IMAGE ANALYSIS AND MACHINE LEARNING CLASSIFICATION FOR SKIN CANCER THERMAL IMAGES USING OPEN SOURCE TOOLS

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Introduction

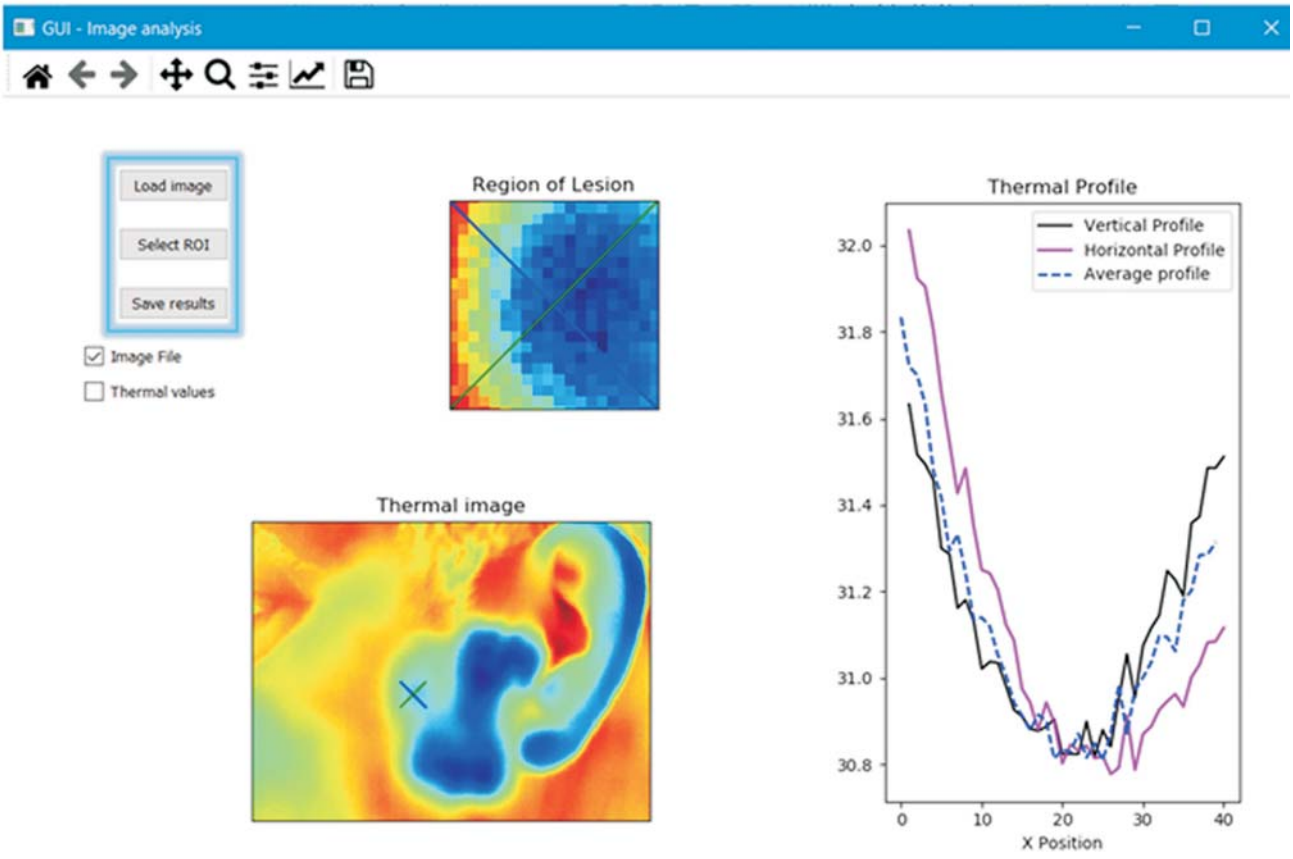
The incidence of skin cancer cases is constantly growing, causing a great burden in health care systems. The interest in using infrared thermal (IRT) imaging to assess atypical skin temperature values associated with skin lesions has grown, as it allows an innocuous and fast evaluation. The processing, collection, and integration of IRT parameters is a challenging task, becoming a tendency to adopt machine learning (ML) strategies. Still, there is not a great number of published research focused on the conception of applications or platforms to perform these tasks. The main aim of this work is the conception and development of two open-source interfaces, using Python programming language, to facilitate and assist in the performance of skin cancer thermograms' image analysis and classification.

Materials and Methods

Static thermograms representative of different skin tumors were analyzed to retrieve features for lesion classification. The infrared thermal images were previously collected at Instituto Português de Oncologia do Porto FG, EPE, including 298 skin tumors (113 benign (29 actinic keratosis (AK), 30 melanocytic nevi (Nevi), 54 other types) and 185 malignant lesions (16 melanoma, 51 squamous cell carcinoma (SCC), 118 basal cell carcinoma (BCC)). The established classification tasks included the differentiation: melanoma vs nevi, SCC vs AK, Melanoma vs Non-melanoma and Benign vs Malignant.

