Dictionary-based Sparse Representations for Automatic Processing and Analysis of Melanocytic Skin Lesions in Macroscopic Images

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***Abstract*—Melanoma is the most lethal type of skin cancer, since it is most prone to metastasis. Specifically, the rate of patients who survive at least five years after early stage diagnosis of this disease is over 99%. However, this rate decreases to about 25% if detection occurs only at the last stage. In this context, systems that assist in the early diagnosis of melanoma can play an extremely important role, especially in regions where access to dermatologists is poor. However, differentiating melanoma from benign melanocytic lesions can be a challenging task, even for experienced specialists. To address this problem, in this thesis, an automatic system is proposed for melanoma detection from a simple digital photograph, which is based on sparse representation models. The results presented by the proposed system are promising and suggest that it can potentially outperform state-of-the-art alternatives and even trained dermatologists.**

I. Introduction

Melanoma is a malignant tumor originating from melanocytes, the cells responsible for producing skin pigment. This malignant melanocytic skin lesion is the deadliest form of skin cancer due to its higher propensity for metastasis [1]. While early detection of melanoma tends to offer a more favorable prognosis, timely diagnosis plays a key role not only in reducing mortality rates but also in minimizing the treatment costs associated with the disease [2].

In this context, the development of systems capable of automatically processing, analyzing, and ultimately classifying melanocytic skin lesions based on simple digital photographs (i.e., macroscopic or clinical images) is of particular interest [3]. The potential applications of such systems include: pre-screening patients in primary health care settings or during consultations with a general practitioner; provide a second opinion to dermatologists, assisting them in computer-aided diagnoses; equip didactic tools in dermatology training courses; and tele-dermatological follow-up of patients who have experienced melanoma or have the atypical nevus syndrome [4].

Nevertheless, accurately discriminating melanomas from certain benign melanocytic lesions known as atypical nevi remains an open research problem. Fig. 1, which displays three samples from the "Atypical Nevus" class (Figs. 1a to 1c), and three samples from the "Melanoma" class (Figs. 1d to 1f), emphasizes the challenging nature of this task. This difficulty arises not only due to the variability among images within the same class but also due to the visual similarities between images from the different classes.

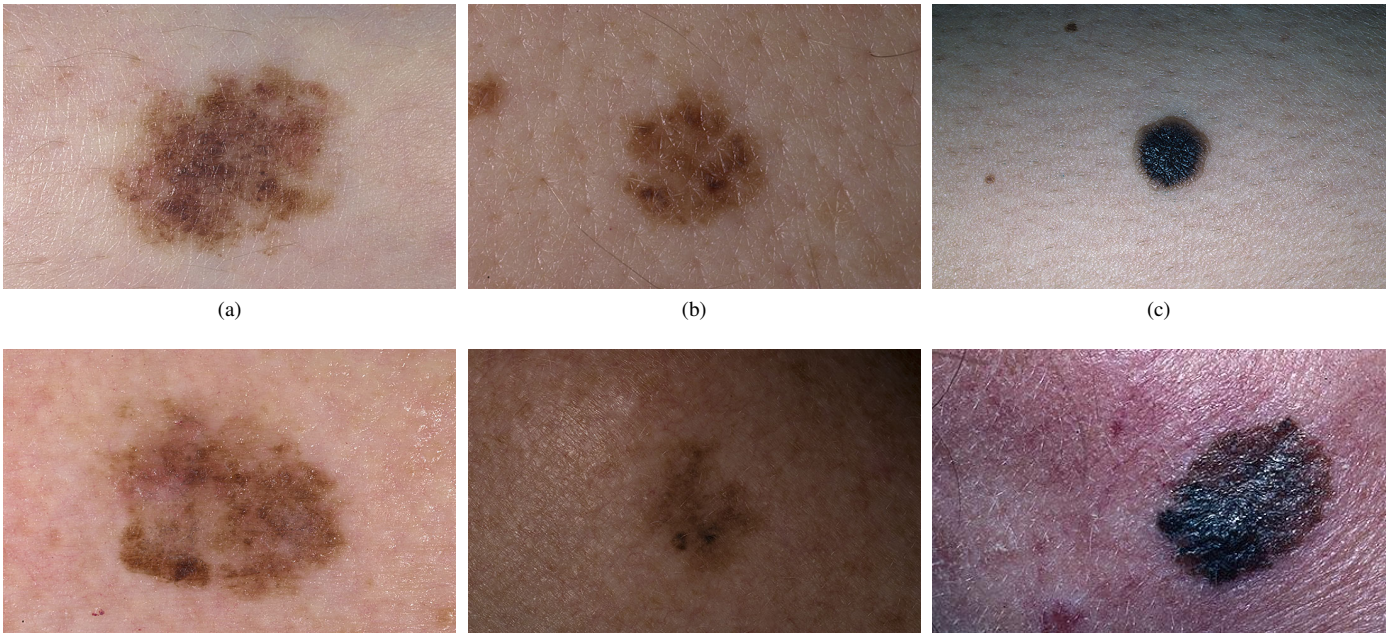
The remainder of this manuscript is structured as follows. A brief overview of the related works for classifying melanocytic skin lesions is provided in Section II, with a particular emphasis on elucidating the limitations of the state-of-the-art methods. The main contributions of the Ph.D. thesis associated with this article are highlighted in Section III. The subsequent section, Section IV, presents the experimental analyses, including the obtained results and their implications. Concluding remarks and potential future investigations are discussed in Section V. Lastly, the publications, achievements and possible distinctions resulting from the Ph.D. research are detailed in Section VI.

