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Neural Network Based Binary Tissue Classification On Wound Images

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Abstract- In this paper we present an automatic segmentation of wound images based on the process of neural network. Clinicians usually evaluate each pressure ulcer by visual inspection of the damaged tissue, which is imprecise manner of assessing the wound state. Here we use filtering process and then the filtered image is segmented, color and texture features are extracted from these segmented regions. Accurate multi-view classification and wound evaluation is a critical task, we detect the region by feature extraction. The obtained results depicts that the classification yields better results in Neural Network when compared with other techniques like support vector machine.

Keywords—Multi-view classification, wound assessments, automatic segmentation, Neural Network.

I. INTRODUCTION

A pressure ulcer is a clinical pathology of localized damage to the skin and underlying tissue caused by pressure, shear, or friction. Diagnosis, treatment, and care of pressure ulcers are costly for health services. Accurate wound evaluation is a critical task for optimizing the efficacy of treatment and care. Clinicians usually evaluate each pressure ulcer by visual inspection of the damaged tissues, which is an imprecise manner of assessing the wound state. Current computer vision approaches do not offer a global solution to this particular problem.In this Project, neural network is used in the design of a Computational system for automatic tissue identification in wound images. A mean shift procedure and a region-growing strategy are implemented for effective region segmentation. Color and texture features are extracted from these segmented regions, and finally the wound tissues are classified using NN.

II. DIGITAL IMAGE PROCESSING

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems. Many of the techniques of digital image processing, or digital picture processing as it often was called, were developed in the 1960s at the Jet Propulsion Laboratory, Massachusetts Institute of Technology, Bell Laboratories, University of Maryland, and a few other research facilities, with application to satellite imagery, wire-photo standards conversion, medical imaging, videophone, character recognition, and photograph enhancement. The cost of processing was fairly high, however, with the computing equipment of that era. That changed in the 1970s, when suman digital pre processing proliferated as cheaper computers and dedicated hardware became available. Images then could be processed in real time, for some dedicated problems such as television standards conversion. As general-purpose computers became faster, they started to take over the role of dedicated hardware for all but the most specialized and computer-intensive operations.

With the fast computers and signal processors available in the 2000 digital image processing has become the most common form of image processing and generally, it is used because it is not only the

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most versatile method, but also the cheapest. Digital image processing technology for medical applications was inducted into the Space Foundation Space Technology Hall of Fame in 1994.

each pixel is a number known as Digital Number(DN) or Brightness Value (BV), that depicts the average radiance of a relatively small area within a scene (Fig. 1). A smaller number indicates low average radiance from the area and the high number is an indicator of high radiant properties of the area. The size of this area effects the reproduction of details within the scene. As pixel size is reduced more scene detail is presented in digital representation.

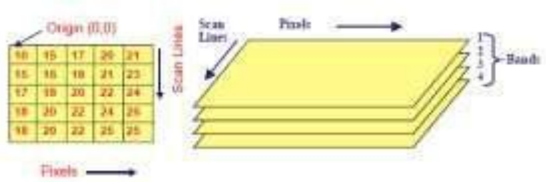

Figure 1: structure of a digital image and multi-spectral image

III. COLOR COMPOSITES

While displaying the different bands of a multispectral data set, images obtained in different bands are displayed in image planes (other than their own) the color composite is regarded as False Color Composite (FCC). High spectral resolution is important when producing color components. For a true color composite an image data used in red, green and blue spectral region must be assigned bits of red, green and blue image processor frame buffer memory

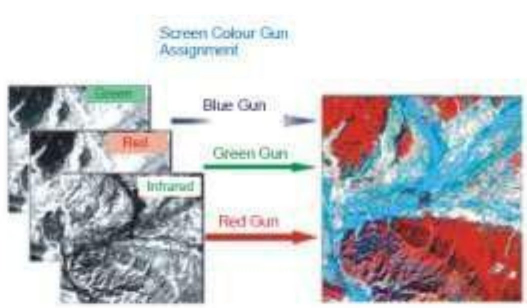

Figure 2**:** False Color Composite (FCC)

. A color infrared composite „standard false color composite‟ is displayed by placing the infrared, red, green in the red, green and blue frame buffer memory (Fig. 2). In this healthy vegetation shows up in shades of red because vegetation absorbs most of green and red energy but reflects approximately half of incident Infrared energy. Urban areas reflect equal portions of NIR, R & G, and therefore they appear as steel grey.

