Automated Pressure Ulcer Lesion Diagnosis for Telemedicine Systems

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Abstract

The timely diagnosis and treatment of pressure ulcers is a critical task and constitutes a challenge in patient rehabilitation. In this work we investigate how a tool for automated pressure ulcer stage classification can be integrated into an asynchronous telemedicine system aiming to increase efficiency and monitoring capabilities for large volumes of patient data. The deployment requirements, the internal architecture as well as the employed techniques are outlined. Furthermore, the initial processing results are provided to demonstrate the feasibility of automated classification of pressure ulcer regions in various grades.

Keywords

Pressure ulcer, lesion classification, telemedicine

I. Introduction

A pressure ulcer is a lesion caused by unrelieved pressure resulting in damage of underlying skin tissue when the body stays in one position for too long without shifting the weight. Pressure ulcers occur in acute and chronic health care settings. Even short time bedridden patients (for example, after surgery or an injury) can be found at high risk of developing pressure ulcers. Long term care facilities nursing the elderly and wheelchair dependent patients face high rates of pressure ulcer incidence. In the United States, pressure ulcer prevalence in acute care hospitals is as high as 17 percent, in long term care facilities is 28 percent and at home care at 29 percent. Moreover, there are more than one million new pressure ulcer cases annually and more than 60,000 deaths every year are associated with pressure ulcers. The treatment of pressure ulcers requires nursing care by especially educated personnel, the use of special support surfaces, nutrition supplements and a variety of products that enhance the healing process of the pressure ulcer area. In the United States the estimated cost involved in management of pressure ulcers is estimated to be $6.4 billion annually and the healing cost of a single pressure ulcer can be as much as $50,000 [1].

The accurate diagnosis and the appropriate treatment are crucial because starting the treatment too late may lead to the development of more severe lesions which may be life-threatening; on the other hand starting early results in the unnecessary deployment of expensive means and measures. In most cases the digital images are adequate for recognizing the case severity by experienced personnel. This indicates that digital images of pressure ulcers can be used for telemedicine purposes as pointed out by works such as [2]. Furthermore, the two-dimensional information contained in the photos, which is analyzed by humans for diagnosis, could be analyzed by machines for the same purpose, provided that proper processing techniques exist and can be employed.

Many tests have been performed in the past, where experts were given images and were requested to identify the lesion severity based only on them, e.g., [3], [2]. Furthermore, many researchers have been occupied with the analysis of pressure ulcer images especially for follow up monitoring. However, none of them has dealt with the problem of automated lesion classification. For example [4] proposes a tool using images for classifying the pressure ulcer and for healing monitoring but the related data are entered manually and the classification is done manually as well. In [5] the lesions are measured from photos using a 3D acquisition system employing a pattern-projecting device, so that the spatial data can be extracted, but the automated lesion classification problem is not handled. The idea of using pressure ulcer images for telemedicine purposes has been examined mainly for synchronous applications, where there is always a human who diagnoses the pressure ulcer stage e.g., in [7].

The major priority of the pressure ulcer prevention can best be accomplished by identifying individuals who are at risk for the development of pressure ulcers (conforming to commonly used scales such as the Norton and Braden) and by the initiation of early preventive measures. However, the timely diagnosis and treatment of pressure ulcers constitutes a challenge in patient rehabilitation, since there is a variety of classification systems and because highly skilled and experienced personnel is required. Consistency in diagnosis from various experts can not be easily achieved as mentioned, e.g., in [3], because the human factor itself implies subjective clinical judgement and bias. Moreover, the patients who develop pressure ulcers have serious mobility problems and therefore experts are required, who will be able to monitor them on-site at regular intervals. However, this is not always possible due to the worldwide nursing shortage (see e.g., [6]) since pressure ulcer management services are mainly run by nurses. Of course the problem is even more acute in areas with difficult access. An additional factor that has to be considered is that frequently the pressure ulcers are identified at later stages and in such cases immediate actions are required. Furthermore, the asynchronous telemedicine systems, which collect large volumes of patient data daily, would benefit from automated and constant classification or filtering; such a process could increase significantly the efficiency and monitoring capabilities of the medical experts who classify such images manually. Therefore, a tool that would be able to perform automated diagnosis in an *objective* and *consistent* manner *at any time* with no *location restrictions* is of obvious utility.