II. Related Work

Recently, several deep learning-based systems have been proposed in the literature for classifying melanocytic skin lesions. These systems combine transfer learning with techniques such as data augmentation, metadata integration, attention mechanisms, and ensemble methods. Representative examples of such systems can be found in references [6]–[9]. However, most of these systems are tailored for dermoscopic images, which limits their applicability in other contexts. This limitation stems from several factors.

First, processing and analyzing a melanocytic skin lesion in a macroscopic image, as opposed to a dermoscopic image, presents a more challenging task, because the lesion classification must rely on an image containing fewer discriminative cues. Additionally, macroscopic images require more robust preprocessing steps to handle extra artifacts such uneven illumination and sharpened hairs. For the sake of illustration, Fig. 2 displays three melanocytic skin lesions acquired by both imaging modalities, with the first row showing them in macroscopic images (Figs. 2a, 2c and 2e), and the second row

†This manuscript summarizes the main contributions of the **Ph.D.** thesis authored by Eliezer Soares Flores and advised by Jacob Scharcanski, which is available at https://lume.ufrgs.br/handle/10183/250649.



(a) (b) (c)

(d) (e) (f)

Fig. 1. Clinical examples of melanocytic skin lesions in macroscopic images [5]. The upper row (i.e., Fig. 1a, Fig. 1b, Fig. 1c) showcases instances of atypical nevi, while the lower row (i.e., Fig. 1d, Fig. 1e, Fig. 1f) features illustrative cases of melanomas.

presenting the same lesions in dermoscopic images (Figs. 2b, 2d and 2f).

Another factor to be considered is that since 2016, the International Skin Imaging Collaboration (ISIC) has been organizing an annual competition [10], providing a public dataset with over 70 thousand dermoscopic images of melanocytic skin lesions. This is one order of magnitude larger than the dataset containing macroscopic images of melanocytic skin lesions commercialized in [11], and two orders of magnitude larger than the ones publicly available by [12]–[14].

Furthermore, a notable issue with existing systems is that they are often evaluated without considering cross-dataset performance. This oversight can lead to an overestimation of their classification performance, making them unreliable for real-world clinical practices. Moreover, most deep learning-based systems proposed for classifying melanocytic skin lesions do not include a dedicated segmentation step, although methods specifically designed for segmentation based on deep learning can be found in the literature (e.g., [15]–[17]), which increases the bias risks reported in [18].

III. Proposed System

The primary objective of this work is to develop a system capable of accurately processing and analyzing melanocytic skin lesions in macroscopic images while addressing the aforementioned challenges. As a result of the research conducted for this thesis, novel dictionary-based sparse representation methods were obtained, serving as key components for the proposed system.

The proposed system for processing and analyzing melanocytic skin lesions in macroscopic images involves a series of sequential steps: preprocessing, pre-segmentation feature extraction, segmentation, pre-classification feature extraction, and classification. For organizational purposes, the steps of preprocessing, pre-segmentation feature extraction, and segmentation are collectively addressed in Subsection III-A, constituting the "proposed segmentation method". The steps of pre-classification feature extraction and classification, on the other hand, are covered in Subsection III-B, and they are collectively referred to as "the proposed classification method".

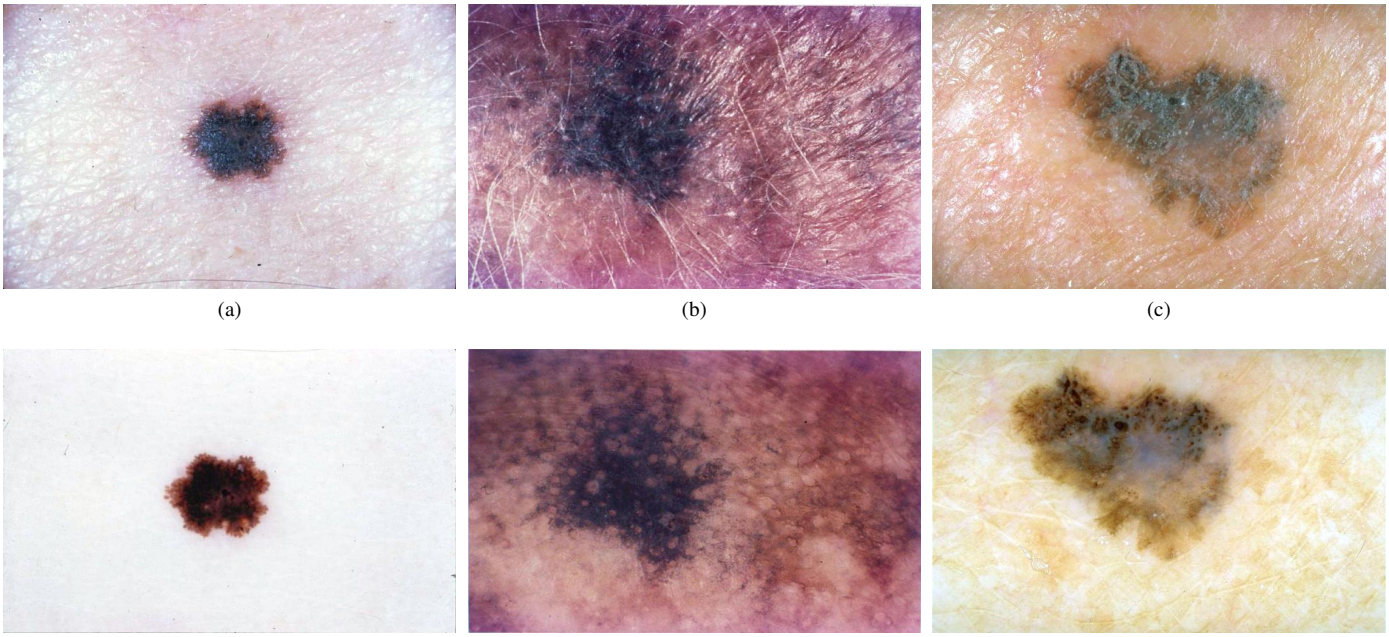
A. Dictionary-based Sparse Representation for Melanocytic Skin Lesion Segmentation