IV. IMAGE ENHANCEMENT TECHNIQUES

Image enhancement techniques improve the quality of an image as perceived by a human. These techniques are most useful because many satellite images when examined on a color display give inadequate information for image interpretation. There is no conscious effort to improve the fidelity of the image with regard to some ideal form of the image. There exists a wide variety of techniques for improving image quality. The contrast stretch, density slicing, edge enhancement, and spatial filtering are the more commonly used techniques. Image enhancement is attempted after the image is corrected for geometric and radiometric distortions. Image enhancement methods are applied separately to each band of a multispectral image. Digital techniques have been found to be most satisfactory than the photographic technique for image enhancement, because of the precision and wide variety of digital processes.

V. SPATIAL FILTERING

A characteristic of remotely sensed images is a parameter called spatial frequency defined as number of changes in Brightness Value per unit distance for any particular part of an image. If there are very few changes in Brightness Value once a given area in an image, this is referred to as low frequency area. Conversely, if the Brightness Value changes dramatically over short distances, this is an area of high frequency.Spatial filtering is the process of dividing the image into its constituent spatial frequencies, and selectively altering certain spatial frequencies to emphasize some image features. This technique increases the analyst‟s ability to discriminate detail. The three types of spatial filters used in remote sensor data processing are : Low pass filters, Band pass filters and High pass filters.

VI. LOW-FREQUENCY FILTERING IN THE SPATIAL DOMAIN

Image enhancements that de-emphasize or block the high spatial frequency detail are low-frequency or low-pass filters. The simplest low-frequency filter evaluates a particular input pixel brightness value, B Vin, and the pixels surrounding the input pixel, and outputs a new brightness value, B V-out , that is the mean of this convolution. The size of the neighborhood convolution mask or kernel (n) is usually 3x3, 5x5, 7x7, or 9x9.The simple smoothing operation will, however, blur the image, especially at the edges of objects. Blurring becomes more severe as the size of the kernel increases.

Using a 3x3 kernel can result in the low-pass image being two lines and two columns smaller than the original image. Techniques that can be applied to deal with this problem include (1) artificially extending the original image beyond its border by repeating the original border pixel brightness values or(2) replicating the averaged brightness values near the borders, based on the image behaviour within a view pixels of the border. The most commonly used low pass filters are mean, median and mode filters.

VI. HIGH-FREQUENCY FILTERING IN THE SPATIAL DOMAIN

High-pass filtering is applied to imagery to remove the slowly varying components and enhance the high-frequency local variations. Brightness values tend to be highly correlated in a nine-element window. Thus, the high frequency filtered image will have a relatively narrow intensity histogram. This suggests that the output from most high-frequency filtered images must be contrast stretched prior to visual analysis.

VII. SEGMENTATION (IMAGE PROCESSING)

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.[1] Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics.

VIII. NEURAL NETWORKS SEGMENTATION

Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen map.

Pulse-Coupled Neural Networks (PCNNs) are neural models proposed by modeling a cat‟s visual cortex and developed for high-performance biomimetic image processing. In 1989, Eckhorn introduced a neural model to emulate the mechanism of cat‟s visual cortex. The Eckhorn model provided a simple and effective tool for studying small mammal‟s visual cortex, and was soon recognized as having significant application potential in image processing. In 1994, the Eckhorn model was adapted to be an image processing algorithm by Johnson, who termed this algorithm Pulse-Coupled Neural Network. Over the past decade, PCNNs have been utilized for a variety of image processing applications, including: image segmentation, feature generation, face extraction, motion detection, region growing, noise reduction, and so on. A PCNN is a two-dimensional neural network. Each neuron in the network corresponds to one pixel in an input image, receiving its corresponding pixel‟s color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation. Compared with conventional image processing means, PCNNs have several significant merits, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns, etc.