Thermogram manipulation and analysis was performed using the software tools ThermaCAM Researcher Profes-

Figure 1
Image analysis GUI: selected image, region of interest, thermal profile and options for saving.



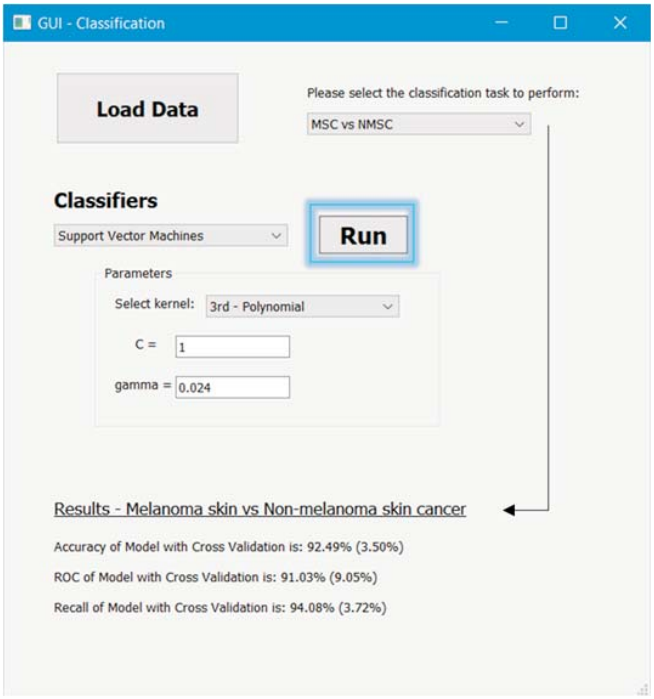


Figure 2
Machine learning classification GUI: classifier run and respective results with label indicating the selected classification task.

sional 2.10 and Anaconda 3 - Spyder 4.0 (Python 3.7), along with QtDesigner for the construction of both graphical user interfaces (GUIs). The Python libraries SciPy, NumPy, OpenCV and Matplotlib were imported to perform tasks concerning file loading, matrix and array manipulation, image processing and plotting and image display, respectively. The GUIs development was performed using the Python library PyQt5 with the modules QtCore, QtGui and QtWidgets. Both GUIs were constructed in a simple manner, being easy to understand and use. Functionality was attributed to each GUI component through the connection of functions and methods to events upon initialization of image analysis GUI (1), the user can load a .mat file representative of the neoplasm of interest, followed by the selection of region of interest. The region of interest (ROI) is process according to Magalhaes et al. 2019 (2), displaying the results, that can then be saved in different format files (Fig. 1). Concerning the classification GUI, the user can load the desired data set, indicate the required classification task, select classifier to use and respective parameters. The classifiers available for selection and respective parameters were chosen based on a previously conducted literature survey for skin cancer images (3). The performance is assessed based on the metrics of accuracy (ACC), Area Under the Receiver Operating Characteristic Curve (ROC(AUC)) and Recall (Fig. 2). A collection of errors is included in both GUIs by pop-windows to inform the user of possible mistakes concerning, per example, image loading, ROI selection, results storage, data set loading and classifier/parameter selection (4).

Results and Discussion

The constructed GUIs were fully operational, allowing the analyses of thermograms in a straightforward manner. In the same line, the classification GUIs eased the testing of different classifier parameters. Promising classification results were achieved with the implementation of a classifier based on Support Vector Machines with a 3rd degree polynomial kernel (SVM - 3rd Poly), specially for the distinction of non-melanoma skin cancer and melanoma (ACC=92.49%, ROC(AUC)=91.03%, Recall=94.08%) and melanoma and nevi lesions (ACC=85%, ROC(AUC)=93.33%, Recall=86.07%) (Table 1). The resemblance of thermal characteristics of SCC and AK complicated its differentiation, since both tumor types presented a decrease in temperature compared to the surrounding tissue (Fig. 3b). The same was verified with the benign and malignant groups. Regardless of the common association of increased temperature with malignant lesions, the malignant group exhibited decreased temperature measurements, due to the integration of non-melanoma skin cancer (squamous cell carcinoma and basal cell carcinoma) in this group (Fig 3c). These neoplasm types were described by a clear hypothermic profile, being mistaken by benign neoplasms by the classifiers.