The entire workflow of the dictionary-based sparse representation method proposed for melanocytic skin lesion segmentation is illustrated in Fig. 3.

Briefly, the first stage of this segmentation proposal involves converting the input image, which has been pre-processed using the "Shading Attenuation" method detailed in our co-authored work in [20],[1] into a color saliency map. This map highlights color differences between healthy and unhealthy skin pixels and is obtained through the average healthy skin color estimation process proposed in our co-authored paper in [22].

Nevertheless, the primary original contribution of the proposed segmentation method is the Unsupervised Information-Theoretic Dictionary Learning (UITDL) scheme introduced into our publication in the Expert Systems with Applications journal [23] that can be seen as an adaptive and unsupervised version of the method in [24]. Essentially, this scheme adopts

[1]Originally proposed in [21].



(a) (b) (c)

(d) (e) (f)

Fig. 2. Comparison between dermoscopic and macroscopic images captured from the same melanocytic skin lesions [19]. The top row (i.e., Fig. 2a, Fig. 2b, and Fig. 2c) displays macroscopic images of melanocytic skin lesions, which are juxtaposed with the corresponding dermoscopic images in the bottom row (i.e., Fig. 2d, Fig. 2e, and Fig. 2f).

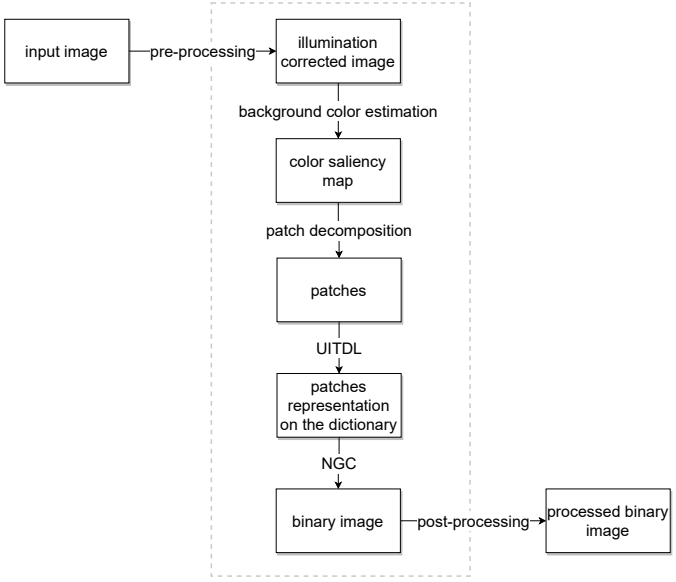


Fig. 3. Overview of the proposed melanocyticy skin lesion segmentation method.

a greedy approach to approximate the optimal dictionary $\boldsymbol{D}^*$ for sparse representations according to:

$$\boldsymbol{D}^* = \arg\max_{\boldsymbol{D}} \left\{ \lambda_1 \mathbb{I}(\boldsymbol{D}, \boldsymbol{Y}) + \lambda_2 \mathbb{I}(\boldsymbol{D}, \boldsymbol{D}^{(0)} - \boldsymbol{D}) \right\}. \quad (1)$$

Here, $\boldsymbol{Y}$ denotes the matrix where each column corresponds to a different patch from the color saliency map, $\boldsymbol{D}^{(0)}$ represents an initial dictionary (e.g., built from $\boldsymbol{Y}$ via Non-negative Matrix Factorization (NMF) [25]), and $\mathbb{I}(\cdot, \cdot)$ denotes mutual information.

Basically, the objective function in Equation (1) is a linear combination (weighted by the hyperparameters λ_1 and λ_2) of two terms: the representativeness term $\mathbb{I}(\boldsymbol{D}, \boldsymbol{Y})$, which quantifies the information content of the atoms in $\boldsymbol{D}$ about the patches in $\boldsymbol{Y}$, and the compactness term $\mathbb{I}(\boldsymbol{D}, \boldsymbol{D}^{(0)} - \boldsymbol{D})$, which assesses the information carried by the dictionary about the atoms left out of its current composition.