IX. FEATURE EXTRACTION

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification

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algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. In the proposed method two features are combined for the classification of micro calcification in the mammogram. They are „S" feature and the Jacobi moments. Two-dimensional discrete Hare wavelet transform is applied to the given ROI image. It decomposes an input image into four sub-bands, one average component (LL) and three detail components (LH, HL,HH). Then SVD is applied to the LL sub band only. After applying SVD to the LL band of Wavelet Transform, three rectangular matrices S, U and V are obtained. S is a diagonal matrix which contains the square root Eigen values from U or V in descending order is selected and stored it separately in the feature set. The Jacobi moments are calculated for the given ROI image using equation (10). Since the image has 256x256 sizes, it produces high number of Jacobi moments. Ant Colony Optimization is used for reducing the Jacobi feature set by selecting a subset of features which contains 10 moments that performs very well in the classification phase. And all the 10 moments are stored combined with the

„S" feature. This combined set is used in the classification phase.

CLASSIFICATION PHASE

In the proposed method SVM is used as a classifier. Classification phase executes two phases. In the first one, the classifier is applied to classify mammograms into normal and abnormal cases. Then the mammogram is considered abnormal if it contains tumor (microcalcification). Finally, the abnormal mammogram is classified into malignant or benign in the second stage. In this classification stage,

SVM classifier in every phase is trained at specific number of training set in each category.

1st Stage Classifier

In the first stage, classifier is tested for normal or abnormal images based on combined feature set of "S" matrix and the Jacobi moments features. Then the calculated combined feature set of training images is first trained with the SVM classifier and then tested for all the images including training images for the classification. The number of training and testing images for the 1st stage is given in table 1.

Table 1: Number of Training and Testing samples for 1st stage classifier

Image	Training Images	Testing Images
194	Normal	30
25	Abnormal	12

2nd Stage Classifier

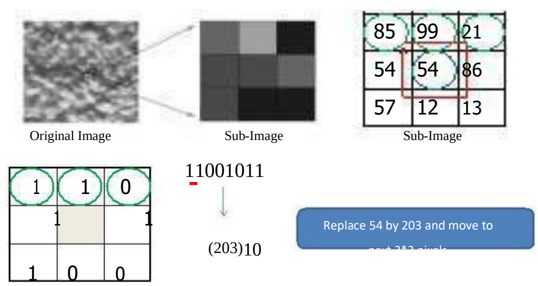
In this stage, the abnormal images from the 1st stage classifier are further classified into Benign or Malignant. The calculated combined feature set of training images is first trained with the SVM classifier and then tested for all the images including training images for the classification of Benign/Malignant. The number of training and testing images for the 2nd stage is given in table 2.

Table 2: Number of Training and Testing samples for 2nd stage classifier

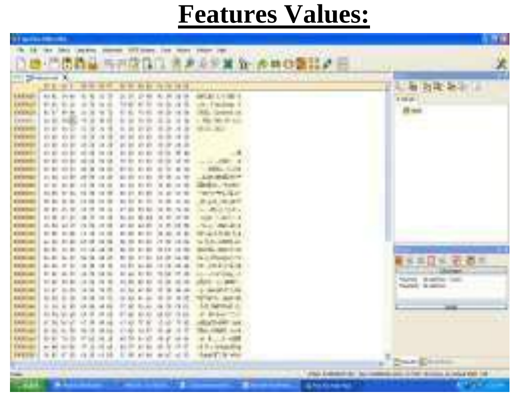
Image	Training set	Testing set
12	Benign	6
13	Malignant	6

LOCAL BINARY PATTERN

Extraction of Local Binary Pattern (LBP)



Features Values:



NEURAL NETWORK

The term neural network was traditionally used to refer to a network or circuit of biological neurons. The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Thus the term has two distinct usages: Biological neural networks are made up of real biological neurons that are connected or functionally related in the peripheral nervous system or the central nervous system. In the field of neuroscience, they are often identified as groups of neurons that perform a specific physiological function in laboratory analysis. Artificial neural networks are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex and includes some features that may seem superfluous based on an understanding of artificial networks. A biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. Connections, called synapses, are usually formed from axons to dendrites, though dendrodendritic microcircuits[2] and other connections are possible. Apart from the electrical signaling, there are other forms of signaling that arise from neurotransmitter diffusion, which have an effect on electrical signaling. As such, neural networks are extremely complex. Artificial intelligence and cognitive modeling try to simulate some properties of biological neural networks. While similar in their techniques, the former has the aim of solving particular tasks, while the latter aims to build mathematical models of biological neural systems. In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, in order to construct software agents (in computer and video games) or autonomous robots. Most of the currently employed artificial neural networks for artificial intelligence are based on statistical estimation, optimization and control theory. The cognitive modeling field involves the physical or mathematical modeling of the behaviour of neural systems; ranging from the individual neural level (e.g. modelling the spike response curves of neurons to a stimulus), through the neural cluster level (e.g. modelling the release and effects of dopamine in the basal ganglia) to the complete organism (e.g. behavioural modelling of the organism's response to stimuli). Artificial intelligence, cognitive modelling, and neural networks are information processing paradigms inspired by the way biological neural systems process data. In the brain, spontaneous order arises out of decentralized networks of simple units (neurons). In the late 1940s Donald Hebb made one of the first hypotheses of learning with a mechanism of neural plasticity called Hebbian learning. Hebbian learning is considered to be a 'typical' unsupervised learning rule and its later variants were early models for long term potentiation. These ideas started being applied to computational models in 1948 with Turing's B-type machines and the perceptron. parameters are adapted with an ad-hoc rule similar to stochastic steepest gradient descent. Because the inner product is a linear operator in the input space, the perceptron can only perfectly classify a set of data for which different classes are linearly separable in the input space, while it often fails completely for non-separable data. While the development of the algorithm initially generated some enthusiasm, partly because of its apparent relation to biological mechanisms, the later discovery of this inadequacy caused such models to be abandoned until the introduction of non-linear models into the field. The cognitron (1975) designed by Kunihiko Fukushima[3] was an early multilayered neural network with a training algorithm. The actual structure of the network and the methods used to set the interconnection weights change from one neural strategy to another, each with its advantages and disadvantages. Networks can propagate information in one direction only, or they can bounce back and forth until self-activation at a node occurs and the network settles on a final state. The ability for bi-directional flow of inputs between neurons/nodes was produced with the Hopfield's network (1982), and specialization of these node layers for specific purposes was introduced through the first hybrid network. The parallel distributed processing of the mid-1980s became popular under the name connectionism. The rediscovery of the back propagation algorithm was probably the main reason behind the re popularisation of neural networks after the publication of "Learning Internal Representations by Error Propagation" in 1986 (Though backpropagation itself dates from 1969). The original network utilized multiple layers of weight-sum units of the type $f = g(w'x + b)$, where g was a sigmoid function or logistic function such as used in logistic regression. Training was done by a form of stochastic

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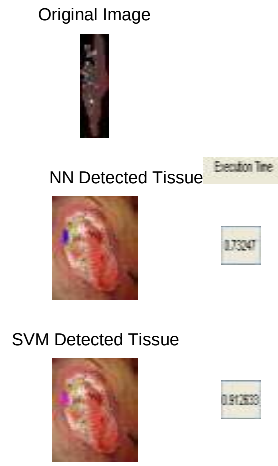
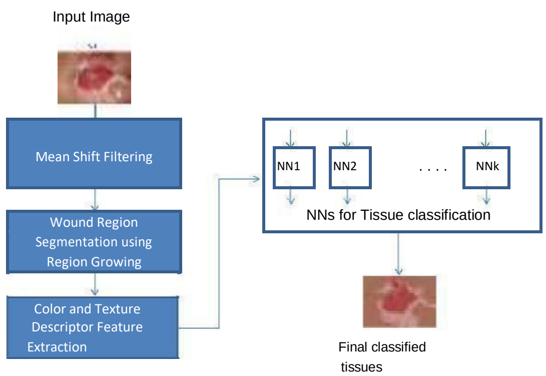
Gradient descent. The employment of the chain rule of differentiation in deriving the appropriate parameter updates results in an algorithm that seems to 'backpropagate errors', hence the nomenclature. In recent times, networks with the same architecture as the backpropagation network are referred to as Multi-Layer Perceptrons. This name does not impose any limitations on the type of algorithm used for learning. The backpropagation network generated much enthusiasm at the time and there was much controversy about whether such learning could be implemented in the brain or not, partly because a mechanism for reverse signaling was not obvious at the time, but most importantly because there was no plausible source for the 'teaching' or 'target' signal.

Detection of Necrosis:





X. CONCLUSION AND FUTURE WORK

In this paper, an evolutionary approach to estimate the classification of wound has been proposed, in which real time information is not provided. Soft computing technique in Neural Network was used in the design of computational system for automatic identification in wound images.

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