In this work we examine the potential of using digital images to classify regions appearing in pressure ulcer images and thus being able to have a diagnosis about the patientís current state. We capitalize on telemedicine infrastructure, which can overcome difficulties posed by remote patient location, and we aim to provide diagnostic tools that will satisfy the above requirements.

The use scenario includes image acquisition, using some simple instructions to ensure high image quality, then logging into the system through a web-browser at any time of the day, uploading the images, marking some regions of interest and giving optionally patient data and comments; then the system provides a diagnosis and proposes therapy; the submitted data are stored so that human experts will be able to monitor selectively the provided results and finalize the diagnosis if necessary.

II. Pressure ulcer characteristics

The National Pressure Ulcer Advisory Panel (NPUAP) define as pressure ulcer *every area of localised damage to the skin and underlying tissue caused by pressure, shear, friction and/or a combination of them* [1].

Pressure ulcers are usually located over bony prominences and are staged to classify the degree of tissue damage observed. The pressure ulcers occur if a wheelchair is used or if the person is bedridden, even for a short period of time (for example, after surgery or an injury). The constant pressure against the skin reduces the blood supply to that area, and the affected tissue dies. The most common places for pressure ulcers are over bony prominences (bones close to the skin) like the heels, back, elbow , hips, ankles, shoulders, and the back of the head (see Fig. 1). A pressure ulcer starts as reddened skin but gets progressively worse, forming a blister, then an open sore, and finally a crater.

Classification grading systems have been developed to assist clinical personnel with gathering consistent information and to define and describe skin damage and to improve diagnosis, treatment and allocation of resources. The classification system proposed by European Pressure Ulcer Advisory Panel (EPUAP) defines the following grades of severity [8]:

- Grade 1: non-blanchable erythema of intact skin. Discolouration of the skin, warmth, oedema, induration or hardness may also be used as indicators, particularly on individuals with darker skin.
- Grade 2: partial thickness skin loss involving epidermis, dermis, or both. The ulcer is superficial and presents clinically as an abrasion or blister.
- Grade 3: full thickness skin loss involving damage to or necrosis of subcutaneous tissue that may extend down to, but not through underlying fascia.
- Grade 4: extensive destruction, tissue necrosis, or damage to muscle, bone, or supporting structures with or without full thickness skin loss.

Additional classes that may coexist with the ones above in pressure ulcers are:

- Black necrosis, which is a sign of dead tissue in arterial insufficiency (of dark color), which can also be seen in parts of an ulcer after an infection.
- White necrosis, which indicates dead tissues and is a preliminary stage of black necrosis (of light color).

The aforementioned classes are depicted in Fig. 2a.

III. Requirements

A classification tool for skin lesions has to fulfill, apart from ease of use, several other requirements so that it is of practical use to the related personnel. We have identified the following:

- *Robustness to acquisition conditions*. The tool has to provide results under a variety of conditions. It can not be assumed that the image acquisition conditions will be uniform or ideal. Therefore, the noise and reflections in the images have to be treated accordingly. Furthermore, the distance of the image acquiring camera, as well as the image orientation, are not known in advance.
- *Discrimination of regions based on color*, since color is one of the most discriminative features for lesion classification into the different stages.
- *Discrimination of regions based on texture*, since texture can provide useful information about the pressure ulcer stage.
- *Consideration of patientís skin color*, since the skin color in case of stage 1 ulcer is quite similar to skin. Different color for stage 1 ulcers is expected when comparing dark skinned patients with light skinned ones.
- *Classification accuracy*, due to the criticality of the task.
- *Ability to classify correctly coexisting different lesion stages*. Different pressure ulcer stages may coexist around the same lesion. It is not correct to classify the whole ulcer to a single class since the separate regions have different properties and consequently need different treatment.

- *Acceptable performance* to enable use for high volumes of data and to ensure response within reasonable time. The performance issue becomes more important as the scale of use grows.