Leveraging UITDL, the Normalized Graph Cut (NGC) method [26] is then employed to partition the patch representations into two groups, resulting in a binary image that labels the pixels of the image as either "healthy" or "unhealthy". Finally, this binary image undergoes post-processing to standardize the labeling process and also eliminate potential artifacts.

B. Dictionary-based Sparse Representation for Melanocytic Skin Lesion Classification

The diagram in Fig. 4 visually depicts the workflow of the melanocytic skin lesion classification method, which encompasses two main stages: 1) deep feature dictionaries learning, and 2) prediction using a more scalable and robust version of the SRC (Sparse Representation-based Classification) method [27]. This method stands as an original contribution of our work and was initially published in the Pattern Recognition journal within the context of remote sensing applied to land-use scene analysis using very high spatial resolution images [28].

Fundamentally, in the stage of learning deep feature dictionaries, each compact and discriminative dictionary is

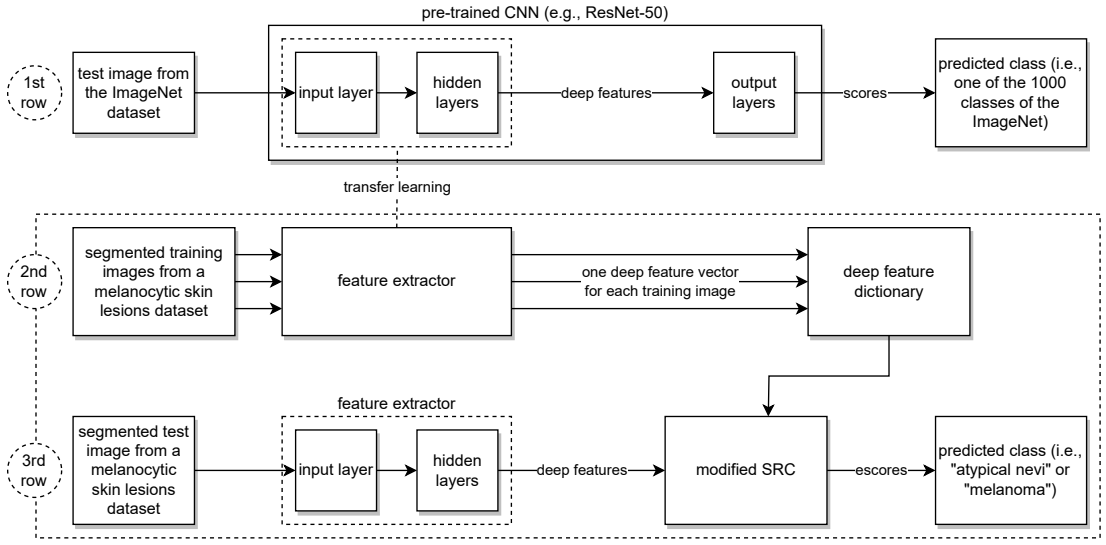


Fig. 4. Overview of the proposed melanocyticy skin lesion classification method.

formed by atoms directly extracted from a Gaussian Mixture Model (GMM), whose parameters are estimated by an Expectation-Maximization (EM) iterative algorithm to maximize a log-likelihood function as follows [29]:

$$\hat{\Theta}_i = \arg\max_{\Theta_i} \left\{ \sum_{j=1}^{q_i} \sum_{k=1}^{C_i} \log \left(\alpha_{i,k} \mathbb{P}(\boldsymbol{f}_{i,j}; \boldsymbol{\mu}_{i,k}, \Sigma_{i,k}) \right) \right\}, \quad (2)$$

where:

$$\Theta_i = \left\{ \boldsymbol{\mu}_{i,1}, \ldots, \boldsymbol{\mu}_{i,C_i}, \Sigma_{i,1}, \ldots, \Sigma_{i,C_i}, \alpha_{i,1}, \ldots, \alpha_{i,C_i} \right\} \quad (3)$$

subjects to the parameters constraint

$$\sum_{k=1}^{C_i} \alpha_{i,k} = 1. \quad (4)$$

In Equation (2), C_i, $i \in \{1, \ldots, n_l\}$, are hyperparameters and $\mathbb{P}(\boldsymbol{f}_{i,j}; \boldsymbol{\mu}_{i,k}, \Sigma_{i,k})$ represents the occurrence probability of the deep feature vector $\boldsymbol{f}_{i,j} \in \mathbb{R}^p$ obtained from the j-th image of the i-th class, $j \in \{1, \ldots, q_i\}$, using a pre-trained Convolutional Neural Network (CNN) as a fixed feature extractor. This probability is given by the conditional probability with respect to the mean vector $\boldsymbol{\mu}_{i,k}$ and the covariance matrix $\Sigma_{i,k}$ associated with the k-th GMM component.

