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Prototype system for feature extraction, classification and study of medical images

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ABSTRACT

Colonoscopy exam images are useful to identify diseases, such as the colorectal cancer, which is one of the most common cancers worldwide. Computational image analysis and machine learning techniques can assist experts to identify abnormalities in these images. In this work, we present and evaluate MIAS 3.0, which aims to help experts to study and analyze colon tissue images. To do so, the system initially extracts features from these images. Currently, Amadasum, Haralick and Laws texture descriptors are supported. Then, the described images are classified into normal or abnormal images. In this version, J48, nearest neighbor, backpropagation based on multilayer perceptron, naive Bayes, and support vector machine classification algorithms are implemented. MIAS was developed with open source technologies using a software engineering approach to improve flexibility and maintainability. In this work, MIAS was quantitatively assessed by its application in a set of 134 tissue image fragments. The classifiers built from this set were compared according to the cross-validation and contingency table strategies. Also, the system was qualitatively evaluated using 12 heuristics by twelve volunteers from Health and Exact Sciences. The issues found were categorized according to Rolf Molich's severity scale. As a result, the J48 classifier achieved the highest sensitivity (85.07%) and reasonable average error (18.68%). In the qualitative evaluation, 61.26% of the issues found were not considered serious. These assessments suggest that MIAS can be useful to assist domain experts with minimum knowledge in informatics to conduct more complete studies of medical images, by identifying patterns regarding different abnormalities.

1. Introduction

Colorectal cancer is the third most common cancer and the third leading cause of cancer death in both men and women in the USA. The American Cancer Society estimates that in 2014, 136,830 people will be diagnosed with colorectal cancer and 50,310 people will die from the disease (Society, 2014). In Brazil, this cancer is the third most common among males and second in females with an expected 15,070 new cases in men and 17,530 in women in 2015 (National Cancer Institute of Brazil, 2014). The colonoscopy examination is an essential tool for the diagnosis and treatment of problems affecting the large intestine, such as ulcers, polyps and inflammatory diseases, which may contribute to the development of colorectal cancer. After the examination, the images of the patient's intestinal wall are collected and used by medical experts in the diagnosis of illnesses (Quilici, 2000). These images are also stored in order to maintain information regarding patient history and to complement future diagnoses.

Nonetheless, with the increase of clinical data storage, experts may require more time to examine such images when compiling medical reports. These images may also contain abnormalities that cannot be a 100% identified by the naked eye even when the abnormalities are visible. As a result, a biopsy, which involves removing a small sample of tissue in a region of interest for detailed pathological analysis, can be necessary. Also, there is still little research on computational systems to characterize and classify colon images. Thus, it becomes necessary to develop methods and tools that assist to organize and manage this clinical data, as well as to efficiently identify abnormalities from the medical images.

Based on these requirements, the Laboratory of Bioinformatics (LABI) at the Western Paraná State University (Unioeste/Foz do

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Iguaçu) in partnership with the Department of Coloproctology at the State University of Campinas (Unicamp), has been developing a multidisciplinary project called Medical Image Analysis. Its aim is to research and develop methods and tools for image analysis (IA) and machine learning (ML) to help medical experts in disease diagnoses by means of feature extraction and classification of medical images. These tasks are related, respectively, to characterize images and to differentiate normal from abnormal images. The project consists of two phases: phase 1 studies and applies IA techniques in images before building classification on images to then buiding classification models using ML techniques; phase 2 uses the models to classify and study new images.

As part of this project, it was developed a computational system called the Medical Image Analysis System (MIAS 1.0) (Ferrero et al., 2009), which assists in the extraction of features from colon tissue images and also permits the construction of Machine Learning Models like decision trees and nearest neighbor. This system makes available feature extraction techniques based on texture, using representation in gray-level co-occurrence matrices (GLCM) (Amadasun & King, 1989; Pedrini & Schwartz, 2008). MIAS 1.0 consists of the following four modules:

1. Image directory visualization module: allows the user to explore directories in a computer to select images;
2. Image listing module: allows the user to view selected data from the previous images module;
3. Image viewing module: allows the user to view two images (one normal and one abnormal) through a graphical interface;
4. Feature extraction module: allows the system to extract image features by the GLCM representation.

Nevertheless, other techniques that can be applied for image feature extraction have been proposed in the literature and, consequently, could be implemented in MIAS 1.0. Furthermore, there were some issues that needed improvement in this system:

- Ease and agility of use in specific experiments;
- Image grouping by class;
- Inclusion of new feature extraction techniques based on texture;
- Semi-automatic export of extracted features into files compatible with ML tools to make classification model building more efficient;
- Use of models built with ML techniques to classify new images.