These requirements have been used as a guide for developing the proposed tool.

IV. Tool overview

In Fig. 3 an overview of the tool and its modules is depicted. It works in two modes: *training*, during which the tool learns the characteristics of the pressure ulcer classes and *operation*, during which image segments are classified. A brief description of the process is given in the following, while the image processing and the classification are described in more detail in the next section.

The *training* process starts by retrieving selected images from a repository, which has to include as many representative cases as possible. After noise filtering the images are automatically segmented to find regions with homogeneous characteristics. The image segments are presented to the user, who then labels them according to the class she/he believes that they belong to. After labeling, for each region color and texture features are extracted. Then the features are input to a learning module, which determines the classifier parameters, which will be used during the operation mode.

In the *operation* mode the tool performs classification using the classifier parameters defined in training. The images coming from remote locations are processed in a fashion similar to training (noise reduction, segmentation and feature extraction) without user intervention. The calculated features per region are input to the trained classifier, which then provides a classification result (pressure ulcer stage) for each segment separately.

V. Image processing and classification

As stated above, one of the primary goals of the tool is to segment the regions according to their color features. It is noticed that the lesions have discriminative colors that differentiate them from the surrounding tissues, so color can be used as the primary feature for their detection. Furthermore, the colors regarding each stage are distinct too, thus enabling us to use them for classification.

Due to non-uniform illumination we expect that reflections will be present mainly in a form similar to ìsalt and pepperî noise due to the uneven nature of the skin and the ulcer (however the noise can be dense in some regions). This noise can be minimised by applying median filtering. The median filtering is undesired in the general case, due to the fact that it eliminates ulcer detail, which may be useful for texture feature extraction; therefore we limit its application to regions where we have unusually low saturation values.

For segmentation after noise reduction we use the method proposed by [9]. It is able to capture perceptually distinct regions even though their interior is characterized by large variability, by considering global image characteristics. Furthermore, it is computationally efficient. It measures the evidence of a boundary between two regions by computing (a) intensity differences across the boundary and (b) intensity differences between neighbouring pixels within each region. Intuitively the intensity differences across the boundary of two regions are perceptually important if they are large relative to the intensity differences inside at least one of the regions. For the color images that we examine the intensity difference is calculated for each channel separately.

For texture processing we used for each region the Gabor functions, which form a complete but non-orthogonal basis set, which can be used for expanding the signal to provide a localized frequency description. A class of self-similar functions, which compose the ìfilter dictionaryî, referred to as Gabor wavelets are obtained by appropriate dilations and rotations of a ìmotherî Gabor function. The redundancy of information due to non-orthogonality is reduced by appropriate definition of scale factors and filter parameters as shown in [10].

Each image segment is represented separately by a feature vector, which includes features related to color and texture:

- The calculated color features are based on color histograms in the HSV space. From these values we exclude the ones with very low saturation because they belong most probably to reflections. Due to varying illumination conditions and different skin colors we use as additional feature the Bhattacharya distance of each region from the color of healthy skin. Since the human skin varies within certain limits in the color space this feature is quite discriminative and less sensitive to illumination changes.
- The texture features are calculated using Gabor wavelets for each region. Due to the unknown pose of the camera relatively to the target ulcer we calculate the features in several scales (achieved by reducing resolution) and orientations (achieved by rotating the filters), as shown in [10]. The histograms of the magnitude of the complex transform coefficients are then used as features.

The size and range of histogram bins are defined using a vector quantization scheme to achieve optimal representation and to limit the number of bins due to performance considerations.

For the segment classification task we employ the Support Vector Machine classifier (SVM), which is known for its computational efficiency and effectiveness, even for high dimensional spaces for classes that are not linearly separable [11]. During training we provide the extracted features along with labels indicating if the features correspond to a class or not for each of the seven classes. The SVM gives as output a number of support vectors, which are then used in operation mode for separating the classes.

The output of the classification is a map of the image where the different classes are displayed. Neighboring regions belonging to the same class appear as single regions.