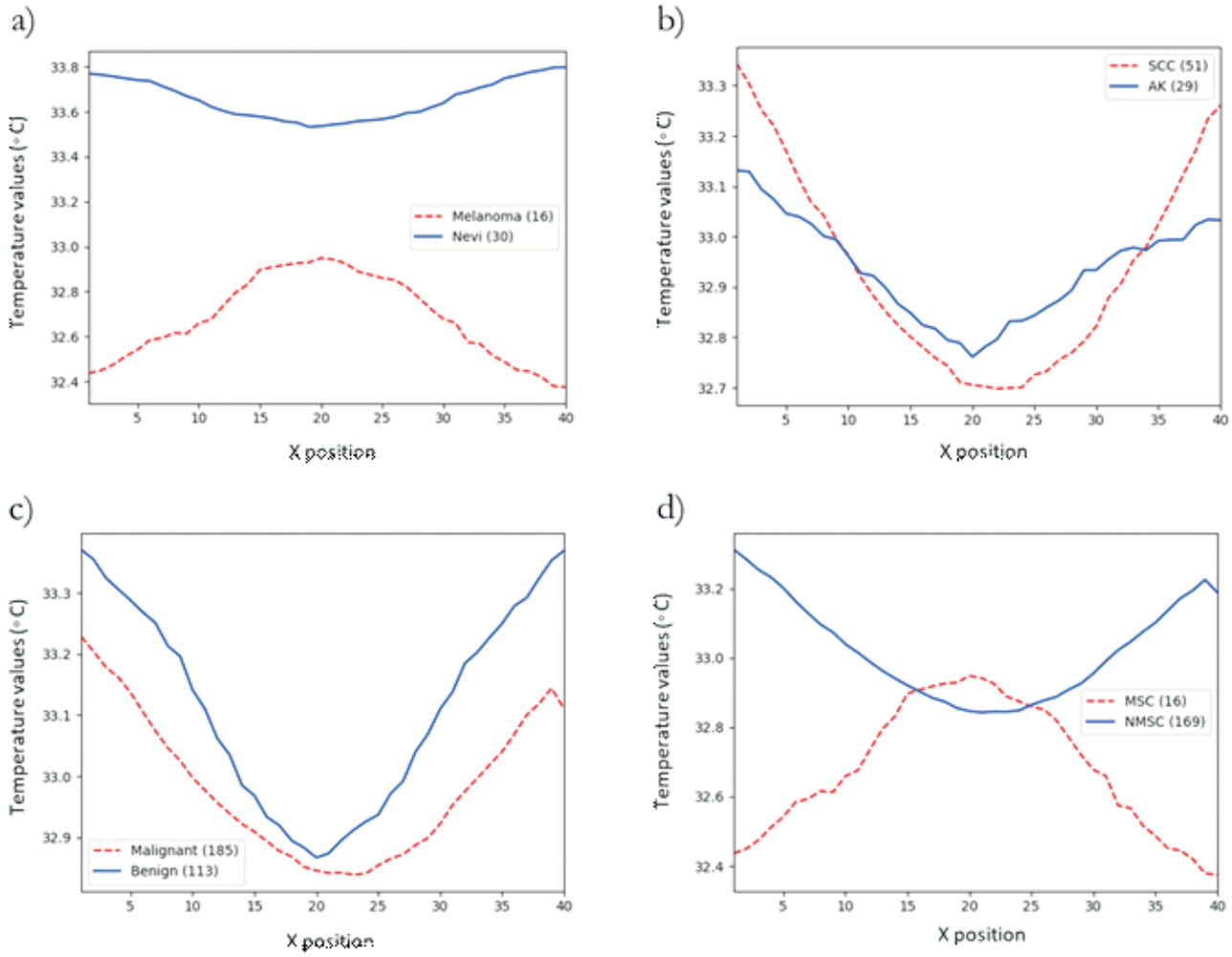
Conclusion

The temperature features retrieved during image analysis proved its potential as input vectors for the constructed ML models, particularly when based on support vector machines. The constructed GUIs eased image analysis and classification. For future work, the use of strategies to deal with class imbalance, perform hyperparameter tuning and

Table 1
Summary of best classification results with top classifier,
average ACC, ROC(AUC) and Recall values and respective standard deviation (std) (results achieved with cross validation 10-fold)

Classification Task	Best Classifier	ACC ± std (%)	ROC(AUC) ± std (%)	Recall ± std (%)
t180Benign vs Malignant	SVM – 3rd poly	67.10±7.32	62.63±9.12	100
SCC vs AK	SVM – 3rd poly	67.25±13.05	69±17.64	71±11.36
Melanoma vs Nevi	SVM – 3rd poly	85±3.42	93.33±13.33	86.67±6.33
MSC vs NMSC	SVM – 3rd poly	92.49±3.50	91.03±9.05	94.08±3.72

Figure 3
Average thermal curve: a) Melanoma vs Nevi, b) SCC vs AK, c) Malignant vs Benign, d) Melanoma vs Non-melanoma.



feature selection are suggested, as well as the combination of dermoscopic and thermal features to improve classification results.

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