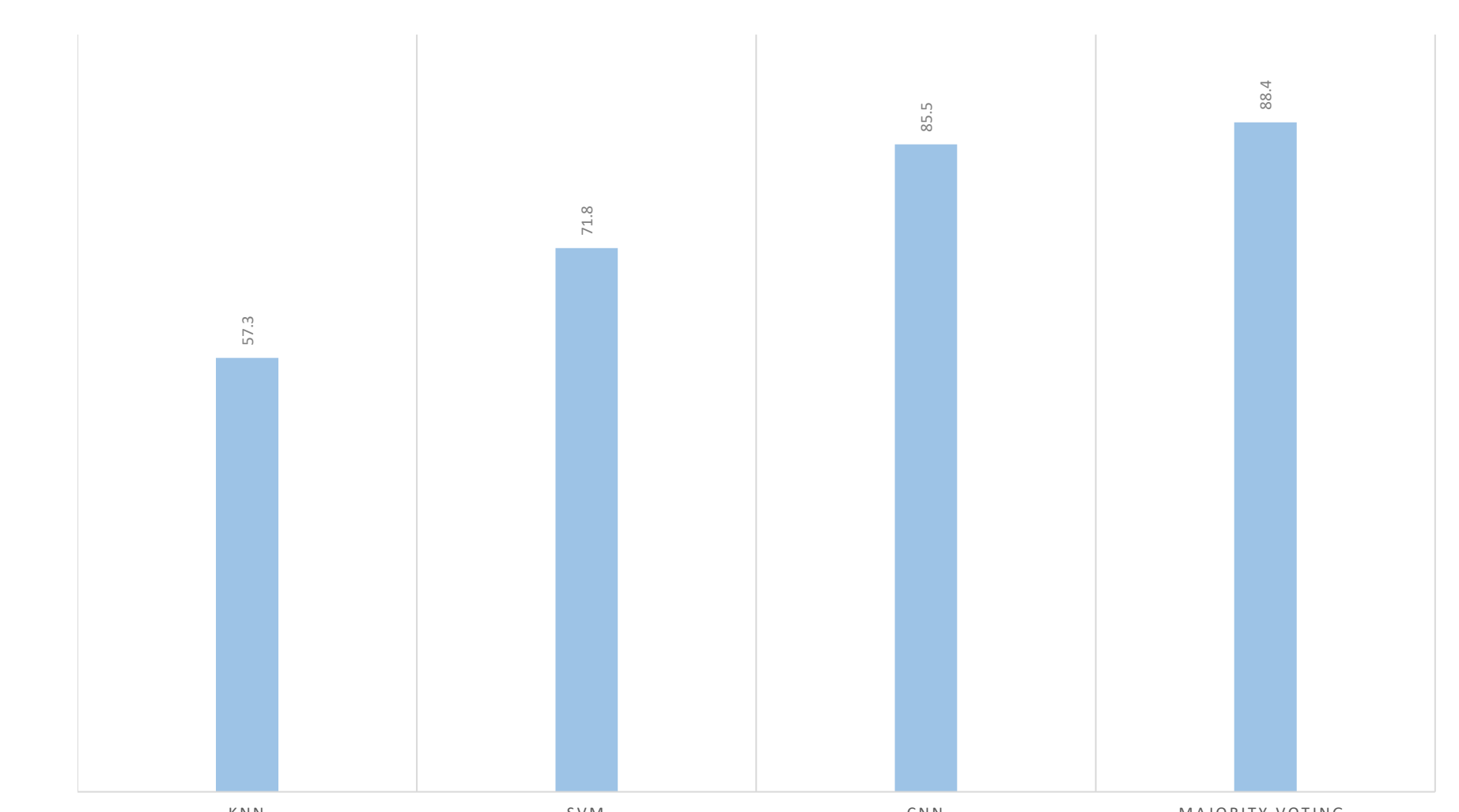
Visual components	Border	Color	Texture
Features	Convexity, circularity, and irregularity indexes	Color Name, Color SIFT	SIFT, HOG

## Results

After extracting the features, two classifiers, K-nearest neighbors (KNN) and Support Vector Machine (SVM) have been trained using 512 skin lesion images collected from the ISIC(International Skin Imaging Collaboration) archive.

On the other hand, we have applied a Convolutional Neural Network (CNN) to detect and classify skin lesions.

128 skin lesion images are used to test the performance of our proposed method by defining the accuracies.



Obviously, fusing results of the three systems, ameliorate the accuracy (skin lesions correctly classified) to 88.4%.

The idea was to take the decision not based on one single prediction but on many others, since two observations is always better than one.