VI Experimental results

The pressure ulcer data used in this research have been acquired in various hospitals. The image acquisition has been performed using mainstream high resolution CCD cameras with a single color sensor. A flash module was enabled providing non-uniform illumination. The acquisition took place from a variety of (approximately known) distances. The images of lower resolution were used as reference for the texture features calculation, i.e., only the scales that matched these lower resolution images were used for calculating texture so that all images could be comparable.

The images were in RGB format, with low or no compression at all, to ensure high quality, using 8 bits per color channel. The color was not normalized during processing.

The images at our disposal were eighty five, and each of them could provide as many as fifty segments, providing samples of different classes. The rectangular regions of interest, which included the pressure ulcer, were manually defined by the operator and then processed by the system for segmentation and classification. Each region included several hundred to several thousand pixels. Approximately one hundred samples were used for training each class. For each patient we also included regions representing healthy skin tissues to compare with pressure ulcer regions in stage 1, which looks quite similar to skin. During the segmentation process we favoured the over-segmentation in order to have as compact regions as possible, but we also defined a minimum segment size, so that we avoided very small regions. The segmentation result was satisfactory in most cases (see Fig. 2b).

For classification we used the linear, the Gaussian radial basis, the polynomial and the sigmoid hyperbolic tangent kernel functions with varying the *C* parameter, which expresses the trade-off between training error and margin. Various kernel parameters were also tested. The training and test samples were of equal size. The overall task was completed in less than 30 seconds in a standard PC for images of about 5Mpixels.

The classification error (average of false positive and false negatives at the region level) is presented in Table 1 for the case of Gaussian radial basis kernel, which provided the best results. Most misclassifications occurred between close stages (difference one). The experimental results can justify that the first approach for this challenging problem is promising despite the difficulties posed by the color and scale variability (due to unconstrained environmental conditions).

The error factors that are inherent in the proposed processing are stemming from (a) the variability of color due to non-uniform illumination, reflections and image sensor properties (b) to scale variations, which affect texture (c) to segmentation errors, and (d) to separation errors during training. The errors stemming from (a) are partially compensated by using the healthy skin color as reference. Errors stemming from (b) can be reduced if a more controlled acquisition process can be executed, i.e., if approximate target distance and camera focal length can be determined, so that the appropriate processing scale can be determined. Errors of type (c) were not that significant to influence the system outcome. Errors stemming from (d) can be reduced by using more specific image features and more complex kernel functions. Our goal is to further automate the feature calculation by applying additional criteria, e.g., class adjacency, to reduce classification errors and to simplify the acquisition process. The scale problem will be able to be automatically calculated by including in the image a simple pattern of known dimensions (marker), placed next to the target.

VII Deployment

An architecture that may be employed is a centralized one, where one (or more) server PCs which will have to receive, process and distribute (if appropriate) the submitted data from several clients over the internet or over intranets. The images along with some additional information (e.g., patient data, comments, regions of interest) have to be submitted through a web-based interface by client PCs. The whole processing functionality in this case is implemented at the server side, thus minimizing complexity for the user. The server has to provide also a secure communication protocol, e.g., https.

The data that have to be typically transmitted are some megabytes per image (normally no more than two or three images need to be analyzed per session for a patient), which necessitates the use of a fast network connection. At the client side only a web browser is required and optionally a compression tool. The additional equipment at the client side includes the image acquisition device and optionally equipment for minimizing reflections (e.g., lamps, optical filters).

Acknowledgement

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References

[1] National Pressure Ulcer Advisory Panel, www.npuap.org

[2] Houghton PE. Kincaid CB. Campbell KE. Woodbury MG. Keast DH. Photographic assessment of the appearance of chronic pressure and leg ulcers. *Ostomy Wound Management.* 46(4):20-6, 28-30, 2000

[3] T. Defloor, L. Schoonhoven, ìInter-rater reliability of the EPUAP pressure ulcer classification system using photographsî, Journal of Clinical Nursing , 13, 952-959, 2004

[4] H. Sanada et al, Reliability and validity of DESIGN, a tool that classifies pressure ulcer severity and monitors healing, Journal of Wound Care, 13(1), 13-18, 2004

