



# Interpretability in CAD Systems for Skin Cancer Diagnosis

Catarina Barata





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# Explainable AI and the Rebirth of Rules



**Tom Davenport** Contributor  
Enterprise & Cloud

By Thomas H. Davenport and Carla O'Dell

Artificial intelligence (AI) has been described as a set of “prediction machines.” In general, the technology is great at generating automated predictions. But if you want to use artificial intelligence in a regulated industry, you better be able to explain how the machine predicted a fraud or criminal suspect, a bad credit risk, or a good candidate for drug trials.





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By Marianne Lehnis  
Technology of Business reporter

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## More clinical evidence needed to accelerate adoption of AI-enabled decision support: report

by Heather Landi | Jan 28, 2019 12:30pm



Regulatory issues, improved product labeling and patient privacy concerns need to be addressed before AI is safely and widely adopted as part of clinical decision support, according to a team of healthcare and AI experts. (monstlr/StockPhoto)

### About the Author



**Heather Landi**  
Senior Editor



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PROBLEM SOLVE

### GDPR regulations put premium on transparent AI

As the EU's GDPR regulations go into effect, enterprises must focus on building transparency in AI applications so that algorithms' decisions can be explained.



George Lawton

The European Union's new GDPR regulations could shake up the way enterprises craft algorithms to make decisions, particularly when it comes to building transparent AI applications.

"GDPR will impact all industries, and has particularly relevant ramifications for AI developers and AI-enabled businesses," said Dillon Erb, CEO at Paperspace Co., an AI cloud provider.

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# Outline

- What do we mean by explainability and interpretability?
- Interpretability in dermoscopy – A historical perspective
- Where to go next?

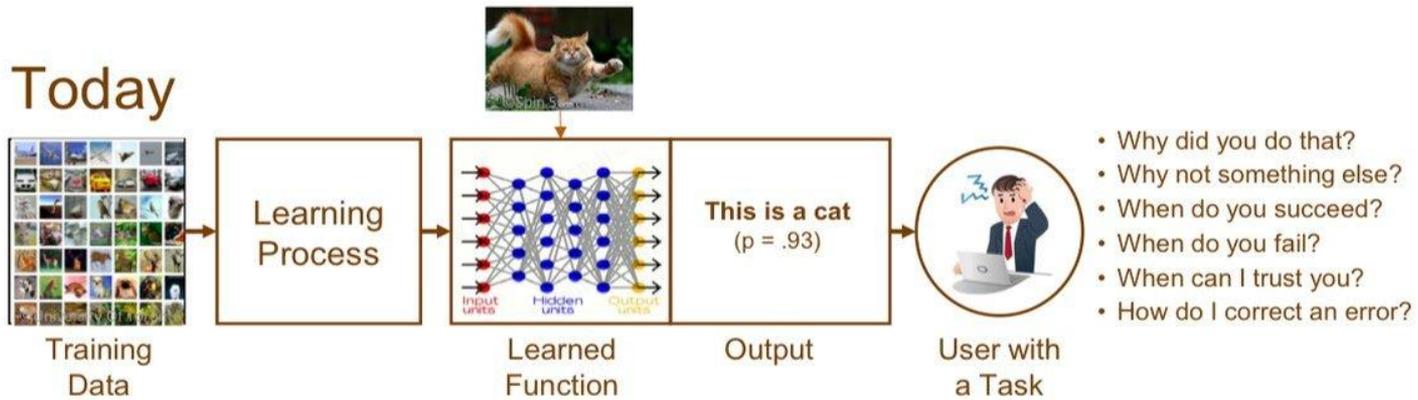


# Explainability and Interpretability



## Explainable AI – What Are We Trying To Do?

Today

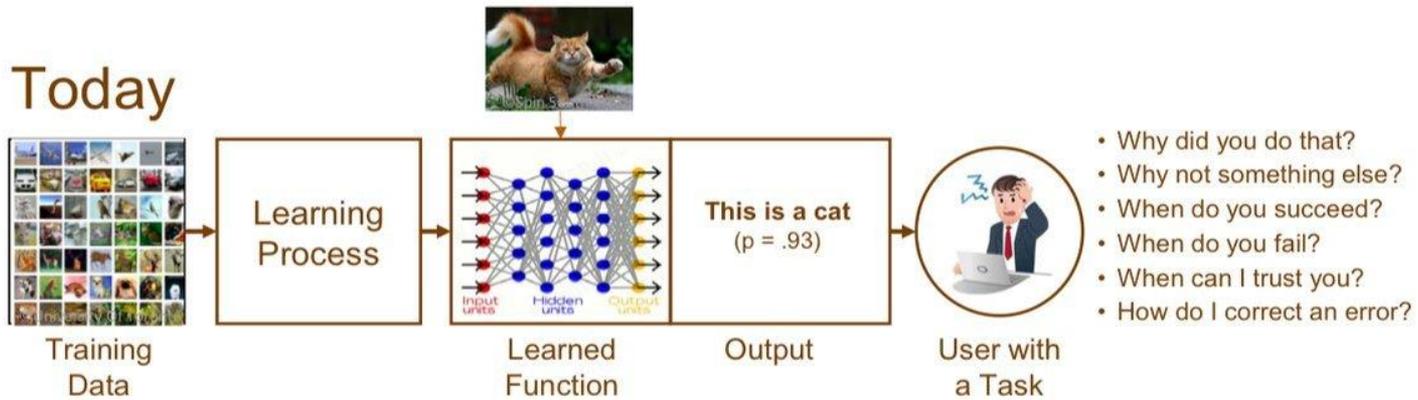


# Explainability and Interpretability

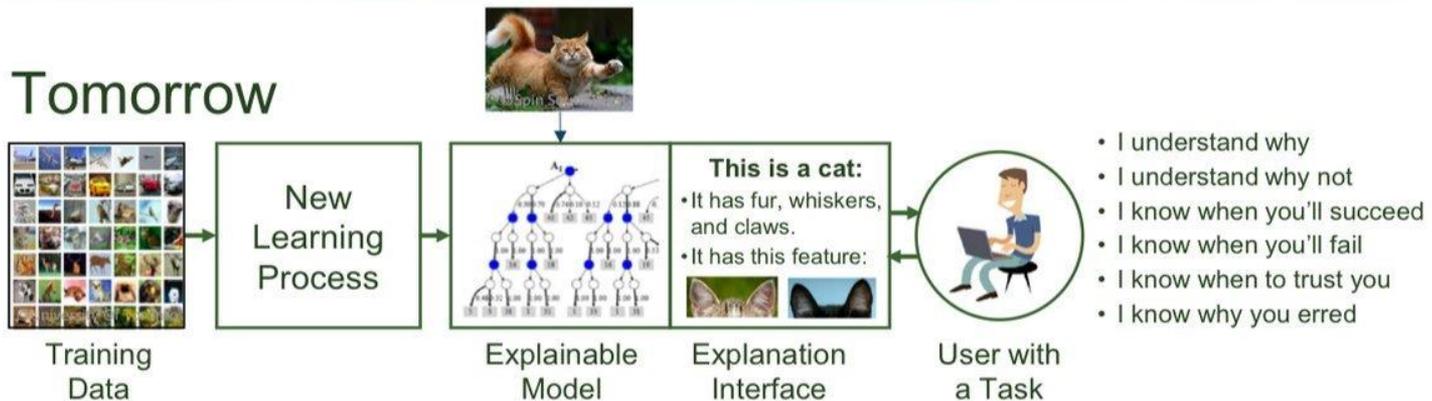


## Explainable AI – What Are We Trying To Do?

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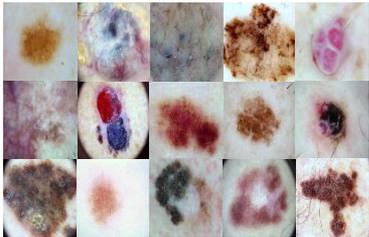
Tomorrow