In short, the prediction stage relies on classifying the deep feature vector $\boldsymbol{y}$ extracted from a test image based on its optimal sparse representation $\boldsymbol{x}_1^*$ determined by the following problem:

$$\boldsymbol{x}_1^* = \arg\min_{\boldsymbol{x}} \left\{ \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{\mathcal{D}}\boldsymbol{x}\|_2^2 + \lambda \|\boldsymbol{x}\|_1 \right\}, \quad (5)$$

where $\boldsymbol{\mathcal{D}}$ denotes the deep feature dictionaries as a whole. Effectively, the solution for this problem is approximated based on the Fast Iterative Shrinkage-Thresholding Algorithm (FISTA) [30].

IV. Experimental Analyses

Throughout the conducted experiments, four datasets consisting melanocytic skin lesions in macroscopic images were employed as benchmarks: DermIS [12], with 69 images (43 melanomas and 26 atypical nevi); DermNet [5], with 152 images (107 melanomas and 45 atypical nevi); DermQuest [12], with 137 images (76 melanomas and 61 atypical nevi); and MClassND [14], with 100 images (20 melanomas and 80 atypical nevi).

The performed performance comparisons between a single proposed method and multiple state-of-the-art alternatives utilized the Friedman statistical test with the Bonferroni-Dunn post-hoc test and a confidence level of 95%. These analyses were carried out using paired datasets as recommended in [31], notably encompassing pixel sets for the evaluation of segmentation methods and image sets for the assessment of classification methods.[2]

The comparative analysis with the proposed melanocytic skin lesion segmentation method is detailed next in Subsection IV-A, followed by the comparative analysis with the proposed melanocytic skin lesion classification method, which can be regarded as the evaluation of the system as a whole and is presented in Subsection IV-B.

A. Comparative Analysis with the Proposed Melanocytic Skin Lesion Segmentation Method

Given the unsupervised nature of the proposed melanocytic skin lesion segmentation method, the experiments to evaluate this method did not require a dedicated training dataset. Instead, the smallest dataset among the considered ones, namely DermIS, was leveraged solely for fine-tuning the

[2]Statistical comparisons among different versions of the proposed methods, which were involved in fine-tuning hyperparameters and conducting ablation studies to demonstrate the effectiveness of the method stages, have not been included in this manuscript due to limitations in scope and available space.

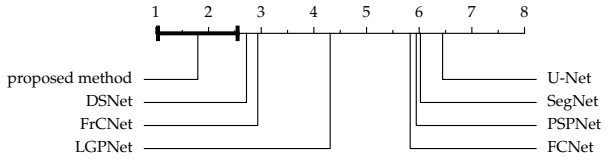
method's configuration hyperparameters. This approach aligns with the experimental protocol established in [32] and used, for instance, in [22].

Subsequently, in order to comprehensively evaluate the robustness and generalizability of the proposed melanocytic skin lesion classification method, two different cross-dataset tests were performed: one utilizing all images from the DermNet dataset, and the other involving the complete set of images from DermQuest. The MClassND dataset, due to the absence of segmentation ground-truths, was not employed for evaluating the proposed melanocytic skin lesion segmentation method.

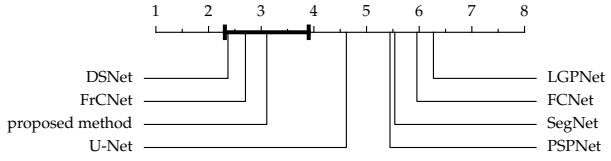
These same cross-dataset tests were also used to evaluate the representative state-of-the-art alternatives listed below:

- Dermoscopic Skin Network (DSNet) [17];
- Fully Convolutional Network (FCNet) [33];
- Full-resolution Convolutional Network (FrCNet) [16];
- Local/Global Patch-based Network (LGPNet) [15];
- Pyramid Scene Parsing Network (PSPNet) [34];
- Segmentation Network (SegNet) [35];
- U-shaped Network (U-Net) [36].

The segmentations produced for each test image were ranked using the BF_1 score as the performance metric. These rankings were then averaged for both the DermNet and DermQuest datasets. The graphical presentation of results is provided through diagrams [31], as shown in Fig. 5a for the DermNet dataset and Fig. 5b for the DermQuest dataset.



(a) Diagram for cross-dataset test with the DermNet dataset.



(b) Diagram for the cross-dataset test with the DermQuest dataset.

Fig. 5. Average ranking comparison of the proposed method against state-of-the-art alternatives (alternatives with ranks outside the indicated interval significantly differ from the proposed method).

B. Comparative Analysis with the Proposed Melanocytic Skin Lesion Classification Method

The proposed melanocytic skin lesion classification method operates under the supervised paradigm. Therefore, first, an initial training and validation phase is performed, which utilizes a 5×2 cross-validation process [37] on a composite dataset comprising both DermIS and DermQuest datasets (among the considered datasets, these are the ones that are publicly available and include segmentation ground truths, thus enabling the reproducibility of the experiments. Specifically, this composite dataset is partitioned into two stratified subsets, namely training and validation sets (the validation sets serve for fine-tuning the method's configuration hyperparameters), a total of five times.

Afterwards, for a rigorous assessment of the system's robustness and generalizability, two distinct cross-dataset tests were carried out: one employing all images from the DermNet dataset, and the other encompassing the entire set of images from MClassND dataset.