[5] C. Roques, L. Theot, N. Frasson, S. Meaume, ìPRIMOS: an optical system that produces three-dimensional measurements of skin surfacesî, Journal of Wound Care, 12(9), 362-364, 2003

[6] S. J. Ross, D. Polsky, J. Sochalski, ìNursing shortages and international nurse migrationî, International Nursing Review, 52 (4), 253-262, 2005

[7] C. Mathewson, V. K. Adkins, M. L. Jones, ìInitial Experiences With Telerehabilitation, and Contingency Management Programs for the Prevention and Management of Pressure Ulceration in Patients With Spinal Cord Injuriesî, Journal of Wound Ostomy and Continence Nurses, 27:269-271, 2000

[8] European Pressure Ulcer Advisory Panel, www.epuap.org

[9] P. F. Felzenszwalb, D. P. Huttenlocher, ìEfficient graph-based image segmentationî, International Journal of Computer Vision, 59(2), 167-181, 2004

[10] B. S. Manjunath, W.Y. Ma, ì Texture features for Browsing and Retrieval of Image Data, IEEE Transactions on Pattern Analysis and Machine Intelligence, 18(8), 837-842, 1996.

[11] N. Cristianini and J. Shawe-Taylor, "Support Vector Machines and other kernel-based learning methods", Cambridge University Press, 2000.

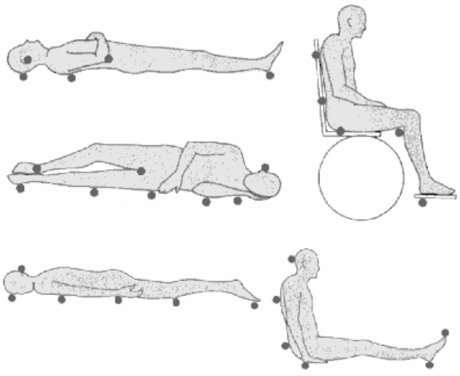
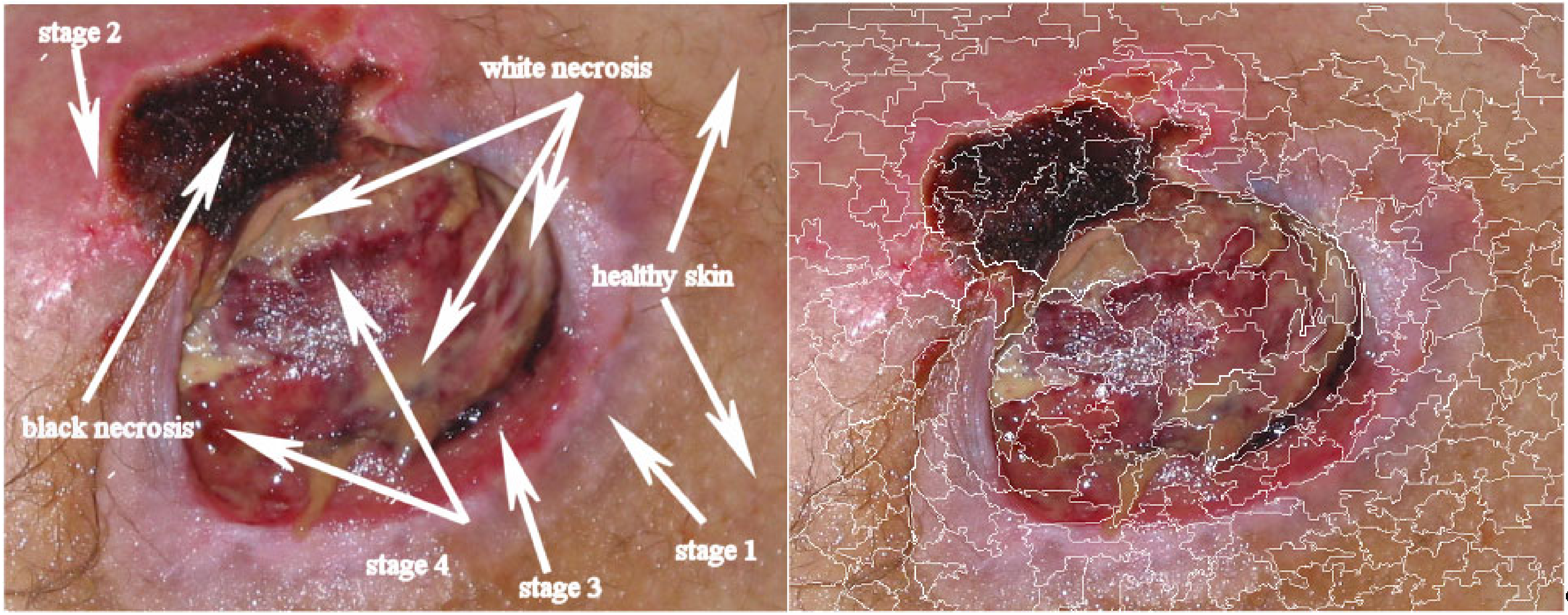