source darpa via @mikequindazzi



# What does it mean for dermoscopy?

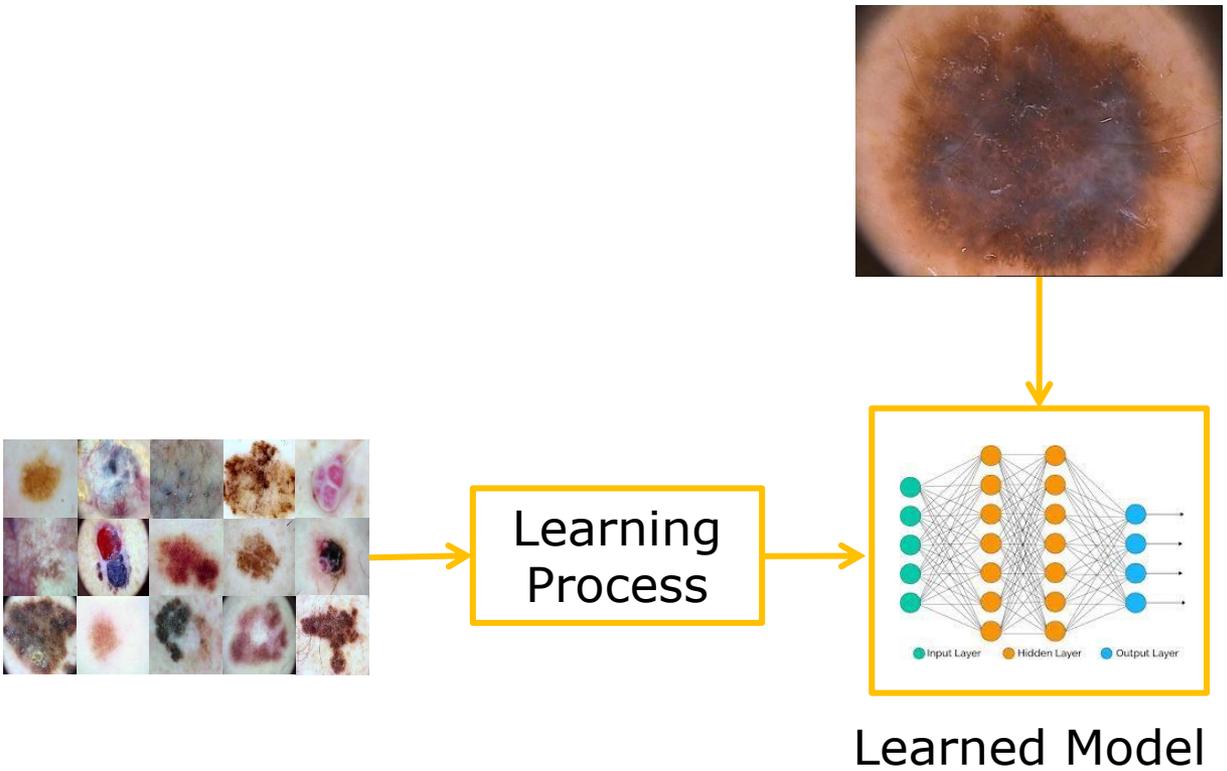


**Learning  
 Process**



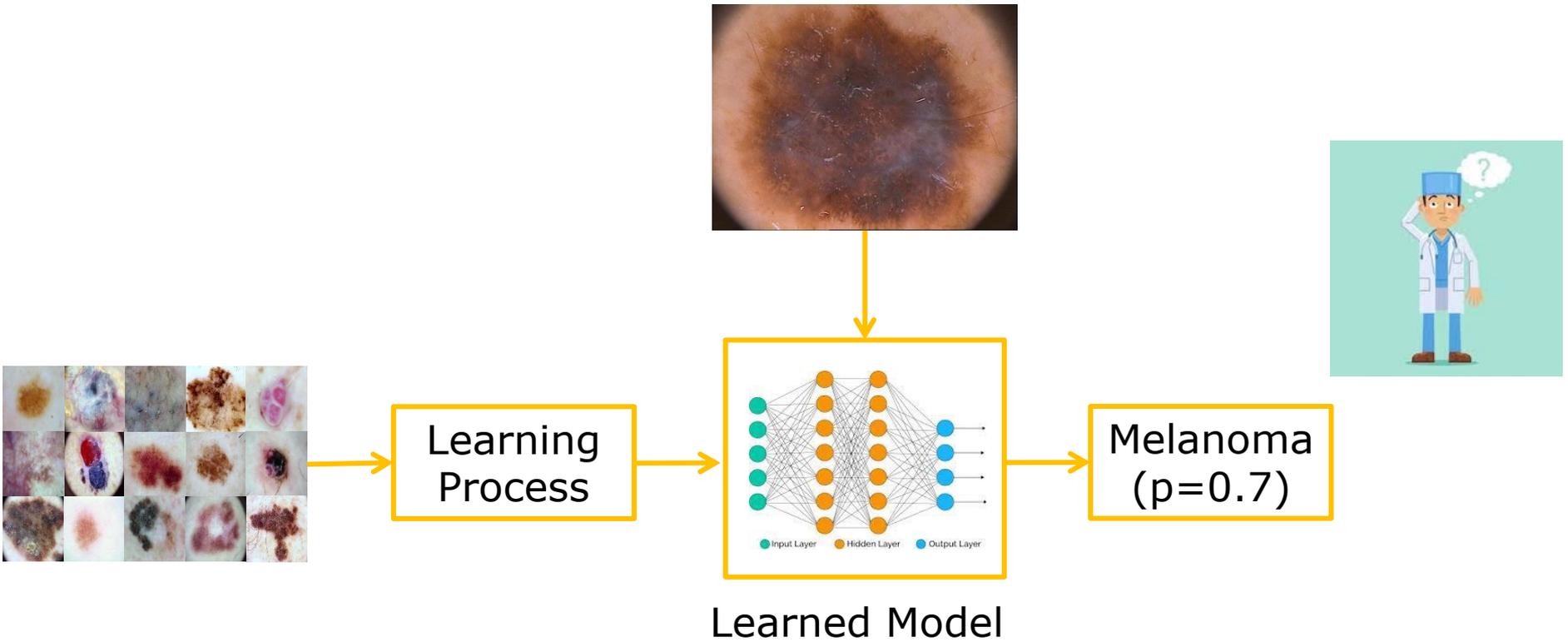


# What does it mean for dermoscopy?



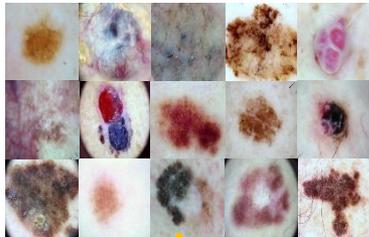


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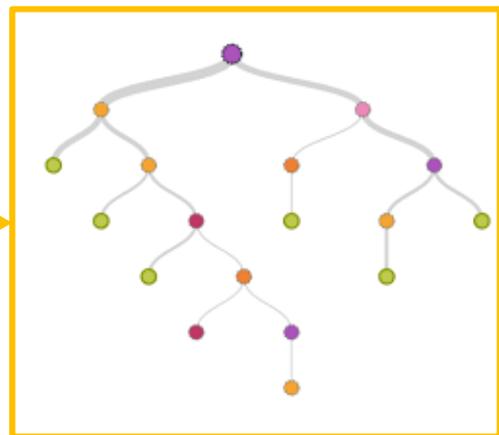




# What does it mean for dermoscopy?



Learning Process



Interpretable & Structured

This lesion is a **melanoma** because:

- It is melanocytic;
- It has more than 3 colors.
- This structure was detected:





# The Design of an Interpretable Model

- What should we have in mind when designing an interpretable model?





# The Design of an Interpretable Model

- What should we have in mind when designing an interpretable model?
  - **The final user! (Dermatologists or Patients)**
  - **This is a collaborative process!**





# The Design of an Interpretable Model

- What should we have in mind when designing an interpretable model?
  - **The final user! (Dermatologists or Patients)**
  - **This is a collaborative process!**
  
- Where should we act to improve interpretability?
  1. Features?
  2. Classifier?
  3. Infer from the black-box model?





# The Design of an Interpretable Model

- What should we have in mind when designing an interpretable model?
  - **The final user! (Dermatologists or Patients)**
  - **This is a collaborative process!**
  
- Where should we act to improve interpretability?
  1. **Clinically Inspired Features**
  2. **Structured & Explainable Classifiers**
  3. **Model Explainability - Visualization**





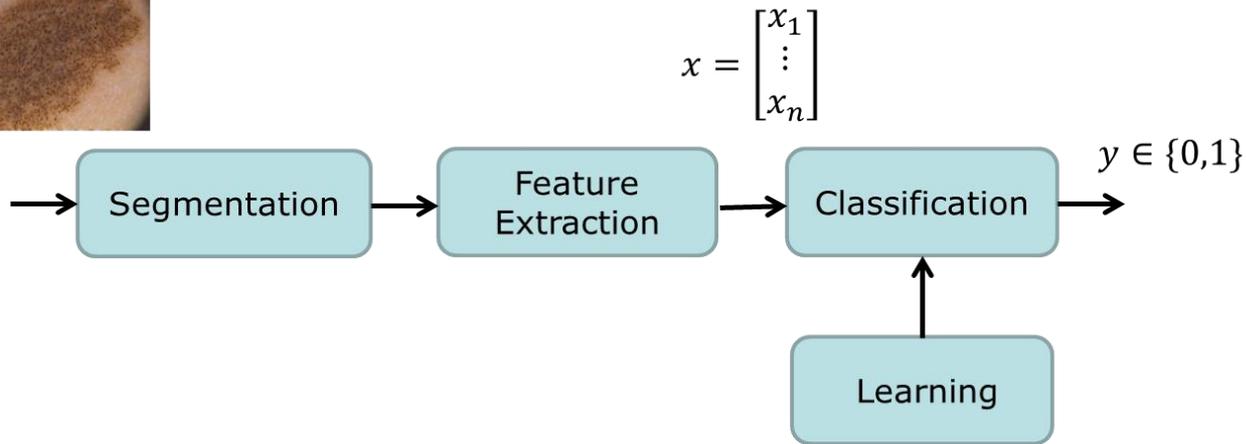
# The Design of an Interpretable Model

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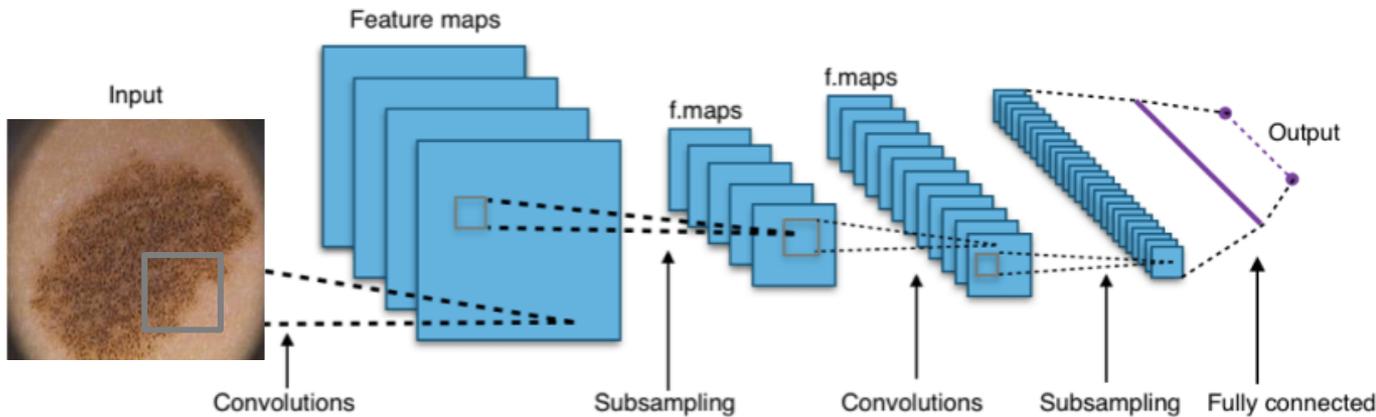




# Dermoscopy Image Diagnosis



Traditional CAD



End-to-End CAD



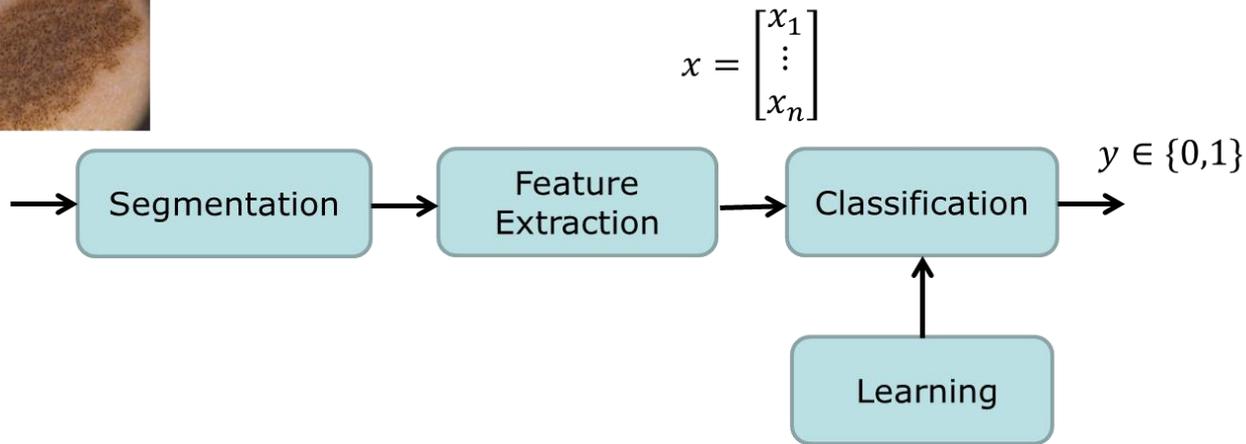


# INTERPRETABILITY IN TRADITIONAL CADS





# Dermoscopy Image Diagnosis

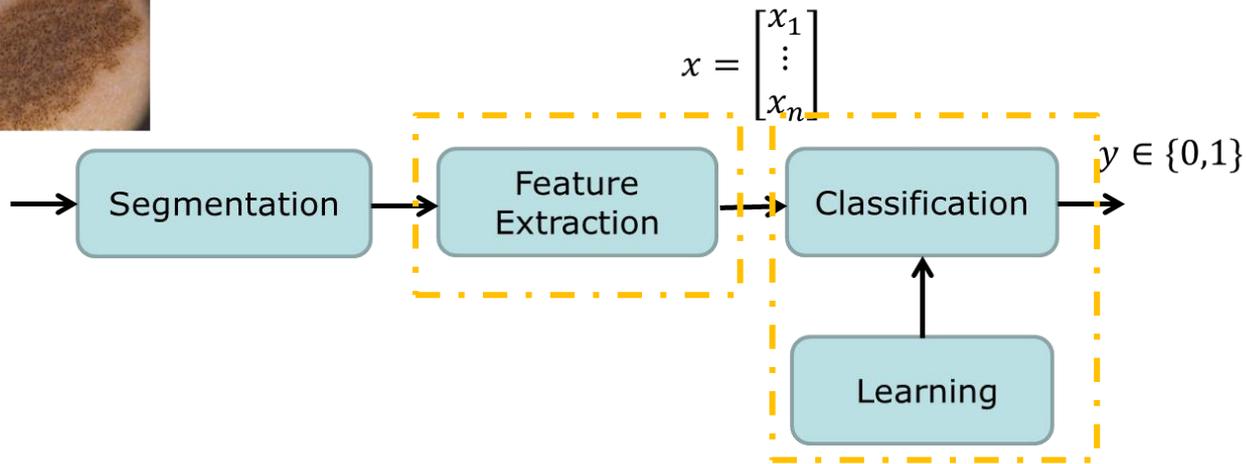


Traditional  
CAD





# Dermoscopy Image Diagnosis



Traditional  
CAD





# Interpretable Features

- What kind of features is interpretable?
  - Inspired by medical knowledge





# Interpretable Features

## Traditional Hand-Crafted Features

### Asymmetry

- Moments of inertia
- Shape, color, and texture maps
- Centroid location

### Border/Shape

- Fractals
- Intensity profiles
- Wavelets

### Color

- Color statistics
- Relative colors
- Color quantization
- Different color spaces

### Texture

- Gabor filters
- Haralick
- LBP
- Gradient based descriptors

- These features were inspired by medical knowledge.
- But were these features interpretable?