These cross-dataset tests were additionally used to assess the following representative state-of-the-art alternatives:

- Attention Residual Learning (ARL) [7];
- Dynamic Weights (DW) [9];
- ISIC Winner (IW) [8];
- Skin Lesion Analyzer (SLA) [6].

Fig. 6a presents a comparative analysis of ROC curves derived from the proposed system and the state-of-the-art alternatives, as applied to tests conducted with the DermQuest dataset images. In a similar vein, Fig. 6b showcases the comparison of ROC curves for tests performed with the images from the MClassND dataset. Notably, as seen in Figs. 6a and 6b, the proposed system consistently outperforms the other investigated alternatives in terms of the AUC metric, suggesting its superior performance across both DermQuest and MClassND datasets.

Fig. 6c, on the other hand, compares the proposed system with the evaluations of 157 specialized dermatologists [14]. Each circle on the ROC plane signifies the performance of one or more of these dermatologists (when multiple dermatologists achieve the same performance, a larger and darker circle is displayed). As evident, the proposed system can potentially outperform the performance of certain dermatologists.

V. Conclusion

This manuscript provided a concise overview of the Ph.D. thesis authored by Eliezer Soares Flores and advised by Jacob Scharcanski, introducing a comprehensive system for automated processing and analysis of melanocytic skin lesions in macroscopic images.

The proposed system relies on dictionary-based sparse representations and consists of two essential components: an unsupervised method for segmenting melanocytic skin lesions, employing an adaptive and unsupervised adaptation of the ITDL method [24]; and a supervised method for classifying melanocytic skin lesions that extends the SRC method [27], enhancing its scalability and flexibility to effectively manage imbalanced class distributions.

Despite the inherent multidisciplinarity of this research, the contributions obtained in this thesis go beyond the application in dermatology that motivated this study (e.g., a preliminary version of the proposed classification method was successfully applied to land-use scene analysis using very high spatial resolution images [28]), with the potential to impact various

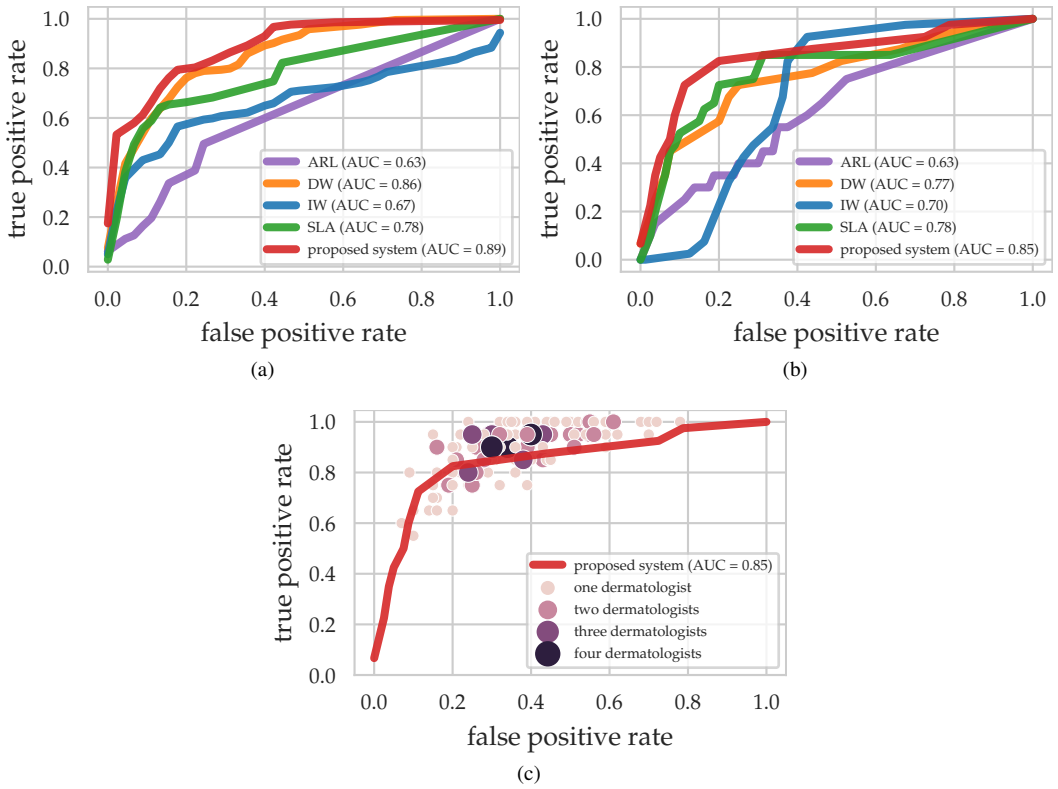


Fig. 6. ROC curves of the proposed system for melanocytic skin lesion classification in macroscopic images compared to (a) state-of-the-art alternatives on DermNet dataset, (b) state-of-the-art alternatives on Brinker dataset, and (c) human expert dermatologists on Brinker dataset.

domains reliant on image processing, computer vision, and pattern recognition.

