DESIGN OF A SCREENING SYSTEM FOR ACUTE LEUKEMIA CELLS BASED ON BONE MARROW **SAMPLES**



2012



DESIGN OF A SCREENING SYSTEM FOR ACUTE LEUKEMIA CELLS BASED ON BONE MARROW SAMPLES

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A thesis submitted in fulfillment of the requirements for the degree of Master of Science (Biomedical Electronic Engineering)

> School of Mechatronic Engineering UNIVERSITI MALAYSIA PERLIS

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LIST OF ABBREVIATIONS

AHE	Adaptive histogram equalization
ALL	Acute lymphoblastic leukemia
AML	Acute myeloblastic leukemia
ANN	Artificial neural network
ASBRG	Automatic seed based region growing
BG	Background
BP	Backpropagation
BR	Bayesian Regularization
CAD	Computer aided diagnosis
CBC	Complete blood count
CLAHE	Contrast-limiting adaptive histogram equalization
CLL	Chronic lymphoblastic leukemia
CML	Chronic myeloblastic leukemia
СТ	Computed tomography
DBC	Differential blood count
DCS	Dark contrast Stretching
EKG	Electrocardiography
FAB	French American British
FCM	Fuzzy C-mean
FN	False negative
FP	False positive
GLCM	Gray level co-occurrence matrix
H ² MLP	Hierarchical hybrid multilayer perceptron

HE	Histogram equalization
HN	Hidden neuron
HSI	Hue Saturation Intensity
HSIL	High grade squamous intraepithelial lesion
HSV	Hue Saturation Value colour space
IBL	Instance-based learning
KNN	K-nearest neighbor
L1	Acute lymphoblastic leukemia subtype
L2	Acute lymphoblastic leukemia subtype
L3	Acute lymphoblastic leukemia subtype
LDA	Linear discriminant analysis
LM	Levenberg Marquardt
LSIL	Low grade squamous intraepithelial lesion
LVQ	Learning Vector Quantization
M0 – M7	Acute myeloblastic leukemia subtype
MAb	Monoclonal antibody
MLP	Multilayer Perceptron
PAS	Periodic acid-shiff
PCS	Partial contrast stretching
RBC	Red blood cell
RBF	Radial basis function
RGB	Red green blue color space
RVM	Relevance vector machine
SBRG	Seed based region growing
SE	Sensitivity

SP	Specificity
SRGFE	Seeded region growing features extraction
SVM	Support Vector Machine
ТА	Training algorithm
ТВ	Tubercle Bacilli
TH	Threshold Value
TN	True negative
TP	True positive
WBC	White blood cell
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LIST OF SYMBOLS

f_i'	Final values of a feature
f _i	Initial values of a feature
$\overline{R_n}$	Mean for red color value
$\overline{G_n}$	Mean for green color value
$\overline{B_n}$	Mean for blue color value
$\overline{VR_n}$	Variance for red color value
$\overline{VG_n}$	Variance for green color value
$\overline{VB_n}$	Variance for blue color value
$\overline{SR_n}$	Standard Deviation for red color value
$\overline{SG_n}$	Standard Deviation for green color value
$\overline{SB_n}$	Standard Deviation for blue color value
Pk ter	Color level of the output pixel
$T_j(p,q)$	Topological distance between p and q
$W_{shea}(f)$	Watershed lines
$d_{Chessboard}$	Distance Transform using 'chessboard'
$d_{Euclidean}$	Distance transform using 'euclidean'
[k]	Number of current region of interest
В	Value of blue
С	Circularity
$\underline{e}(\underline{x})$	Network error

f _{max}	Maximum color level values in the input image
f_{min}	Minimum color level values in the input image
G	Value of green
<i>i</i> ₁ , <i>j</i> ₁	Coordinate of object (WBC) pixel
<i>i</i> ₂ , <i>j</i> ₂	Coordinate of non-object (Background) pixel
in(x,y)	Color level of the input pixel.
min & max	Desired color levels that determine color range of the output
	image
тахТН	Upper threshold value
minTH	Lower threshold value
n	Area of white blood cell
NewmaxTH	New upper stretching value
NewminTH	New lower stretching value
NewTH	Dark stretching factor
out(x,y)	Color level of the output pixel
p xell	Perimeter
q_k $(h)^{k}$	Color level of the input pixel
R	Value of red
r	Radius
size [k]	Area of k
Т	Threshold value for thresholding
ТН	Threshold value for dark contrast stretching
$\mu(f_i)$	Mean of all the values of class that features belong to
$\sigma(f_i)$	Standard Deviation of all the values of class that features belong