# Interpretable Features

## Traditional Hand-Crafted Features

### Asymmetry

- Moments of inertia
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- Gradient based descriptors

## Medical Counterparts (ABCD Rule)

### Asymmetry

- Maximum of 2 axes
- Contour, colors, and structures

### Border/Shape

- Abrupt ending of pigments
- Analysis of 8 segments

### Color

- Identification of up to six colors

### Structures

- Identification of up to 5 structures





# Interpretable Features

## Traditional Hand-Crafted Features

### Asymmetry

- Moments of inertia
- Shape, color, and texture maps
- Centroid location

### Border/Shape

- Fractals
- Intensity profiles
- Wavelets

### Color

- Color statistics
- Relative colors
- Color quantization
- Different color spaces

### Texture

- Gabor filters
- Haralick
- LBP
- Gradient based descriptors

- These features were inspired by medical knowledge.
- But they did not have a **true match** with medical findings.





# Interpretable Features

- What kind of features is interpretable?
  - **Inspired by medical knowledge**
  - **Have a direct relationship with clinical findings**





# Interpretable Features

- What kind of features is interpretable?
  - **Inspired by medical knowledge**
  - **Have a direct relationship with clinical findings**
- How can we extract them?





# Interpretable Features

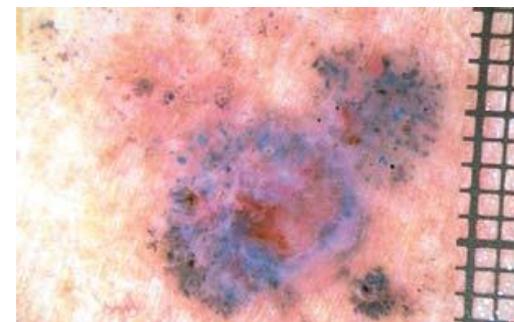
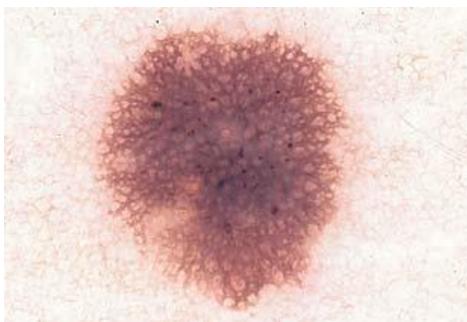
- What kind of features is interpretable?
  - **Inspired by medical knowledge**
  - **Have a direct relationship with clinical findings**
  
- How can we extract them?
  - Dermatologists use multiple cues to diagnose skin lesions
  - These cues can be seen as “**clinically inspired features**”





# Clinically Inspired Features

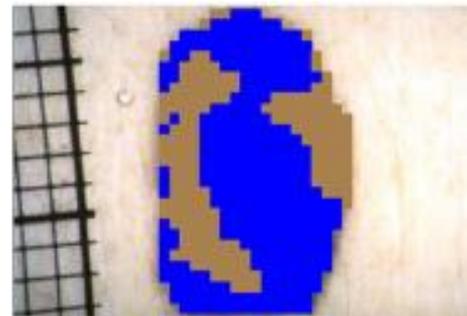
- Different groups addressed the detection of at least one medical feature.
- There are **three** types of medical features
  - Global patterns (Pehamberger, 1987)





# Clinically Inspired Features

- Different groups addressed the detection of at least one medical feature.
- There are **three** types of medical features
  - Global patterns (Pehamberger et al. 1987)
  - Colors (ABCD Rule, Stolz et al. 1994)



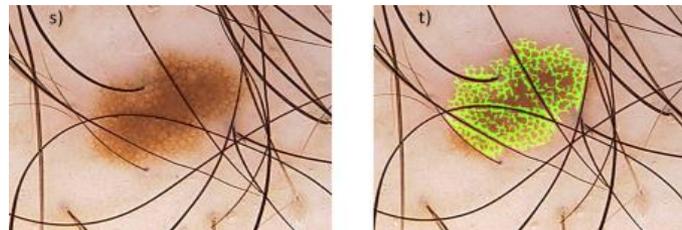
Barata et al., CVIU, 2016





# Clinically Inspired Features

- Different groups addressed the detection of at least one medical feature.
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  - Global patterns (Pehamberger et al. 1987)
  - Colors (ABCD Rule, Stolz et al. 1994)
  - Dermoscopic structures (ABCD Rule/7-point checklist)



Barata et al. IEEE TBME, 2012





# Clinically Inspired Features

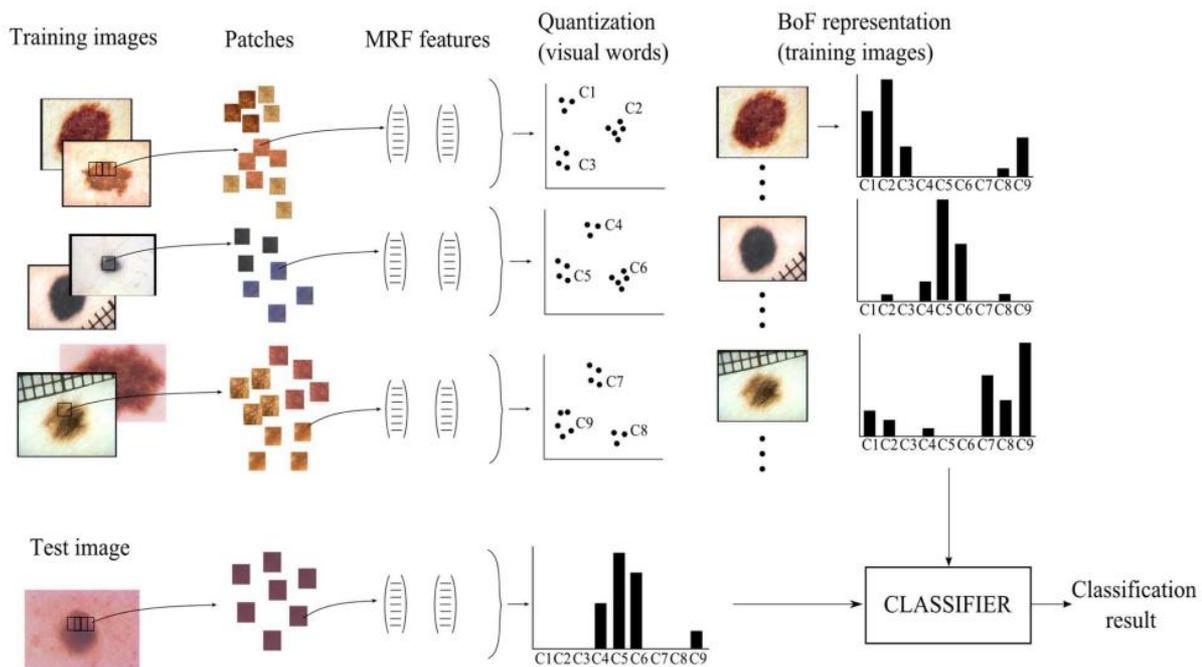
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# Global Patterns

- Detection of 5 patterns:
  - Globular
  - Homogeneous
  - Reticular
  - Multicomponent



Saéz et al., IEEE TMI, 2014



# Clinically Inspired Features

- Different groups addressed the detection of at least one medical feature.
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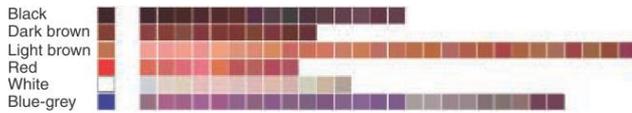




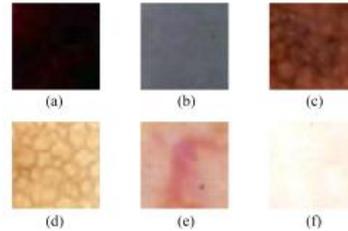
# Detection of Colors

- Main idea

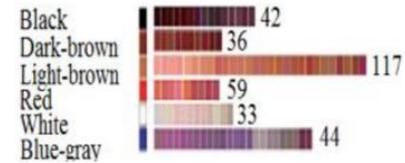
1. Extract representative patches for each color



Seidenari et al., BJD, 2003



Sáez et al., IEEE JBHI, 2019



Sabbaghi et al., IEEE JBHI, 2019

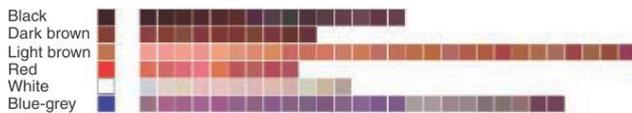




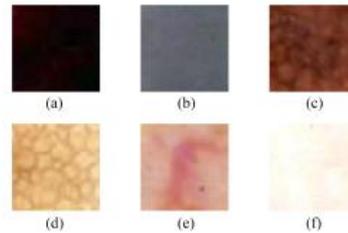
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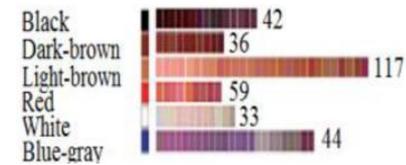
1. Extract representative patches for each color