To do so, we developed the MIAS 3.0 to expand the feature extraction and image representation techniques, as well as to enable the use of classification models built using ML techniques. In this way, we intend to assist medical experts to study diseases and to develop new diagnostic techniques.

2. Related work

In the literature several methods for medical image processing have been proposed. Computational systems that combine these methods with ML techniques can assist domain experts in the study of medical images in different domains, such as colonoscopy. In what follows, some approaches that apply this idea in colon tissue images are briefly described.

Mahapatra, Schueffler, Tielbeek, Buhmann, and Vos (2013) proposes a supervised learning technique in order to identify regions affected by Crohn's disease through abdominal magnetic resonance image processing. This method was applied in a set of 15,708 abdominal magnetic resonance images, in which 6827, 5156 and 3725 images respectively illustrate diseased, normal and background regions. In this set, features based on texture and shape were extracted by using the 2-D Gabor filter banks (2-DGFB) (Liu & Wechsler, 2002) and shape asymmetry (SA) (Liu, Smith, Sun, Smith, & Warr, 2011) methods, respectively. Afterwards, support vector machines (SVM) (Aizerman, Braverman, & Rozoner, 1964), random forest (RF) (Breiman, 2001), and naive Bayes (NB) (Alpaydin, 2014) techniques were applied to build classifiers. The SVM classifiers reached the highest values for accuracy (86.40%), specificity (71.10%), sensibility (96.70%), and precision (96.30%).

In Tamaki et al. (2013), a recognition system for classifying narrow band imaging (NBI) images of colorectal tumors into three types was evaluated according to its performance. A set of 1412 NBI images (908 real images and 504 test images) was used for the experimental evaluation. In this set, the scale invariant feature transform (SIFT) method (Lowe, 2004) was applied to extract features and the SVM technique was employed to build a classifier. In the performance evaluation, the SVM classifier reached accuracy of 96.00% and 93.00%, respectively, in the real and test sets of images. Lastly, the *t*-test (Fredman, Pisani, & Ourvers, 1988) was applied among the outputs, finding no statistically significant difference.

The authors in Fu, Yu, Lin, Chai, and Chen (2014) developed a computer-aided diagnostic system in order to classify colorectal polyps by type. In this sense, an experimental evaluation was applied in a set of 365 colonoscopic images, from which 214 and 151 contain hyperplastic and adenomatous polyps, respectively. To describe the images, GLCM features (based on texture) were extracted. Also, other image features, such as pixel intensity variance (PIV) (Zhang et al., 2006), energy variance (EV) (Zhang et al., 2006), block activity (BA) (Shan, Cheng, & Wang, 2012), and spectral entropy (SE) (Shan et al., 2012), were extracted. Subsequently, a SVM classifier was built by the method, achieving accuracy of 96.00% in the evaluation.

In Kominami et al. (2015), a real-time image recognition system was developed in order to predict histologic diagnoses of colorectal lesions. In an experimental evaluation, the system was applied in a set of 118 colorectal lesion images. From these images, the system extracted texture features using the SIFT method (Lowe, 1999). Afterwards, a classifier was built by SVM. The evaluation of this classifier achieved reasonable accuracy (97.50%), sensitivity (93.00%), specificity (93.00%), positive predictive value (PPV) (93.00%), and negative predictive value (NPV) (93.30%).

A patch-based recognition system presented in Li, Coats, Zhang, and McKenna (2015) aims to build models to classify polyp images. In this study, a 90 polyp dataset was subjected to the feature extraction based on texture using the local binary patterns (LBP) (Ojala, Pietikäinen, & Mäenpää, 2002), random projection (RP) (Dasgupta & Gupta, 2003), and independent subspace analysis (ISA) (Hyvärinen, 2013) methods. The classifiers were built using SVM, *k*-nearest-neighbor (kNN) (Alpaydin, 2014), RF, and artificial neural networks (ANN) (Haykin, 2009) techniques. The learning performance was evaluated according to error rates, *F*-measures, and receiver operating characteristic (ROC) surface. It was found that the classifiers built using RP features achieved best values for these measures. Posteriorly, The McNemar's test (Dietterich, 1998) was applied to verify the existence of a statistically significance difference among classifiers. This test found extremely significant difference with the SVM classifier performing better to classify polyp images.

Table 1 compares our approach with 10 methods for colonoscopy image analysis and classification, including the strategies previously described. To do so, the following criteria are considered:

- **Image set size**: the number of images used in the study;
- **Texture feature(s)**: the methods used to extract features based on texture;