	to
$CB(m_i)$	Catchment basin
$\nabla^2 V(\underline{x})$	Hessian matrix
Ι	Identity matrix
$J(\underline{x})$	Jacobian matrix
S	Saturation component
f(x,y)	Input image
$\nabla V(\underline{x})$	Gradient
g(x,y)	Output of thresholded image
maxBlue	Maximum blue level values
maxGreen	Maximum green level values
maxRed	Maximum red level values
maxTH	Average number of these maximum color level values for each
	color space
minBlue	Minimum blue level values
minGreen	Minimum green level values
minRed	Minimum red level values
minTH	Average number of these minimum color level values for each
	color space

MEREKABENTUK SISTEM UJIAN SARINGAN SEL LEUKEMIA AKUT

BERDASARKAN SAMPEL SUM - SUM TULANG

ABSTRAK

Kebolehan untuk mengesan kehadiran sel leukemia berdasarkan sampel sum - sum tulang dapat membantu para doktor untuk mengesahkan ujian saringan yang dibuat melalui darah. Walau bagaimanapun, imej slaid sum - sum tulang mempunyai beberapa kekangan seperti kehadiran kawasan latar belakang dan kontras imej yang rendah. Imej slaid sum-sum tulang adalah lebih baik jika kawasan latar belakang dan kesan kontras imej yang rendah dapat dikurangkan. Sehubungan itu, satu sistem pemprosesan imej bersama dengan keupayaan untuk mengelas imej sum – sum tulang telah dibangunkan bertujuan untuk mengurangkan kekangan – kekangan yang boleh mengganggu keputusan diagnosis leukemia yang dibuat secara manual. Terdapat dua jenis teknik peningkatan kontras yang telah diimplemen ke atas imej slaid sum - sum tulang. Teknik - teknik yang telah di implemen adalah algoritma tidak seluruh (partial contrast stretching) dan algoritma kontras gelap (dark contrast stretching). Walaupun, kedua dua teknik peningkatan kontras yang dicadangkan telah memberikan keputusan yang baik ke atas imej slaid sum – sum tulang, algoritma kontras gelap telah dipilih untuk digunakan dalam penyelidikan ini. Proses penyingkiran latar belakang dan sel darah merah telah dimulakan dengan menggunakan komponen ketepuan daripada imej warna HSI. Kehadiran kawasan selain sel darah putih akan disingkir dengan menggunakan algoritma penapisan median. Selain daripada itu, penapisan median juga digunakan untuk mengisi ruang kosong (piksel putih) yang terdapat pada sel darah putih. Teknik peruasan kawasan pula digunakan untuk meruas, menyingkirkan kawasan – kawasan tertentu, serta mengekstrak ciri luas permukaan sel darah putih. Teknik ini mampu mengekalkan saiz dan bentuk asal sel darah putih yang terdapat di dalam imej slaid sum-sum tulang. Tidak seperti didalam darah, sel-sel yang terdapat di dalam kawasan sum – sum tulang saling bertindih di antara satu sama lain. Algoritma batas air (watershed algorithm) telah dilaksanakan ke atas sel-sel darah putih ini untuk memisahkan sel - sel tersebut. Selain daripada ciri luas permukaan, ciri - ciri geometrikal vang lain juga turut diekstrak daripada sel-sel darah putih seperti 'circularity', jejari dan perimeter sel. Ciri – ciri lain seperti warna juga diekstrak termasuk purata, sisihan piawai dan varians untuk setiap RGB komponen; merah, hijau dan biru. Ciri - ciri yang telah diekstrak ini akan dijadikan sebagai data masukan kepada rangkaian MLP dan k-NN untuk dikelaskan kepada imej normal, tidak normal jenis M3 dan tidak normal lain - lain. Algoritma pembelajaran Levenberg Marquardt (LM) dan Bayesian Regularization (BR) telah digunakan untuk menganalisis keupayaan rangkaian MLP untuk tujuan pengesanan. Rangkaian MLP (1A)-BR standard telah memperoleh kejituan yang paling tinggi berbanding rangkaian MLP (1A)-LM dan juga KNN (2A) untuk mengesan imej normal, tidak normal jenis M3 dan tidak normal lain - lain iaitu sebanyak 93.9% ke atas data ujian. Rangkaian MLP hierarki (1B) dan (1C) pula telah memperoleh kejituan sebanyak 99.8% ke atas data latihan dan 98.57% ke atas data ujian Secara keseluruhan, kesemua rangkaian MLP berupaya mengatasi k-NN untuk pengesanan imej sum – sum tulang dengan peratusan kejituan yang tinggi.