Seidenari et al., BJD, 2003



Sáez et al., IEEE JBHI, 2019



Sabbaghi et al., IEEE JBHI, 2019

2. Learn some representation for the palette







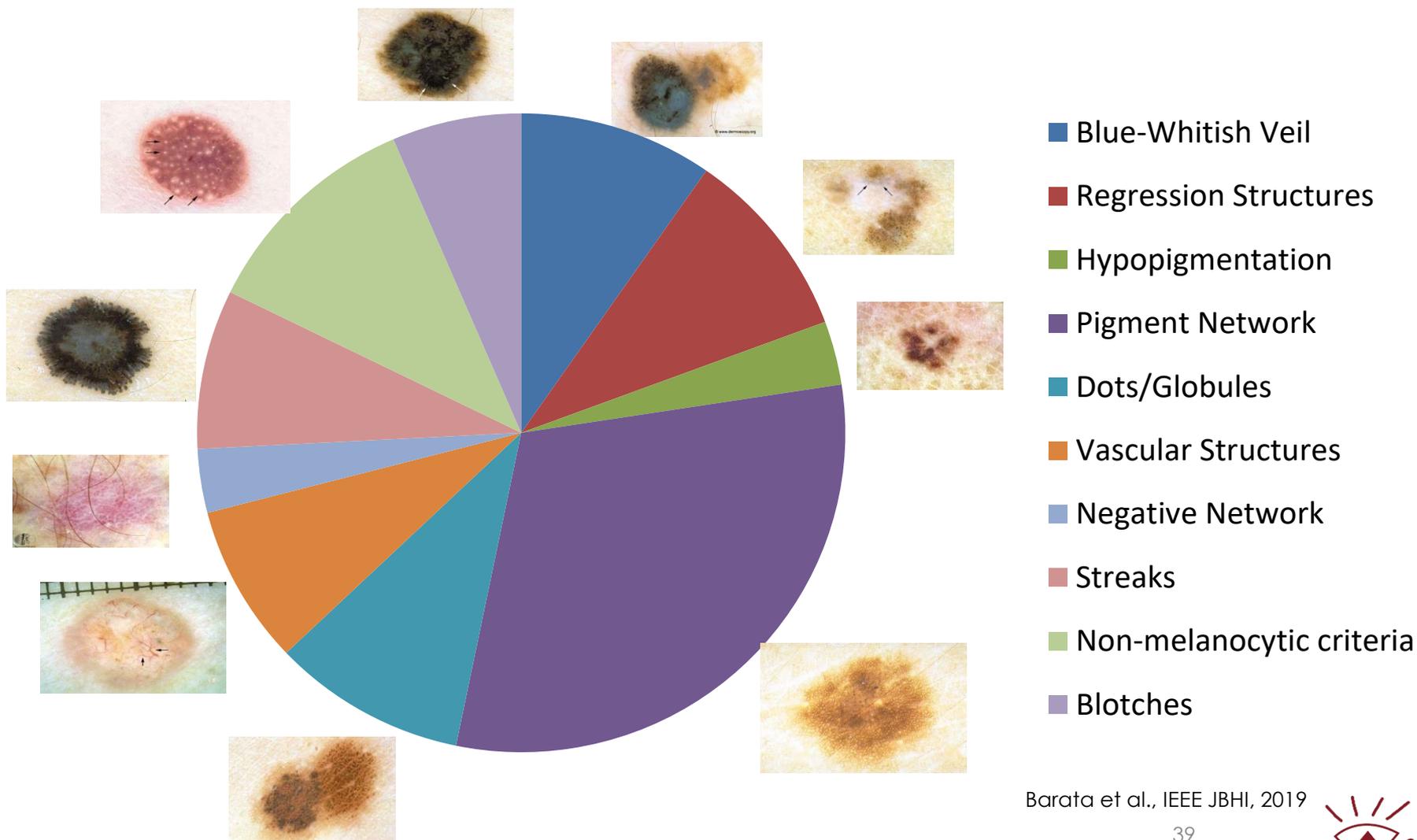
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# Detection of Dermoscopic Structures

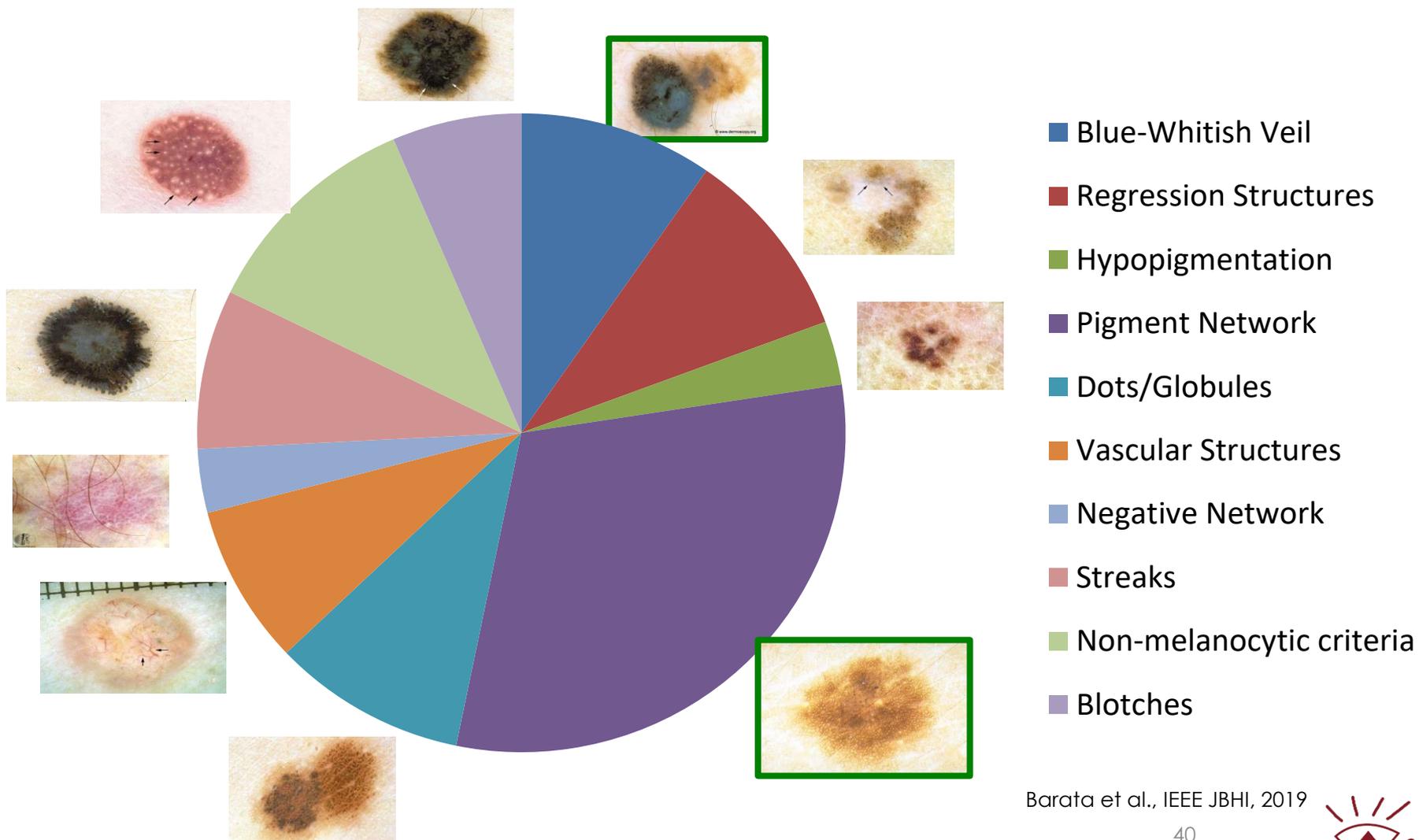


Barata et al., IEEE JBHI, 2019





# Detection of Dermoscopic Structures



Barata et al., IEEE JBHI, 2019





# Pigment Network

- **Main ideas:**

1. Explore the geometric and color properties of pigment network



PERGAMON

Computerized Medical Imaging and Graphics 22 (1998) 375–389

Computerized  
Medical Imaging  
and Graphics

## Techniques for a structural analysis of dermatoscopic imagery

Matthew G. Fleming<sup>a</sup>, Carsten Steger<sup>b</sup>, Jun Zhang<sup>c</sup>, Jianbo Gao<sup>c</sup>, Armand B. Cognetta<sup>d</sup>, Ilya Pollak<sup>e</sup>, Charles R. Dyer<sup>f</sup>

<sup>a</sup>Department of Dermatology, Medical College of Wisconsin and Zablocki VA Hospital, Milwaukee, WI, USA

<sup>b</sup>Forschungsgruppe Bildverstehen, Informatik IX, Technische Universität München, Munich, Germany

<sup>c</sup>Department of Computer Science and Electrical Engineering, University of Wisconsin, Milwaukee, WI, USA

<sup>d</sup>Private Practice, Tallahassee, FL, USA

<sup>e</sup>Laboratory for Information and Decision Systems, Massachusetts Institute of Technology, Cambridge, MA, USA

<sup>f</sup>Department of Computer Science, University of Wisconsin, Madison, WI, USA

Received 15 May 1998; received in revised form 14 September 1998; accepted 14 September 1998

### Abstract

Techniques were developed for automated detection and characterization of dermatoscopic structures, including the pig brown globules. These techniques incorporate algorithms for grayscale shape extraction based on differential geometry, a snake algorithm, and a modification of the region competition strategy of Zhu and Yuille. A novel approach was developed for segmentation of pigmented lesions, based on stabilized inverse diffusion equations. Procedures for detection of air bubble dermatoscopic images are also reported. © 1998 Elsevier Science Ltd. All rights reserved.

**Keywords:** Melanoma; Nevus; Dermatoscopy; Dermoscopy; Epiluminescence microscopy; Image analysis

The value of the statistical approaches should become clearer with time, as more lesions are evaluated and additional groups involved. However, we have been interested in exploring an alternative, structural approach to dermatoscopic image analysis. This approach seeks to model human interpretation more closely, by extracting and assessing the classical dermatoscopic features. If such extraction

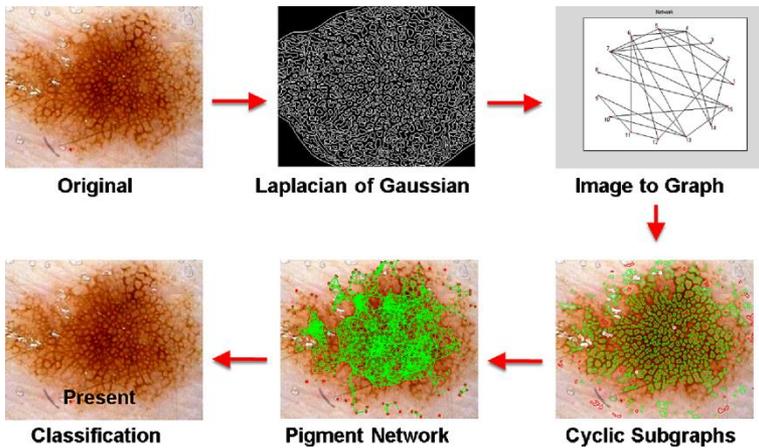
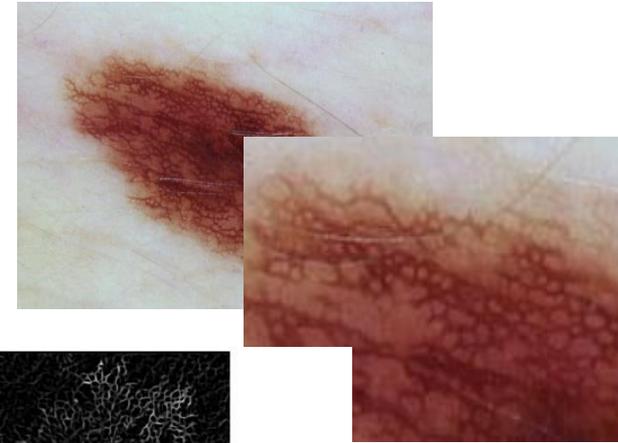




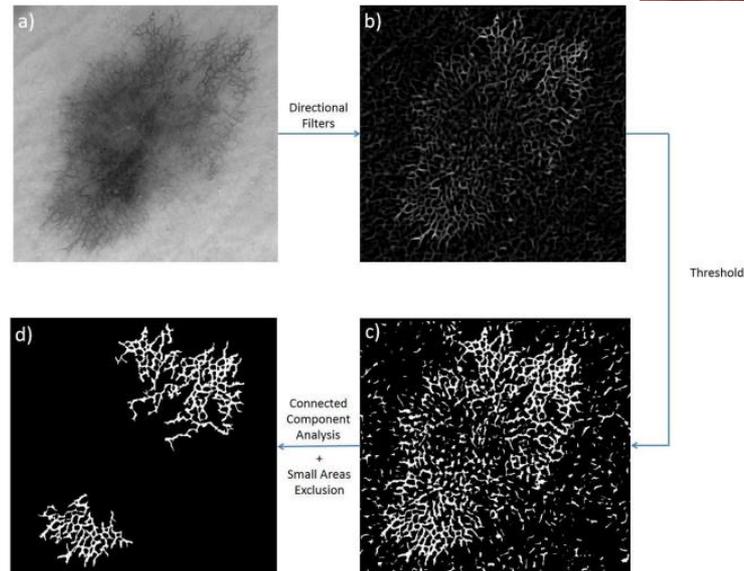
# Pigment Network

- Main ideas:

- Explore the geometric and color properties of pigment network



Sadeghi et al., CMIG, 2011

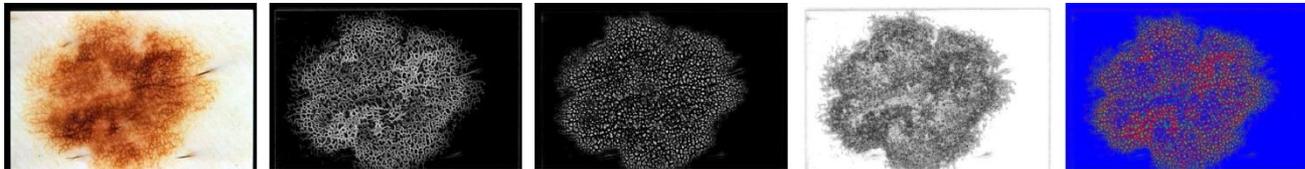
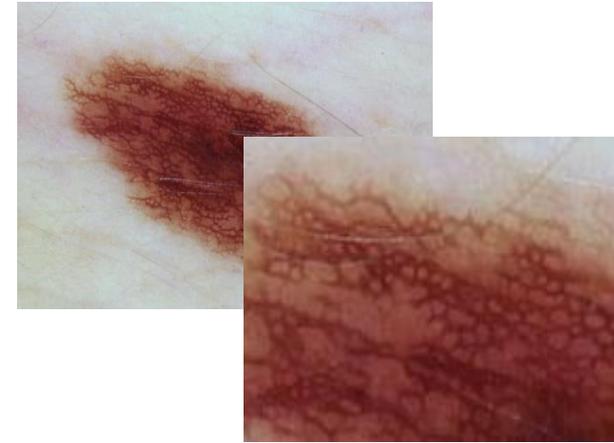




# Pigment Network

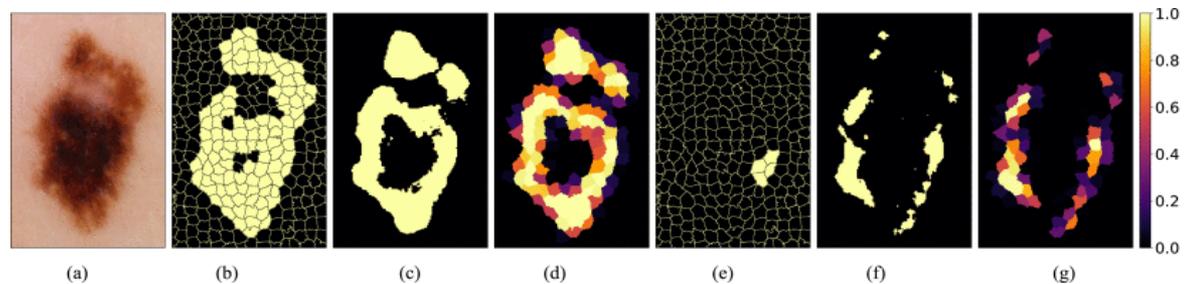
- **Main ideas:**

1. Explore the geometric and color properties of pigment network
2. Rely on machine learning algorithms



Garcia-Arroyo et al., CMIG, 2018

Kawahara et al., IEEE JBHI, 2019





# Blue-Whitish Veil

- **Main idea:**
  1. Learn a color palette



Madooei et al., MICCAI'13





# Blue-Whitish Veil

- **Main idea:**

1. Learn a color palette



Madooei et al., MICCAI'13



2. Learn a representation





# Blue-Whitish Veil

- **Main idea:**

1. Learn a color palette

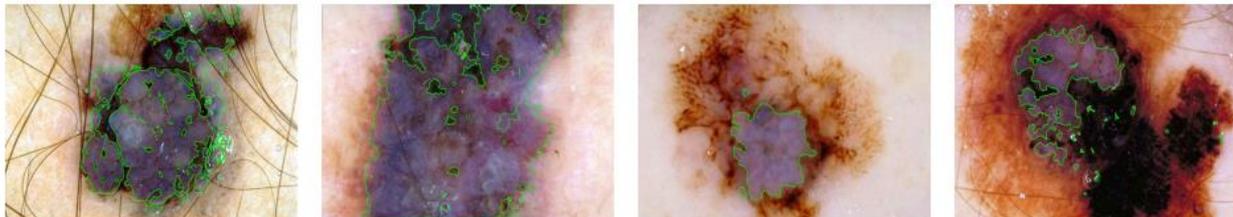


Madooei et al., MICCAI'13



2. Learn a representation

3. Match new patches/pixels

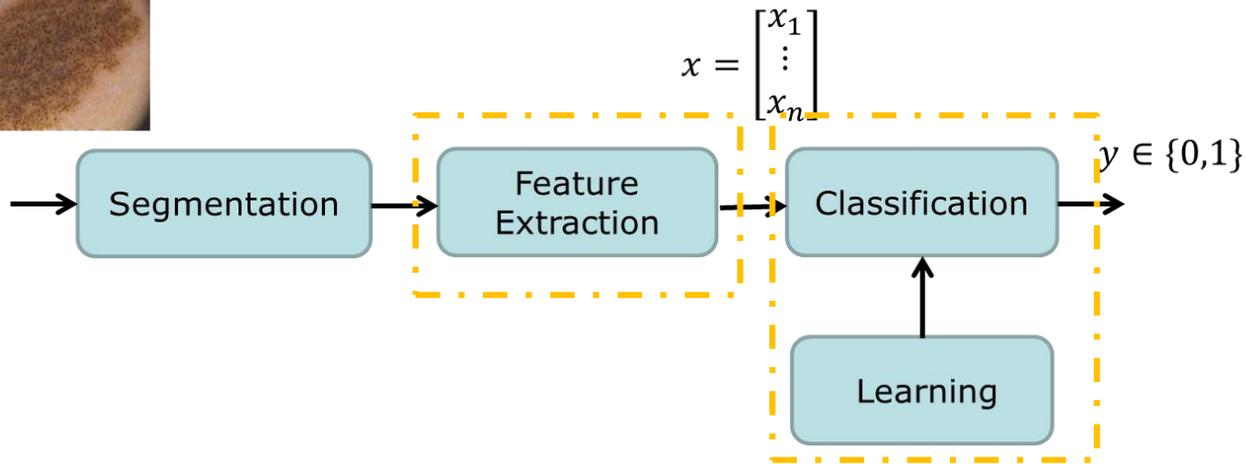


Madooei et al., MICCAI'13





# Dermoscopy Image Diagnosis



Traditional CAD





# Interpretable Classifiers

- What is an interpretable classifier?
  - **A classifier that is able to explain its decision**





# Interpretable Classifiers

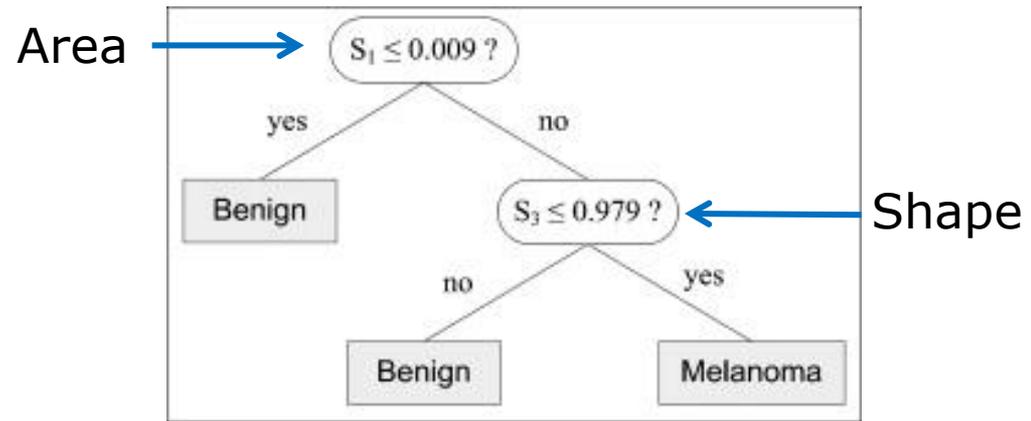
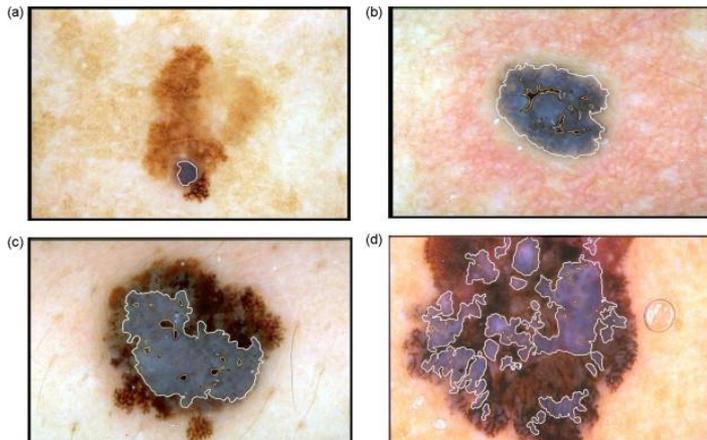
- What is an interpretable classifier?
  - **A classifier that is able to explain its decision based on medical knowledge**





# Interpretable Classifiers

- What is an interpretable classifier?
  - A classifier that is able to explain its decision based on medical knowledge



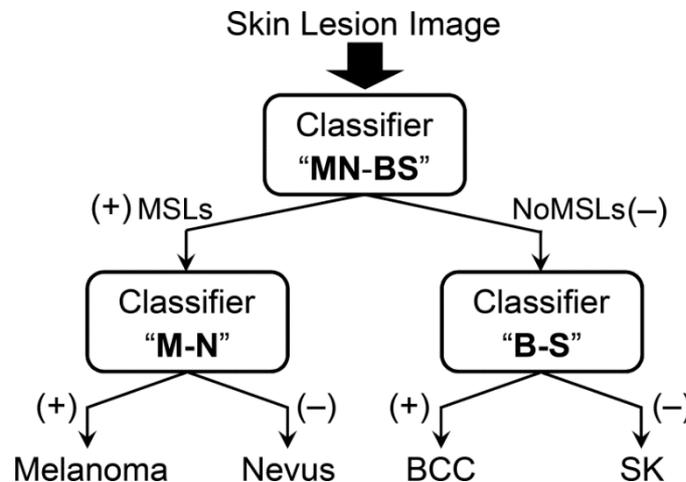
Celebi et al., CMIG, 2008





# Interpretable Classifiers

- What is an interpretable classifier?
  - **A classifier that is able to explain its decision based on medical knowledge**
  - **A structured classifier that incorporates medical knowledge**