Some important issues that were not addressed in this thesis and could be explored in future works include the integration of segmentation and classification methods into a single network, as well as adapting the system to provide more interpretable predictions.

VI. Academic Accomplishments

It is worth mentioning that the PhD thesis summarized in this manuscript was entirely developed in conjunction with the author's engagement as a professor at the Federal University of Pampa (UNIPAMPA).[3] It was successfully defended on August 10, 2022, and received unanimous approval with the highest grade ("A") from an examining committee composed of PhD professors André Carlos Ponce de Leon Ferreira de Carvalho (USP), Claudio Rosito Jung (UFRGS), and Eduardo Antônio Barros da Silva (UFRJ).

It is worth highlighting that the core components of the proposed system have been published in top-tiers journals, as outlined below:

- "Dictionaries of deep features for land-use scene classification of very high spatial resolution images," published in **Pattern Recognition**, with **first-authorship** by the thesis' author [28].
- "Segmentation of melanocytic skin lesions using feature learning and dictionaries," published in **Expert Systems with Applications**, with **first-authorship** by the thesis' author [23].
- "A simple weighted thresholding method for the segmentation of pigmented skin lesions in macroscopic images," published in **Pattern Recognition**, co-authored by the thesis' author [22].

Moreover, stemming from the culmination of this research, a survey chapter intimately aligned with the thesis' scope was also published:

- "Macroscopic Pigmented Skin Lesion Prescreening," featured in the **Encyclopedia of Biomedical Engineering**, equally contributed by both the thesis' author and the primary author [20].

Furthermore, the thesis merited an honorable mention award in the Artur Ziviani Prize for Theses and Dissertations (second best doctoral thesis).

[3]Undergraduate human resources training related to the thesis included publishing 5 papers in conference proceedings, supervising 3 undergraduate thesis projects, and a substantial involvement in 18 thesis defense committees.

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REFERENCES

[1] A. Riker, *Melanoma: a modern multidisciplinary approach*, 1st ed. Cham: Springer, 2018.

[2] F. C. Morgan, J. Duran, B. Fraile, P. S. Karia, J. Y. Lin, P. A. Ott, E. S. Ruiz, D. M. Wang, Y. Zhang, and C. D. Schmults, "A comparison of skin cancer screening and treatment costs at a massachusetts cancer center, 2008 versus 2013," *Journal of the American Academy of Dermatology*, vol. 79, no. 5, pp. 921–928, 2018.

[3] J. Scharcanski and M. E. Celebi, *Computer Vision Techniques for the Diagnosis of Skin Cancer*, 1st ed., ser. Series in BioEngineering. Berlin, Heidelberg: Springer, 2014.

[4] R. D. Melamed, I. T. Aydin, G. S. Rajan, R. Phelps, D. N. Silvers, K. J. Emmett, G. Brunner, R. Rabadan, and J. T. Celebi, "Genomic characterization of dysplastic nevi unveils implications for diagnosis of melanoma," *Journal of Investigative Dermatology*, vol. 137, no. 4, pp. 905–909, 2017.

[5] J. F. Alcón, C. Ciuhu, W. ten Kate, A. Heinrich, N. Uzunbajakava, G. Krekels, D. Siem, and G. de Haan, "Automatic imaging system with decision support for inspection of pigmented skin lesions and melanoma diagnosis," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 1, pp. 14–25, 2009.

[6] M. Woza. Skin lesion analyzer. Available at: http://skin.test.woza.work/. Accessed on: 09 sep. 2022.

[7] J. Zhang, W. Li, P. Ogunbona, and D. Xu, "Recent advances in transfer learning for cross-dataset visual recognition: A problem-oriented perspective," *ACM Computing Surveys*, vol. 52, no. 1, pp. 1–38, 2019.

[8] Q. Ha, B. Liu, and F. Liu. Identifying melanoma images using efficientnet ensemble: Winning solution to the SIIM-ISIC melanoma classification challenge. Available at: https://arxiv.org/pdf/2010.05351.pdf. Accessed on: 09 sep. 2022.

[9] A. G. Pacheco, T. Trappenberg, and R. A. Krohling, "Learning dynamic weights for an ensemble of deep models applied to medical imaging classification," in *Proceedings of the 2020 IEEE International Joint Conference on Neural Networks (IJCNN)*, 2020, pp. 1–8.

[10] N. C. F. Codella, D. Gutman, M. E. Celebi, B. Helba, M. A. Marchetti, S. W. Dusza, A. Kalloo, K. Liopyris, N. Mishra, H. Kittler, and A. Halpern, "Skin lesion analysis toward melanoma detection: a challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), hosted by the International Skin Imaging Collaboration (ISIC)," in *Proceedings of the 15th IEEE International Symposium on Biomedical Imaging (ISBI)*. Washington, DC, USA: IEEE, April 2018.

[11] University of Edinburgh. Dermofit image library. Available at: https://licensing.edinburgh-innovations.ed.ac.uk/product/dermofit-image-library. Accessed on: 09 sep. 2022.

[12] R. Amelard, A. Wong, and D. A. Clausi, "Extracting high-level intuitive features (hlif) for classifying skin lesions using standard camera images," in *Proceedings of the 9th Canadian Conference on Computer and Robot Vision (CRV)*. Toronto, ON, Canada: IEEE, May 2012.