DESIGN OF A SCREENING SYSTEM FOR ACUTE LEUKEMIA CELLS

BASED ON BONE MARROW SAMPLES

ABSTRACT

The capability to screen for leukemia based on bone marrow samples could facilitate the doctors in confirming the occurrence of leukemia from blood test. However, the images of the bone marrow slide have several drawbacks such as the appearance of unwanted regions and lack of contrast. The acquired images of the bone marrow slide could be better improved if these drawbacks are reduced. Due to these matters, a digital image processing system with classification capability is built up in this research which aims to reduce the drawbacks arise from manual screening of bone marrow slide. In this research, two enhancement techniques were used to improve the appearance of the acquired bone marrow slide images. These techniques include partial contrast stretching (PCS) and dark contrast stretching (DCS). Although both techniques produced good results, DCS has been chosen to be utilized in this research due to several reliable reasons. The elimination of unwanted regions leaving only the white blood cells (WBCs) in the bone marrow slide images is initiated by using the saturation component of the HSI (Hue, Saturation, Intensity) color space. Some noises (unwanted small particles) that still appeared were removed with median filter. Simultaneously, median filter fills 'holes' (white color pixel) which are enclosed within the WBCs. Subsequently, seed-based region growing (SBRG) algorithm is used to remove unwanted regions based on predefined criteria and at the same time extract the area of WBCs in the bone marrow slide images. SBRG technique is capable to maintain the original size and shape of the WBCs in the image. Unlike in blood, the cells present in bone marrow are packed and often overlapped with each other. The watershed algorithm is used to separate the overlapped white blood cells in the bone marrow slide images. Besides area, several other geometrical features were also extracted from the WBCs include circularity, radius and perimeter. Other color features include mean, standard deviation and variance were also extracted for red, green and blue color respectively. These features were used as input data to the MLP network (standard and hierarchical MLP) and k-NN to be classified as Normal, Abnormal type M3 and Other Abnormal bone marrow slide images. Levenberg Marquardt (LM) and Bayesian Regularization (BR) training algorithms were used to train the MLP networks. Standard MLP, network (1A)-BR has managed to achieve the highest accuracy, which is 93.9% on testing dataset in classification of bone marrow slide images into Normal, Abnormal (M3) and Other Abnormal, outperformed MLP network (1A)-LM and k-NN classifier (2A). Hierarchical classifier, MLP network (1B) and (1C) has managed to achieve an average accuracy of 99.8% on training and 98.57% in testing outperformed the k-NN (2B) and (2C). In general, MLP networks have outperformed the KNN classifiers in the classification tasks of the bone marrow slide images.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Cancer is a disease that conjures up deep fears of a silent killer that creeps up on us without warning. Cancer is a leading cause of death worldwide and accounted for 7.6 million deaths in 2008 (World Health Organization, 2011). Nearly 70,000 new cancer cases were diagnosed among Malaysians in Peninsular Malaysia between 2003 and 2005, according to a report released in early 2008 on the incidence of the disease in West Malaysia (National Cancer Council, Malaysia, 2011). Lung cancer, breast cancer, leukemia and cervical cancer are the most widespread cancers that occur in Malaysia.

Leukemia is a type of blood disease or so-called cancer of the blood. It is the most common form of childhood cancer. In Malaysia, a total of 529 cases of myeloblastic leukemia and 433 cases of lymphocytic leukemia were reported comprising 4.5% of the total number of cancers (National Cancer Registry, Malaysia, 2003). Males predominated over females at a ratio of 1.7:1 for lymphocytic leukemia and 1.1:1 for myeloblastic leukemia. It was the 4th most common cancer with 7.1% in males after lung cancer, 13.8%, nasopharynx cancer, 8.8% and colon cancer, 7.6%. In females, it was the 7th most common cancer with 4.0% after breast cancer, 31%, cervix uteri, 12.9%, colon cancer, 6%, corpus uteri, 4.3%, rectum cancer 4.1% and ovary cancer, 4.1%.

Generally, there are 4 main types of leukemia; acute lymphoblastic leukemia (ALL), acute myeloblastic leukemia (AML), chronic lymphoblastic leukemia (CLL)