Shimizu et al., IEEE TBME, 2014



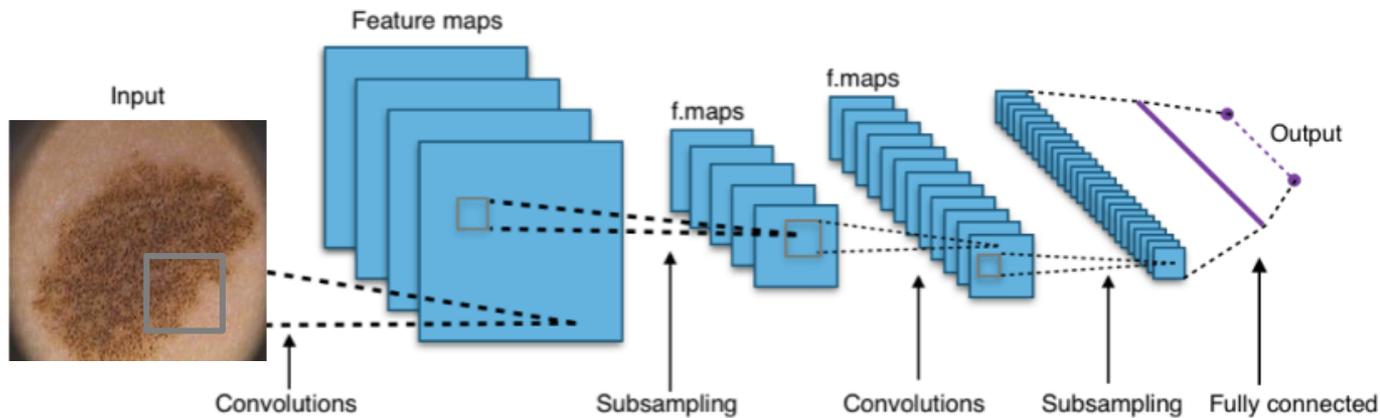


# INTERPRETABILITY IN END-TO-END CADS





# Dermoscopy Image Diagnosis

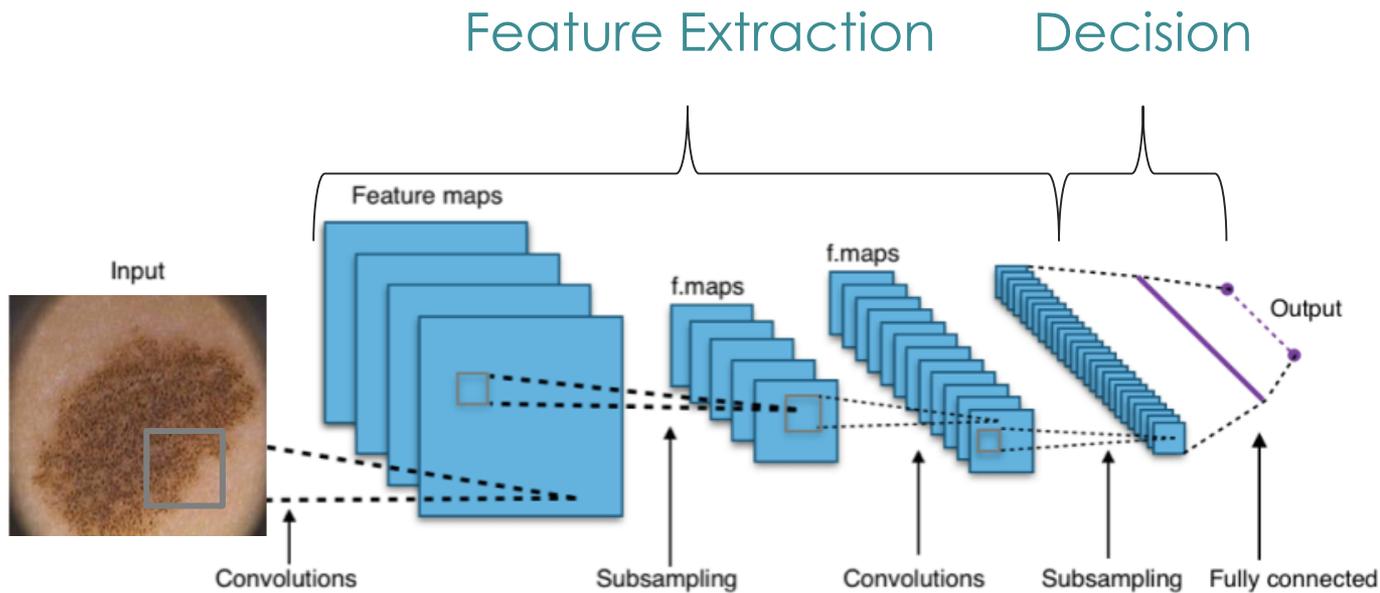


End-to-End CAD





# Dermoscopy Image Diagnosis



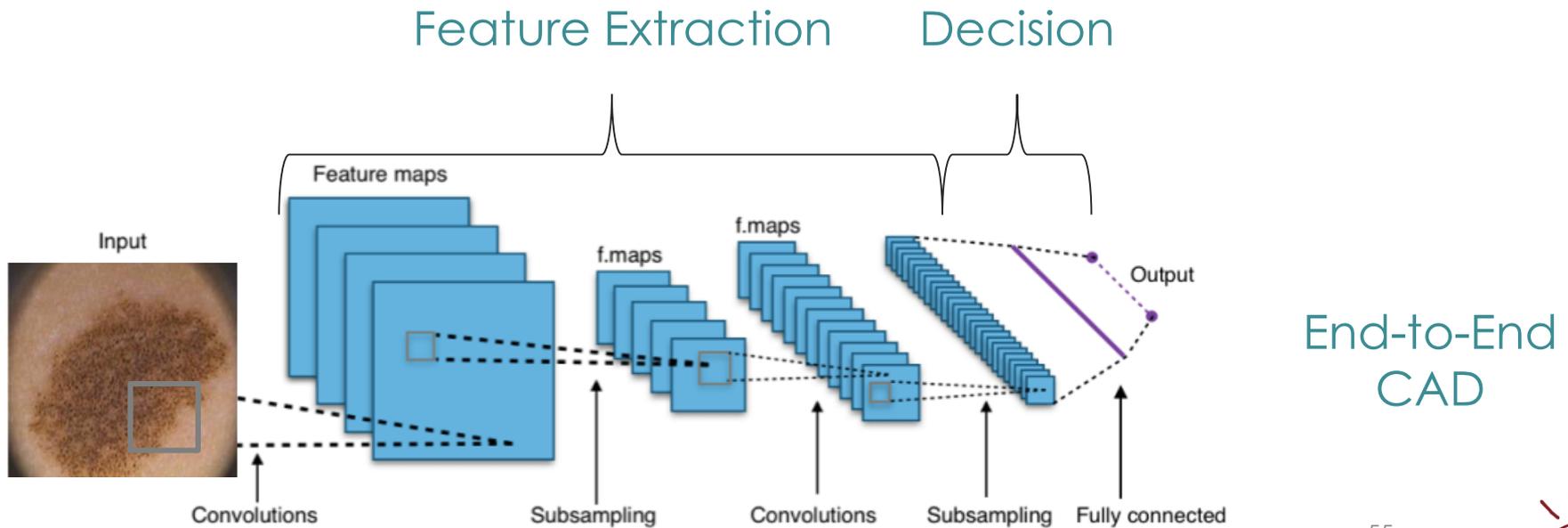
End-to-End CAD





# Dermoscopy Image Diagnosis

- How can we infer interpretability when we do not impose the features nor the classifier?

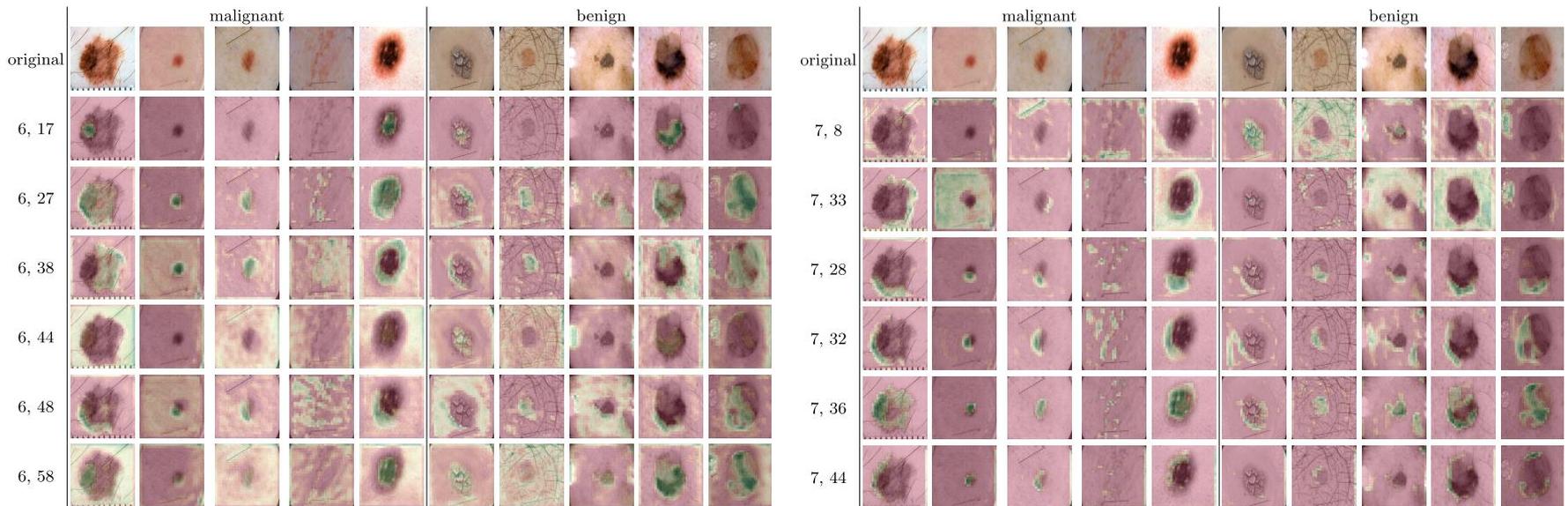




# Model Explainability

- Different visualization techniques can be used to
  - **Understand what the network is “seeing”**

## Feature Maps



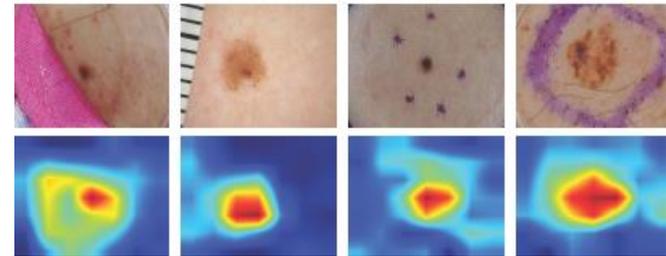
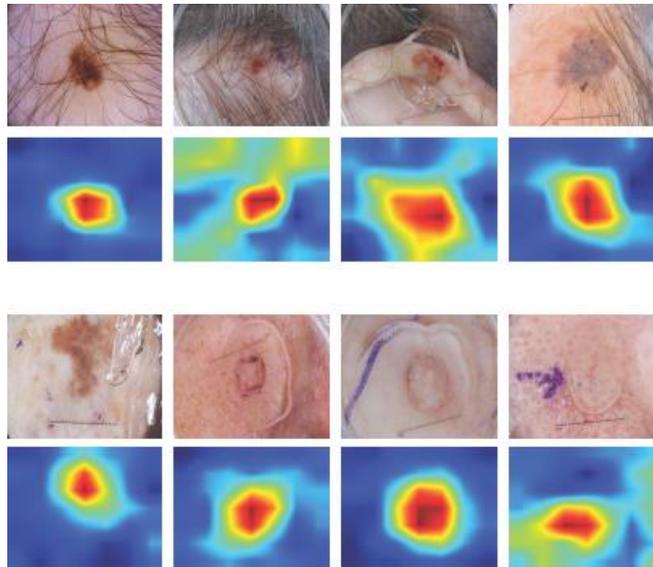
Van Molle et al., MICCAI-W, 2018





# Model Explainability

- Different visualization techniques can be used to
  - **Understand what the network is “seeing”**
  - **Understand what guides the decision**



Zhang et al., IEEE TMI, 2019

Class Activation Maps





# Model Explainability

- Different visualization techniques can be used to
  - Understand what the network is “seeing”
  - Understand what guides the decision
- These techniques **improve explainability** but **may not lead to interpretability!**