Figure 1 Common locations of pressure ulcer development (source: www.health.nsw.gov.au)



a b

Figure 2 (a) Example of coexisting classes in the same pressure ulcer lesion (b) The same image after segmentation

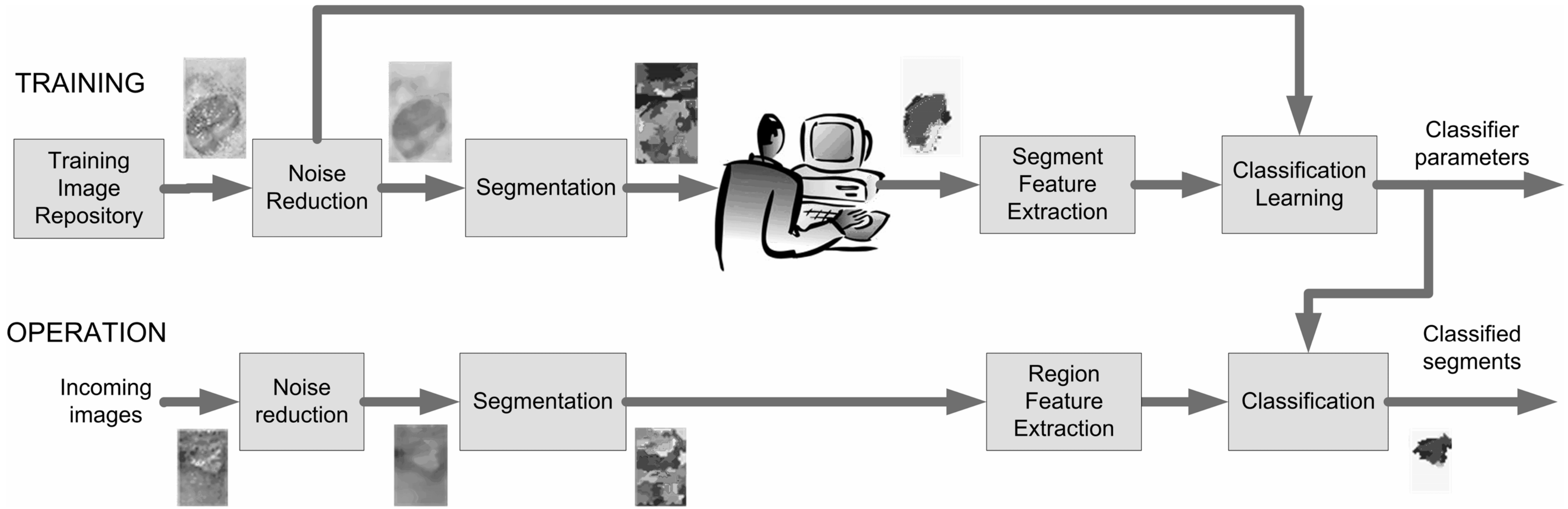


Figure 3 Processing stages for training and operation modes

Table 1: Experimental classification results

Class	**Success rate (%)**
Stage 1	78.32%
Stage 2	75.44%
Stage 3	82.73%
Stage 4	84.11%
White necrosis	87.65%
Black necrosis	91.20%