[13] I. Giotis, N. Molders, S. Land, M. Biehl, M. F. Jonkman, and N. Petkov, "MED-NODE: a computer-assisted melanoma diagnosis system using non-dermoscopic images," *Expert Systems with Applications*, vol. 42, no. 19, pp. 6578–6585, 2015.

[14] T. J. Brinker, A. Hekler, A. Hauschild, C. Berking, B. Schilling, A. H. Enk, S. Haferkamp, A. Karoglan, C. von Kalle, M. Weichenthal *et al.*, "Comparing artificial intelligence algorithms to 157 german dermatologists: the melanoma classification benchmark," *European Journal of Cancer*, vol. 111, pp. 30–37, 2019.

[15] M. H. Jafari, N. Karimi, E. Nasr-Esfahani, S. Samavi, S. M. R. Soroushmehr, K. Ward, and K. Najarian, "Skin lesion segmentation in clinical images using deep learning," in *Proceedings of the 23rd International Conference on Pattern Recognition (ICPR)*. Cancún, Mexico: IEEE, December 2016.

[16] M. A. Al-Masni, M. A. Al-Antari, M.-T. Choi, S.-M. Han, and T.-S. Kim, "Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks," *Computer Methods and Programs in Biomedicine*, vol. 162, pp. 221–231, 2018.

[17] M. K. Hasan, L. Dahal, P. N. Samarakoon, F. I. Tushar, and R. Martí, "DSNet: Automatic dermoscopic skin lesion segmentation," *Computers in Biology and Medicine*, vol. 120, p. 103738, 2020.

[18] A. Bissoto, M. Fornaciali, E. Valle, and S. Avila, "(de) constructing bias on skin lesion datasets," in *Proceedings of the 2019 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. Long Beach, CA, USA: IEEE, June 2019.

[19] J. Kawahara, S. Daneshvar, G. Argenziano, and G. Hamarneh, "Seven-point checklist and skin lesion classification using multitask multimodal neural nets," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 2, pp. 538–546, 2018.

[20] E. Bernart, E. S. Flores, and J. Scharcanski, "Macroscopic pigmented skin lesion prescreening," in *Encyclopedia of Biomedical Engineering*, R. Narayan, Ed. Amsterdam: Elsevier, 2019, vol. 2, pp. 561–573.

[21] P. G. Cavalcanti, J. Scharcanski, and C. B. O. Lopes, "Shading attenuation in human skin color images," in *Proceedings of the 6th International Symposium on Visual Computing (ISVC)*. Las Vegas, NV, USA: Springer, November 2010.

[22] M. Zortea, E. Flores, and J. Scharcanski, "A simple weighted thresholding method for the segmentation of pigmented skin lesions in macroscopic images," *Pattern Recognition*, vol. 64, pp. 92–104, 2017.

[23] E. Flores and J. Scharcanski, "Segmentation of melanocytic skin lesions using feature learning and dictionaries," *Expert Systems with Applications*, vol. 56, pp. 300–309, 2016.

[24] Q. Qiu, V. M. Patel, and R. Chellappa, "Information-theoretic dictionary learning for image classification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 11, pp. 2173–2184, 2014.

[25] D. D. Lee and H. S. Seung, "Learning the parts of objects by non-negative matrix factorization," *Nature*, vol. 401, no. 6755, pp. 788–791, 1999.

[26] J. Shi and J. Malik, "Normalized cuts and image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 888–905, 2000.

[27] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust face recognition via sparse representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 31, no. 2, pp. 210–227, 2009.

[28] E. Flores, M. Zortea, and J. Scharcanski, "Dictionaries of deep features for land-use scene classification of very high spatial resolution images," *Pattern Recognition*, vol. 89, pp. 32–44, 2019.

[29] C. M. Bishop, *Pattern Recognition and Machine Learning*, 1st ed. Singapore: Springer, 2006.

[30] A. Beck and M. Teboulle, "A fast iterative shrinkage-thresholding algorithm for linear inverse problems," *SIAM Journal on Imaging Sciences*, vol. 2, no. 1, pp. 183–202, 2009.

[31] J. Demšar, "Statistical comparisons of classifiers over multiple data sets," *Journal of Machine Learning Research*, vol. 7, no. 1, pp. 1–30, 2006.

[32] J. Glaister, A. Wong, and D. A. Clausi, "Segmentation of skin lesions from digital images using joint statistical texture distinctiveness," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 4, pp. 1220–1230, 2014.

[33] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in *Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Boston, MA, USA: IEEE, June 2015.

[34] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, "Pyramid scene parsing network," in *Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Honolulu, HI, USA: IEEE, June 2017.

[35] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: a deep convolutional encoder-decoder architecture for image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 12, pp. 2481–2495, 2017.

[36] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, "U-Net: Convolutional networks for biomedical image segmentation," in *Proceedings of the 18th International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI)*. Munich, Germany: Springer, June 2015.

[37] T. G. Dietterich, "Approximate statistical tests for comparing supervised classification learning algorithms," *Neural Computation*, vol. 10, no. 7, pp. 1895–1923, 1998.