# Incorporating Medical Features

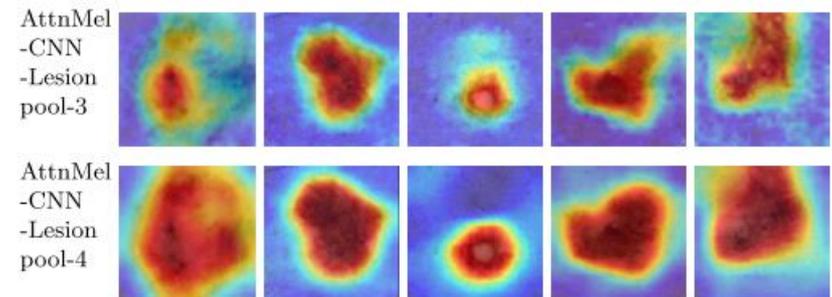
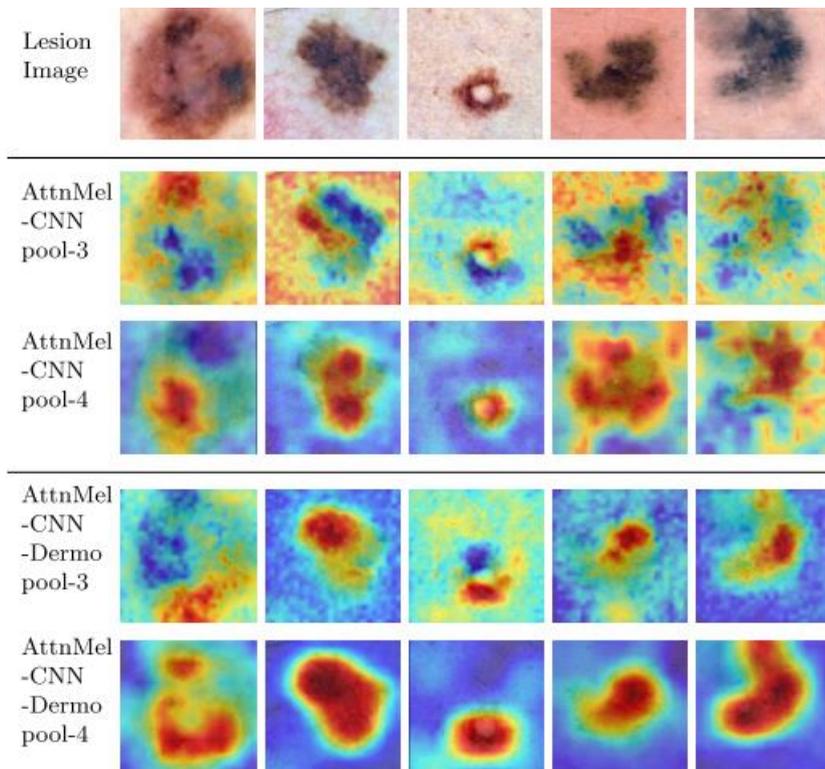
- Can we incorporate medical features in DNNs?





# Incorporating Medical Features

- Can we incorporate medical features in DNNs?



Yan et al., IPMI, 2019

Attention Regularized with Segmentation Masks





# Incorporating Medical Features

- Can we incorporate medical features in DNNs?

## DermaKNet: Incorporating the Knowledge of Dermatologists to Convolutional Neural Networks for Skin Lesion Diagnosis

Iván González-Díaz , Member, IEEE

**Abstract**—Traditional approaches to automatic diagnosis of skin lesions consisted of classifiers working on sets of hand-crafted features, some of which modeled lesion aspects of special importance for dermatologists. Recently, the broad adoption of convolutional neural networks (CNNs) in most computer vision tasks has brought about a great leap forward in terms of performance. Nevertheless, with this performance leap, the CNN-based computer-aided diagnosis (CAD) systems have also brought a notable reduction of the useful insights provided by hand-crafted features. This paper presents DermaKNet, a CAD system based on CNNs that incorporates specific subsystems modeling properties of skin lesions that are of special interest to dermatologists aiming to improve the interpretability of its diagnosis. Our results prove that the incorporation of these subsystems not only improves the performance, but also enhances the diagnosis by providing more interpretable outputs.

**Index Terms**—Skin lesion analysis, melanoma, convolutional neural networks, dermoscopy, CAD.

improve it by providing valuable information about the clinical case, and serving as filtering tools that automatically detect those cases with a high confidence of benignity, which can have a great impact in the final amount of moles that must be analyzed by the clinicians.

However, despite the research efforts devoted to the topic, these systems have yet to become part of everyday clinical practice. From our point of view, there are two factors currently hampering the adoption of CAD systems by dermatologists. Firstly, the lack of large, open, annotated datasets, containing images of lesions gathered by different medical institutions and a great variety of dermatoscopes, has undermined the generalization capability of developed CAD systems, leading to poor results when applied to different datasets. Additionally, it has prevented standard and fair comparisons between proposed methods, thus hindering the scientific advances in the field. Secondly, most of CAD systems simply provide a tentative diagnosis to the clinicians, which does not actually help them much in practice.

## Seven-Point Checklist and Skin Lesion Classification Using Multitask Multimodal Neural Nets

Jeremy Kawahara , Sara Daneshvar , Giuseppe Argenziano, and Ghassan Hamarneh , Senior Member, IEEE

**Abstract**—We propose a multitask deep convolutional neural network, trained on multimodal data (clinical and dermoscopic images, and patient metadata), to classify the 7-point melanoma checklist criteria and perform skin lesion diagnosis. Our neural network is trained using several multitask loss functions, where each loss considers different combinations of the input modalities, which allows our model to be robust to missing data at inference time. Our final model classifies the 7-point checklist and skin condition diagnosis, produces multimodal feature vectors suitable for image retrieval, and localizes clinically discriminant regions. We benchmark our approach using 1011 lesion cases, and report comprehensive results over all 7-point criteria and diagnosis. We also make our dataset (images and metadata) publicly available online at <http://derm.cs.sfu.ca>.

**Index Terms**—Classification, convolutional neural networks, deep learning, dermatology, melanoma, skin, 7-point checklist.

dermoscopy compared to the unaided eye. However, accurate diagnosis is challenging for non-experts.

Pattern analysis, which subjectivity assesses multiple subtle lesion features, is commonly used by experienced dermatologists to distinguish between benign and malignant skin tumors. To simplify diagnoses, rule-based diagnostic algorithms such as the ABCD rule [5] and the 7-point checklist [6] have been proposed and are commonly accepted [7]. In this work we focus on the 7-point checklist, which requires identifying seven dermoscopic criteria (Table I) associated with melanoma, where each criteria is assigned a score. The lesion is diagnosed as melanoma when the sum of the scores exceeds a given threshold [6], [8]. Although some literature recommends pattern analysis over the 7-point checklist [9], some works report a trade-off between melanoma sensitivity and specificity. For example, among dermatology residents, the 7-point checklist was





# Structured & Explainable Decision

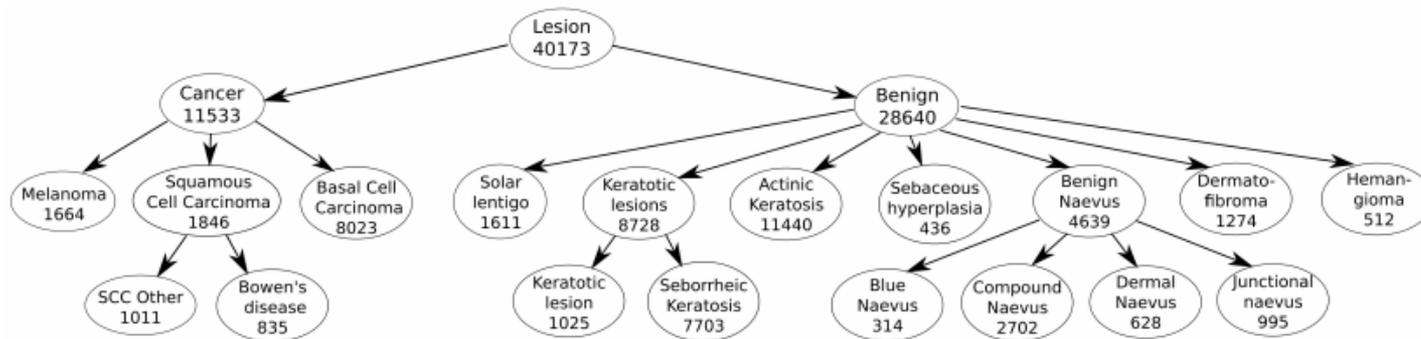
- How can we improve the interpretability of the classifier?





# Structured & Explainable Decision

- How can we improve the interpretability of the classifier?
  - **Some authors explored taxonomies**



Demyanov et al., ISBI, 2017

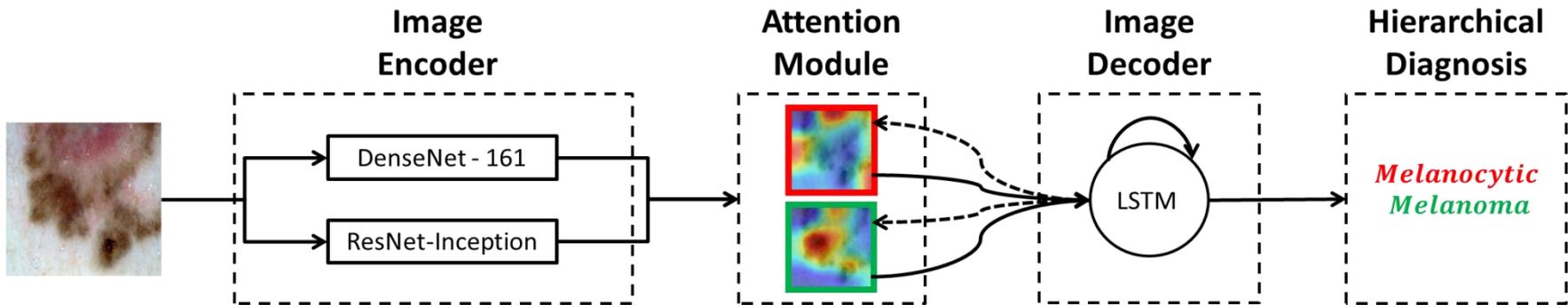
Proposal of a **Tree-loss function** to train the DNN





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Barata et al., ISIC@CVPR, 2019

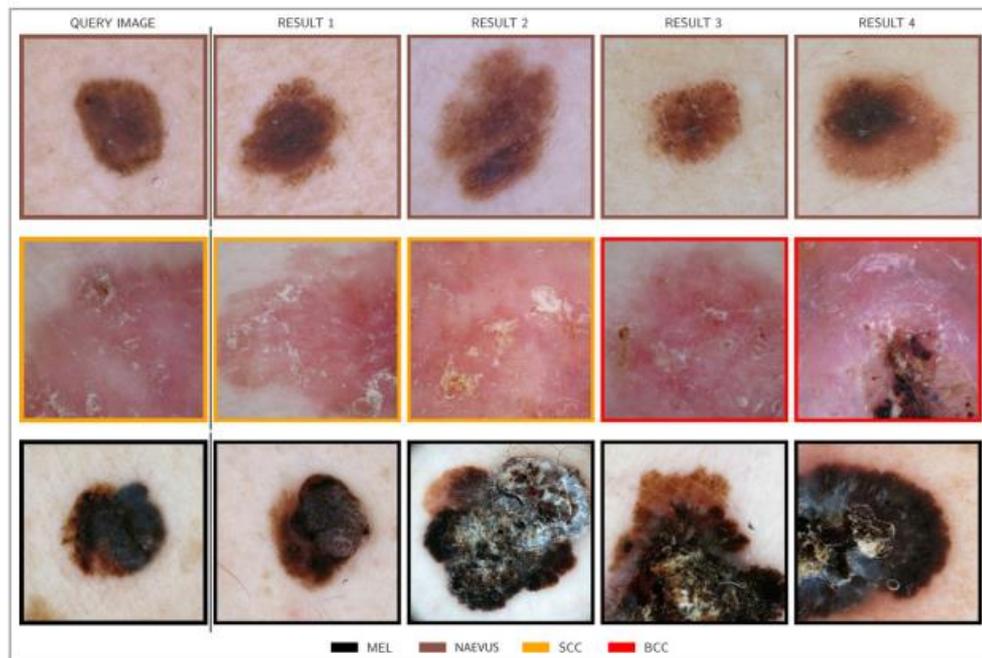
Fusion of **structured classifier** with **visualization**





# Structured & Explainable Decision

- How can we improve the interpretability of the classifier?
  - **Some authors explored taxonomies**
  - **Other explored content based image retrieval (CBIR)**



Decision Based on  
CBIR

Tschandl et al., BJD, 2018





# CHALLENGES & FUTURE





# Some Usual Misconceptions

- Interpretable methods require a **great amount of detailed annotations**





# Some Usual Misconceptions

- Interpretable methods require a **great amount of detailed annotations**



Clinically inspired analysis of dermoscopy images using a generative model

Catarina Barata<sup>a,\*</sup>, M. Emre Celebi<sup>b</sup>, Jorge S. Marques<sup>a</sup>, Jorge Rozeira<sup>c</sup>

<sup>a</sup> Instituto de Sistemas e Robótica, Instituto Superior Técnico, Lisboa, Portugal  
<sup>b</sup> Louisiana State University, Shreveport LA, USA  
<sup>c</sup> Hospital Pedro Hispano, Matosinhos, Portugal

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 Computer-aided diagnosis  
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 ABCD rule  
 Correspondence: LDA  
 Non-Mixed Gaussian distributions

**ABSTRACT**

Dermatologists often prefer clinically oriented Computer Aided Diagnosis (CAD) Systems that provide medical justifications for the estimated diagnosis. The development of such systems is hampered by the lack of detailed image annotations (medical labels and segmentations of the associated regions). In most cases, we only have access to weakly annotated images (raw labels) that are not sufficient to learn proper models. In this work we address this issue and propose a CAD System that uses medically inspired color information to diagnose skin lesions. We deal with the weakly annotated dermoscopy images using the Correspondence-LDA algorithm to learn a probabilistic model. The algorithm is applied with success to the identification of relevant colors in dermoscopy images, obtaining an average Precision of 83.83 and a Recall of 80.83. The proposed color representation is then used to classify skin lesions, resulting in a Sensitivity of 77.65 and Specificity of 77.35 using Random Forests, and a Sensitivity of 75.31 and Specificity of 77.25 using SVM. These results comparable favorably with related works.

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All of these works use weakly annotated sets!!

## Learning to Detect Blue–White Structures in Dermoscopy Images With Weak Supervision

Ali Madooei<sup>a</sup>, Mark S. Drew, and Hossein Hajimirsadeghi

**Abstract**—We propose a novel approach to identify one of the most significant dermoscopic criteria in the diagnosis of cutaneous melanoma: the blue–white structure (BWS). In this paper, we achieve this goal in a multiple instance learning (MIL) framework using only image-level labels indicating whether the feature is present or not. To this aim, each image is represented as a bag of (nonoverlapping) regions, where each region may or may not be identified as an instance of BWS. A probabilistic graphical model is trained (in MIL fashion) to predict the bag (image) labels. As output, we predict the classification label for the image (i.e., the presence or absence of BWS in each image) and we also localize the feature in the image. Experiments are conducted on a challenging dataset with results outperforming state-of-the-art techniques, with BWS detection besting competing methods in terms of performance. This study provides an improvement on the scope of modeling for computerized image analysis of skin lesions. In particular, it propounds a framework for identification of dermoscopic local features from weakly labeled data.

**Index Terms**—Biomedical image processing, feature extraction, microscopy, computer aided diagnosis, dermatology.

Increased interest in computer-aided diagnosis systems through automatic analysis of digital dermoscopy images.

In this paper, we focus on the identification of blue-white structures (BWS), one of the most important findings in dermoscopic examination for making a diagnosis of invasive melanoma [1]. The term BWS is a unified heading for features also known as blue-white veil and regression structures (this is discussed below in Section II). To this aim, a typical approach would be based on the classical paradigm of supervised learning, requiring extensive annotation of each dermoscopic training image possessing an instance of BWS. This is difficult (or even impossible) to carry out accurately and consistently due to subjectivity in feature identification and definition, leading to poor inter-observer agreement. (Notwithstanding the problem of subjectivity to give the whole image a label.)

The dermoscopy data in fact available to us underlies a different, more challenging, research problem. In the dataset [2], image-level labels encode only whether an image contains a dermoscopic feature or not—the features themselves are not

## Seven-Point Checklist and Skin Lesion Classification Using Multitask Multimodal Neural Nets

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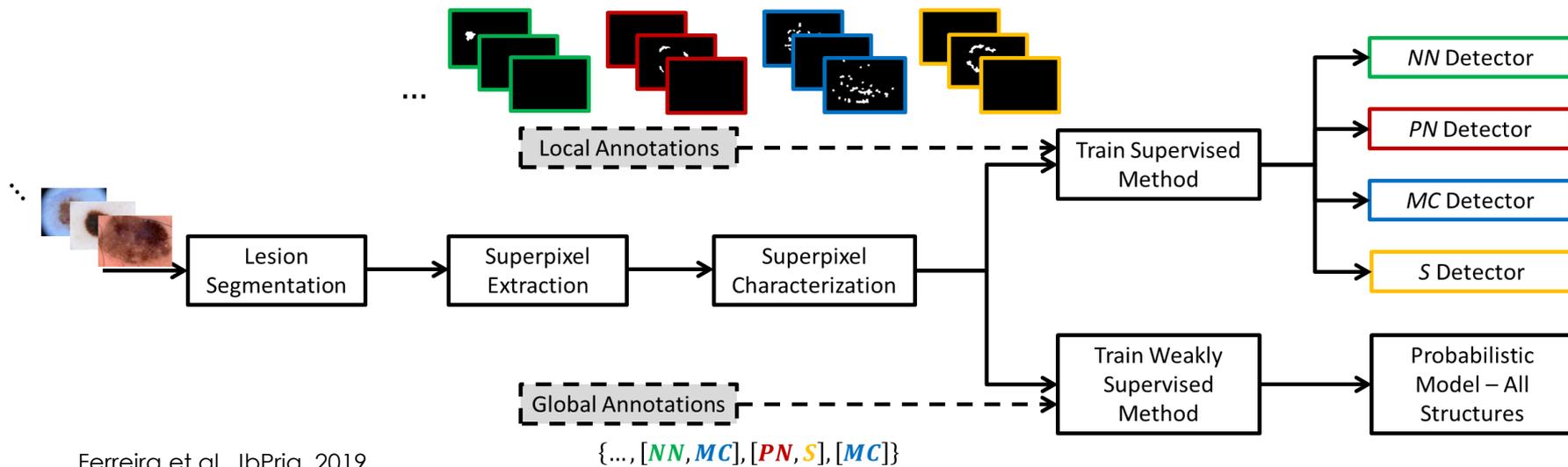
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# Some Usual Misconceptions

- Interpretable methods require a **great amount of detailed annotations**



Ferreira et al., IbPria, 2019

Method	Sensitivity	Specificity	BACC	#Annotations
Supervised	84,6%	69,2%	76,9%	≈ 460k
Weakly-Supervised	73,3%	76,0%	74,7%	2000





# Some Usual Misconceptions

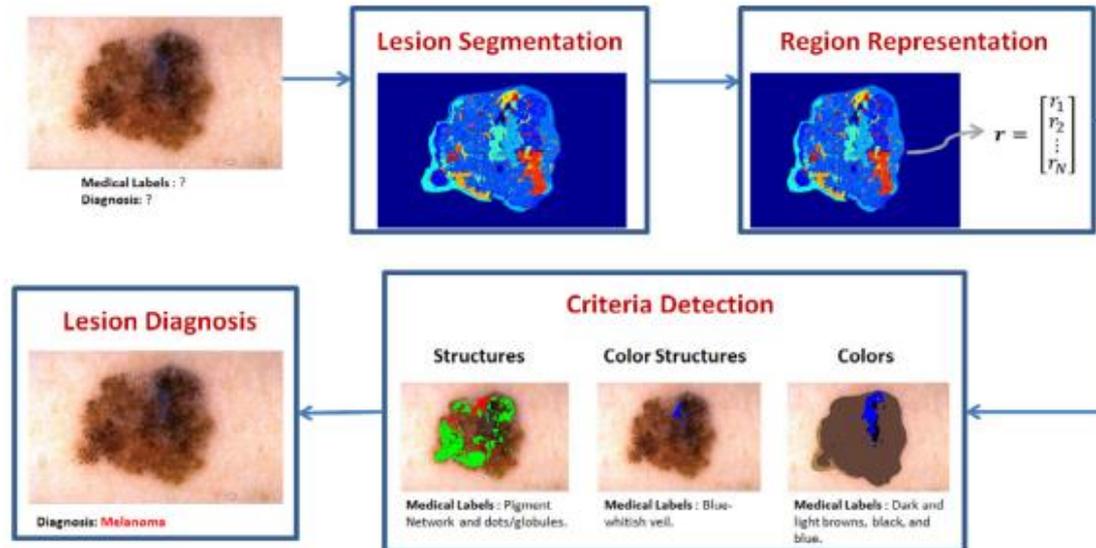
- ~~Interpretable methods require a~~ **great amount of detailed annotations**
- It is **not possible** to apply **clinically inspired features** to **automatic diagnosis**





# Some Usual Misconceptions

- Interpretable methods require a **great amount of detailed annotations**
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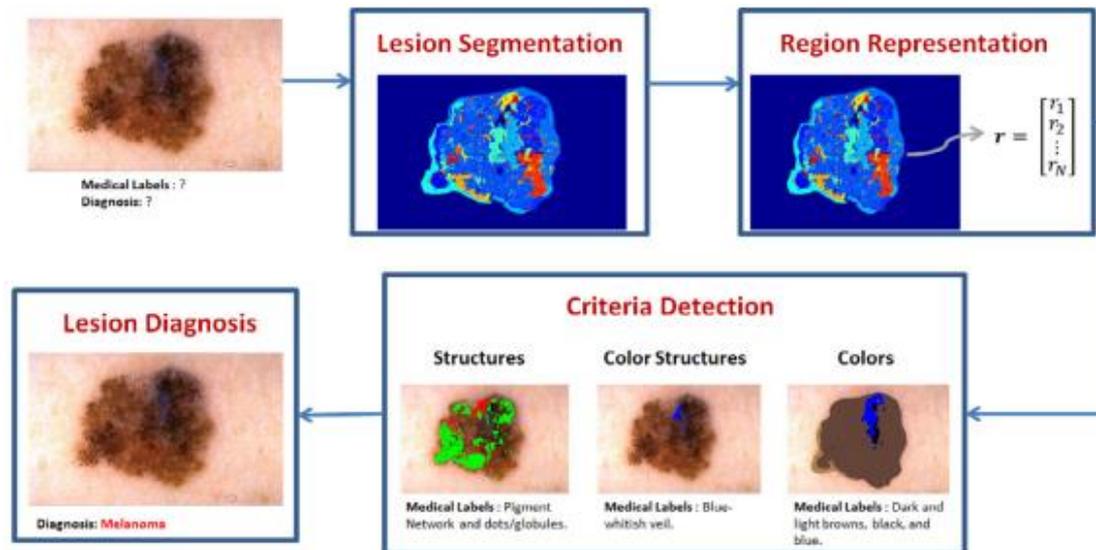
Barata et al., PR, 2017





# Some Usual Misconceptions

- Interpretable methods require a **great amount of detailed annotations**
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Barata et al., PR, 2017





# What lies ahead?

- How can we combine model explainability and interpretation?
  - **Fine grained attention/activation maps**
  - **Learn to translate the maps into medical terms**





# What lies ahead?

- How can we combine model explainability and interpretation?
  - **Fine grained attention/activation maps**
  - **Learn to translate the maps into medical terms**
- How relevant is our data?
  - **Identify the most difficult/misleading examples**
  - **Leverage the available data**





**THANK YOU FOR YOUR  
ATTENTION!**

**QUESTIONS?**

